Closing Costs, Refinancing, and Inefficiencies in the Mortgage Market

David Zhang*
Rice University

(Click here for latest version)

February 3, 2023

Abstract

I use a structural model to quantify the cross-subsidization in the US mortgage market due to heterogeneous borrower refinancing tendencies. Actively refinancing borrowers gain up to 3% of their loan amount relative to non-refinancing borrowers in expectation. In equilibrium, the presence of borrowers with high refinancing inertia reduces mortgage interest rates particularly on lower upfront closing cost mortgages which have more valuable refinancing options. As a result, actively refinancing borrowers refinance excessively relative to a perfect information, no cross-subsidization benchmark, an effect that accounts for around 28% of the overall refinancing volume and generates significant deadweight losses due to administrative resource costs. Alternative contract designs can simultaneously reduce transfers and increase total welfare.

*I thank John Campbell, Ed Glaeser, Adi Sunderam, Ariel Pakes, and Robin Lee for continuous advice on this paper. I also thank João Cocco, Matthew Curtis, Mark Egan, Xiang Fang, Jiacheng Feng, Xavier Gabaix, Daniel Green, Shiyang Huang, Jun Ishii, Larry Katz, Amir Kermani, Alex Kopytov, David Laibson, Doug McManus, Konstantin Milbradt, Fabrice Tourre, Pascal Noel, Henry Overman, Frank Pinter, David Scharfstein, Jeremy Stein, Dragon Tang, Audrey Tiew, Fabrice Tourre, Boris Vallee, Nancy Wallace, Jeffrey Wang, Paul Willen, Ron Yang, and seminar/conference participants at CityUHK, HKU, TAMU, SMU, BC, UofT, Purdue, Rice, Fed Board, Minnesota, CU Boulder, 2022 Chicago Booth Household Finance Conference, 2022 NBER Summer Institute Real Estate, 2022 North American Summer Meeting of the Econometric Society, 2022 Asian Meeting of the Econometric Society, and 2023 ASSA/AREUEA Meeting for valuable comments which greatly improved the paper. All errors are my own. This research was conducted while the author was a Visiting Fellow at the Federal Reserve Bank of Boston. The views expressed in this paper are solely those of the author and not necessarily those of the Federal Reserve Bank of Boston nor the Federal Reserve System.

1 Introduction

In the US, many borrowers are slow to refinance, or never refinance, their mortgages when interest rates fall, while others are more quick at doing so. This heterogeneity in refinancing inertia which has long been recognized as an important friction in household finance.[1] In this paper, I use a structural model to quantify the distributional and efficiency implications of the heterogeneous consumer refinancing inertia.

My model identifies two main channels through which heterogeneous consumer refinancing inertia affects on the US mortgage market. First, the existence of borrowers with refinancing inertia implies that lenders can afford to charge lower interest rates upfront. This interest rate reduction effect reflects a cross-subsidization from slow to refinance borrowers to the more quick to refinance borrowers. Second, I identify a non-uniformity of the interest rate reduction effect across upfront closing cost choices which distorts borrower contract choice, further increases cross-subsidization, and generates economic inefficiencies. In particular, the interest rate reduction effect is particularly large for lower upfront closing cost mortgages, which generates excessive refinancing by quick to refinance borrowers leading to deadweight administrative costs.

By way of background, mortgage originating lenders must cover their costs. They can do so in two ways. First, they can charge the borrower upfront, though upfront closing costs. Second, they can raise the interest rate on the mortgage, holding fixed its principal balance and then recovering their costs from the secondary market. Most lenders offer a menu of rate and upfront closing cost options to prospective borrowers through a choice of how many "points" to pay to or receive from the lender.[2] Borrowers therefore have a choice of getting a lower rate, higher upfront closing cost mortgage, or a higher rate, lower upfront closing

[1]See, e.g., Schwartz and Torous (1989), Archer and Ling (1993), McConnell and Singh (1994), Stanton (1995), Green and LaCour-Little (1999), Campbell (2006), Agarwal, Rosen, and Yao (2016), Keys, Pope, and Pope (2016), Johnson, Meier, and Toubia (2018), Andersen, Campbell, Nielsen, and Ramadorai (2018), and Gerardi, Willen, and Zhang (2021).

[2]In the industry, each mortgage point refers to 1% of the loan amount that borrowers pay upfront. Positive points in the form of discount points increase the upfront closing cost while reducing the interest rate, while negative points the form of lender credit to reduce upfront closing cost while increasing the interest rate.

cost mortgage.

Higher rate, lower upfront closing cost mortgages by construction carry a more valuable refinancing option compared to lower rate, higher upfront closing cost mortgages, and I show that their prices are more affected by the existence of borrowers with refinancing inertia in equilibrium. This incentivizes actively refinancing borrowers to refinance more often than they otherwise would, due to two mechanisms. First, actively refinancing borrowers become less likely to pay points to reduce their rate, and end up with mortgages with a higher refinancing incentive.[3] Second, actively refinancing borrowers are able to refinance more frequently than they otherwise would by taking out a lower upfront closing cost mortgage when they do refinance. Note that these mechanisms involve changes in the actively refinancing borrowers' upfront closing cost choices and expected refinancing activity, rather than their levels. Because mortgage refinancing involves administrative resources that could have been used for other economic activity, the extra refinancing that quick to refinance borrowers undertake solely to receive transfers generates deadweight losses from a social perspective.

To quantify the size of the cross-subsidy by borrower refinancing tendencies and study its efficiency consequences, I develop a structural equilibrium model that captures borrower heterogeneity in refinancing and moving tendencies while endogenizing borrower choices of upfront closing costs. To do so, I embed the time and state dependence of borrower refinancing behavior described in Andersen, Campbell, Nielsen, and Ramadorai (2020) into a life-cycle model that gives welfare estimates interpretable in dollar-equivalent terms. A zero-profit condition with a Monte Carlo model of mortgage-backed securities pricing pins down the supply side.

Borrowers in my model are heterogeneous in terms of their (i) refinancing costs, including a time-varying ability to refinance and a hassle cost conditional on them being able to

[3]This is consistent with Dave Ramsey's financial advice, which says that: "most buyers won't regain their money on mortgage points because they usually refinance, pay off, or sell their homes before they reach their break-even point." Source: https://www.ramseysolutions.com/real-estate/what-are-mortgage-points. This financial advice turns out to be correct for my benchmark optimally refinancing borrower, but only due to the cross-subsidization from slow to refinance borrowers.

refinance, (ii) moving or exogenous prepayment probabilities, (iii) discount factors, and (iv) liquid wealth and income. The time-varying ability to refinance and the refinancing hassle cost are separately identified from borrower delays in refinancing after their refinancing thresholds has been reached (Andersen et al., 2020), and could reflect both demand-side differences in preferences as well as any supply-side driven differential costs to refinance coming from potential discrimination in the market. Moving or exogenous prepayment probabilities are identified based on prepayment during periods of low interest rate incentives. Discount factors are identified based on choices of upfront closing costs. Borrowers' liquid wealth and income are calibrated using data from the Survey of Consumer Finances (SCF).

I estimate the model using maximum likelihood on a novel data set linking borrower upfront closing cost choices to their subsequent prepayment behavior. Three main conclusions emerge from my empirical work. First, cross-subsidization from slow-to-refinance borrowers significantly affects equilibrium prices and is larger on mortgages with lower upfront closing costs. For a calibrated borrower who is always able to refinance at a hassle cost of \$200, a mortgage with a one percent upfront closing cost carries a 0.97% lower interest rate in the existing market equilibrium relative to a world without cross-subsidization. For mortgages with a four percent upfront closing cost, the difference is smaller at 0.21%. The intuitive reason for the larger cross-subsidization of lower upfront closing cost mortgages is that, from the perspective of the lender, slow to refinance refinance borrowers overpay for their mortgage closing costs when they pay it through the rate because they keep paying the higher interest rate for longer.

A key advantage of my approach is that I am able to quantify the consequences of this cross-subsidization. The economic consequences of this are significant. As my second conclusion, I find that the cross-subsidization of mortgage closing costs generates large transfers between borrowers. Black and Hispanic borrowers are particularly worse off in the pooling equilibrium. As my third conclusion, I show that the efficiency consequences of price distortions are large. In particular, I estimate that around one quarter of all US refinancing would not have occurred but for this cross-subsidization, leading to a welfare loss of around $3.5 billion per year relative to the no cross-subsidization benchmark.

Using the model, I conduct two counterfactual analyses. First, I investigate borrower welfare under an alternative contract design where their closing costs have to be added to the mortgage balance. I find a reduction in cross-subsidization from $1339/borrower to $698/borrower, a decrease of 48%. Furthermore, I find an increase in average borrower utility of $556/borrower in dollar terms. Second, I study the case of automatically refinancing mortgages. This contract eliminates the cross-subsidization between borrowers with different refinancing speeds, and leads to a bigger increase in average borrower utility of $1215/borrower. My results suggests that the equity-efficiency trade-off is not binding in the US mortgage context: it is possible to reduce inequality while increasing total welfare.

My model generates cross-sectional in borrower refinancing behavior through heterogeneous refinancing costs that could come from either the demand or supply side and is consistent with all borrowers being rational. Nevertheless, if one instead views the slow to refinance borrowers as behavioral agents who do not understand the true cost of a higher interest rate, it can also be interpreted as an empirical model of a shrouded equilibrium as in Gabaix and Laibson (2006) where the quick to refinance borrowers select against the slow to refinance borrowers. Since I focus on the dollar value consequences of heterogeneous refinancing behavior and the value of alternative contract designs, my conclusions are invariant to either interpretation.

My paper is related to the literature on borrower heterogeneity in mortgage refinancing behavior. Many papers document large borrower heterogeneity in refinancing behavior conditional on the interest rate savings available, including Archer and Ling (1993), McConnell and Singh (1994), Stanton (1995), Deng, Quigley, and Van Order (2000), Agarwal, Rosen, and Yao (2016), Keys, Pope, and Pope (2016), Johnson, Meier, and Toubia (2018), Andersen et al. (2018), Beraja, Fuster, Hurst, and Vavra (2018), Ambokar and Samaee (2019), Belgibayeva, Bono, Bracke, Cocco, and Majer (2020), and Gerardi, Willen, and Zhang (2021).

Most of this literature has studied this heterogeneity in the reduced form, and none quantifies the cross-subsidization across borrowers with different refinancing tendencies in market equilibrium and studies its efficiency implications.

More closely related to my paper are Fisher, Gavazza, Liu, Ramadorai, and Tripathy (2022) and Berger, Milbradt, Tourre, and Vavra (2023), which uses structural models to study refinancing heterogeneity and cross-subsidization in the UK and US mortgage market, respectively. Neither studies the inefficiencies generated by this cross-subsidization due to distortions in the choices of quick to refinance borrowers, which is the main conceptual contribution of this paper. I show that these inefficiencies are economically important and presents a reason to consider alternative contract designs beyond redistribution. Furthermore, I compute results by race and ethnicity and show that their expected loss under the current US system relative to a no cross-subsidization benchmark is sizable even in an ex ante sense.

My paper also contributes to the literature on life-cycle models of mortgage choice. This includes Campbell and Cocco (2003), Mayer, Piskorski, and Tchistyi (2013), Corbae and Quintin (2015), Campbell and Cocco (2015) Eichenbaum, Rebelo, and Wong (2018), Chen, Michaux, and Roussanov (2020), Campbell, Clara, and Cocco (2021), Guren, Krishnamurthy, and McQuade (2021) and MacGee and Yao (2022). My model builds in both state and time dependence in refinancing costs in a life-cycle model of mortgage choice with endogenous mortgage premia. Of these papers, only Eichenbaum, Rebelo, and Wong (2018) incorporate equilibrium cross-sectional heterogeneity in refinancing behavior, which they use to model the state-dependent behavior of monetary policy, but they do not endogenize the mortgage premia and subsequently do not study its implications in terms of borrower cross-subsidization and efficiency.

In terms of institutions, my paper is related to a growing literature on choices of mortgage upfront closing costs, which are also called points. In this literature, Brueckner (1994) LeRoy (1996), and Stanton and Wallace (2003) present theories of mortgage points that emphasize the role of selection on borrowers' expected prepayment speeds. My empirical work takes the selection effect explored in these theories seriously and evaluates their welfare implications under heterogeneous refinancing tendencies. Chari and Jagannathan (1989) studies the role of insurance to income shocks for the institution of mortgage points, which I also incorporate in my quantitative model. Empirical work on consumer behavior with mortgage points includes Woodward and Hall (2012) who document how points may lead to sub-optimal shopping, Agarwal, Ben-David, and Yao (2017) who show that many borrowers make the "mistake" of paying too much in points given their predicted refinancing propensities, and Benetton, Gavazza, and Surico (2020) who look at the UK context and finds that lenders may exploit heterogeneity in demand elasticities between rates and points to increase profits. Another strand of literature on mortgage points focuses its role in mortgage discrimination, including Bhutta and Hizmo (2019), Bartlett, Morse, Stanton, and Wallace (2019), and Willen and Zhang (2023).

The rest of this paper is structured as follows. Section 2 presents the background about the upfront closing cost and interest rate trade off. Section 3 describes the data used in the study. Section 4 presents motivating facts. Section 5 presents my model and simulation results. Section 6 presents estimation results. Section 7 describes the counterfactual analyses. Section 8 concludes.

2 Background

US borrowers face a choice between a mortgage with a higher interest and a lower upfront closing cost or a mortgage with a lower interest rate and a higher upfront closing cost. I illustrate this choice in Figure 1, which shows a series of options for rates and upfront closing costs from a lender ratesheet. The first column of the table in Figure 1 shows the choices of interest rates that are available to a borrower, while the 15 Day, 30 Day, and 45 Day columns show the corresponding upfront closing costs, quoted in percentages of the loan amount, that borrowers would have to pay in order to receive the rate once the loan is originated within the given lock period. A rate is "locked" when a lender commits to originating a mortgage with the given terms within the stated lock period of, e.g., 15, 30, or 45 days. The quoted upfront payment to the lender which vary by lock period are also called "points." In particular, Figure 1 shows how borrowers might choose a mortgage with a lower interest rate by paying more points, or a mortgage with a higher interest rate by paying fewer (or, even, negative) points.[4] Appendix Figure A.1 shows an example of how borrowers were shown a series of rate and upfront closing cost choices from a price comparison website.

In this paper, I characterize mortgages with low or negative upfront closing costs as mortgages with their price of mortgage origination added to the rate. To be more precise about the definition of the price of mortgage origination added to the rate, focusing on the setting where lenders are selling the mortgages they originate on the secondary market,[5] I decompose lenders' total origination revenue from making a loan as:

$$\underbrace{\text{lender origination revenue}}_{\text{price of mortgage origination}} = \underbrace{\text{upfront closing costs}}_{\text{paid upfront}} + \underbrace{\text{secondary marketing income}(c)}_{\text{added into rate}} \quad (1)$$

where secondary marketing income(c) refers to the net income lenders derive from selling a loan with interest rate c on the secondary market. The secondary marketing income can be alternatively described as the premium of the mortgage relative to par. Mortgages with higher interest rates tend to be more valuable on the secondary market and that originating a mortgage with a high enough interest rate generates positive secondary marketing income. To illustrate what the secondary marketing income as a function of interest rates might look like on a given day, Figure A.2 plots the secondary market value of mortgages based on MBS TBA prices as a percentage of the loan amount at various interest rates on January 2, 2014. The TBA market is a highly liquid market where most MBS are traded, and is described in

[4]Negative points are possible to cover the other upfront closing costs borrowers may have to pay, such as transfer taxes and application fees.

[5]Or, equivalently, where lenders are evaluating the value of their portfolio based on their potential secondary market value.

more detail in Vickery and Wright (2013).

3 Data

For my loan-level analyses, I use a combination of three data sets. The first data set is the 2013–2019 data from Optimal Blue on rate locks. Optimal Blue is a rate-locking platform used by lenders constituting about 40% of all U.S. mortgage originations. Mortgage lenders use rate-locking platforms such as Optimal Blue to assist their loan originators and mortgage brokers in identifying options for rate and upfront closing costs for their clients. It contains information about interest rates, points paid or received by the borrower, and time of the lock. Second, I use the 2013–2021 CRISM (Equifax Credit Risk Insight Servicing McDash Database) data, which is an anonymous credit file match from Equifax consumer credit database to Black Knight's McDash loan-level mortgage data set. It contains information on loan performance and a time-varying borrower characteristic in terms of their Equifax Risk Score. The CRISM data also allows me to classify prepayments as moves or refinances.[6] It has been frequently used to study borrower refinancing behavior.[7] Third, I use the 2013–2019 Home Mortgage Disclosure Act (HMDA) data to capture borrower demographics.

For my main empirical analysis, I construct a match of these data sets, leading to 2013–2021 Optimal Blue-HMDA-CRISM match. I present some summary statistics of this 2013–2021 Optimal Blue-HMDA-CRISM match in Table 1. I focus on 30-year, conforming, fixed-rate mortgages for my study due to their status as the most commonly chosen form of mortgage contract in the US.[8] Further details of the matching procedure as well as additional summary statistics can be found in the Appendix A.2.1 and A.2.

[6] I follow the procedure of Lambie-Hanson and Reid (2018) and Gerardi, Willen, and Zhang (2021) to identify moving by classifying a prepayment as a move if the borrower's address changed within a 6-month window surrounding the prepayment date.

[7] See, e.g., Beraja et al. (2018), Lambie-Hanson and Reid (2018), Di Maggio, Kermani, and Palmer (2020), Cunningham, Gerardi, and Shen (2021), Abel and Fuster (2021), and Gerardi, Willen, and Zhang (2021).

[8] Complex mortgage contracts used to be more common before the financial crisis, but have largely vanished by the start of my sample period (Amromin, Huang, Sialm, and Zhong, 2018).

Finally, I obtain actual data on the rate and upfront closing cost menus from LoanSifter.[9] Summary statistics and more detailed descriptions of the LoanSifter data are shown in Appendix A.2.3. I show that the rate and upfront closing cost trade-off from LoanSifter on average closely matches the rate and secondary marketing income relationship as implied by MBS TBA prices from Morgan Markets in Appendix A.3.

4 Motivating facts

In this section, I present some stylized facts that motivate my model. First, I show that borrowers have heterogeneous refinancing tendencies in Section 4.1. Second, I explore evidence on the selection of borrowers with different prepayment tendencies into upfront closing cost choices in Section 4.2.

4.1 Heterogeneous refinancing tendencies

It is well-known that some borrowers are slow to refinance, while others are more quick to refinance when interest rates fall.[10] This is also true in my Optimal Blue-HMDA-CRISM sample. In particular, Figure 2 plots the Kaplan-Meier survival hazards of prepayment following months where the interest rate incentive for refinancing, here defined as the decrease in the 30-year Freddie Mac survey rate, is greater than 1.2%, which is larger than the optimal refinancing threshold in typical calibrations of both the Agarwal, Driscoll, and Laibson (2013) model and my model as presented in Section 5.

Specifically, the Kaplan-Meier estimates are calculated as follows. Let the number of terminations due to prepayment at time t be p_t, and the number of loans remaining at time t be n_t, where t is monthly. Then, the Kaplan-Meier hazard function is: $\hat{\lambda}_p(t) = \frac{p_t}{n_t}$. The Kaplan-Meier survival function is then the cumulative effect of the Kaplan-Meier hazard

[9] These two data sets have also been used in Fuster, Lo, and Willen (2017) to study the time-varying price of mortgage intermediation.

[10] See, e.g., Archer and Ling (1993), McConnell and Singh (1994), Stanton (1995), Agarwal, Rosen, and Yao (2016), Keys, Pope, and Pope (2016), Johnson, Meier, and Toubia (2018), and Andersen et al. (2018).

function, or $\hat{S}_p(t) = \prod_{t'<t} \left(\frac{p_{t'}}{n_{t'}} \right)$.

Figure 2 shows the results. In particular, more than half of mortgages are not prepaid after 10 months of a relatively high refinancing incentive. While this could be due to supply-side constraints, it also shows that the same pattern holds among a group of borrowers who maintained an Equifax Risk Score of greater than or equal to 700 and an LTV of less than or equal to 80% throughout the sample and are hence unlikely to be unable to refinance due to unemployment, eligibility, or cash flow constraints. Even among this group of borrowers, I find that more half are not prepaid after 10 months of a relatively high refinancing incentive.

4.2 Selection in choices of upfront closing costs

Second, I examine borrower choices of upfront closing costs in my Optimal Blue-HMDA-CRISM data, paying particular attention to selection by borrower type. If borrowers all know their prepayment types and choose upfront closing costs solely based on their expected prepayment propensities, then there would be no cross-subsidization between borrowers despite heterogeneity in prepayment propensities. The choice of upfront closing costs would serve as a screening device that separates borrowers by type, as described in the models of Brueckner (1994), LeRoy (1996), and Stanton and Wallace (2003). While I find some selection in the data, I also find evidence of within-choice heterogeneity in ex-post prepayment and refinancing behavior, which leaves room for cross-subsidization.

In this section, I measure borrower upfront closing costs in terms of "points," where each point is customarily one percent of the loan amount used to reduce the interest rate. Upfront closing costs consist of points plus an application fee. Negative points, also called "lender credit," that reduce the total upfront closing costs paid are also possible. The reason I use points rather than upfront closing costs in this analysis is that, unlike the 2018–2019 Optimal Blue-HMDA data used to analyze upfront closing cost choices in Appendix Section A.4, the 2013–2021 Optimal Blue-HMDA-CRISM data contains only information on points and not any other application fees the lender may charge. To the extent that these application fees are constant within lender and loan type, my lender by county by year fixed effects within the sample of 30-year, fixed rate mortgages alleviates the effects of the potential measurement error.

First, I examine the extent to which borrowers with different prepayment behavior choose different levels of upfront closing costs measured in terms of points. Figure 3 plots the distribution of borrower choices of points by their eventual refinancing or prepayment behavior. I define a non-refinancing borrower as one who did not refinance or otherwise prepay within five years despite facing a Freddie Mac Survey Rate decrease of at least 1.2%. As the figure shows, although non-refinancing borrowers on average pay more points, and borrowers who prepay within five years on average pay fewer points, the difference is small in terms of the overall distribution.

To make sure that the result of Figure 3 holds even after controlling for underwriting variables, I run an OLS regression of the number of points paid with (1) an indicator function for whether the borrower is a non-refinancing borrower, and (2) an indicator function for whether the borrower prepaid within five years. Results are shown in Table A.3. Indeed, while I find a statistically significant positive correlation between non-refinancing borrowers and their payment of points, and a statistically significant negative correlation between borrowers who prepay within five years and their choices of points, the magnitude of the difference in points paid is small at no more than 13 basis points. This analysis suggests that most of the heterogeneity between borrower prepayment behavior remains conditional on choices of upfront closing costs.

Next, I present regression estimates of how borrower choices of points correlate with their prepayment behavior with choices of points and prepayment as the dependent variable. The regressions are of the form:

$$\mathbb{1}_{i,t} = \beta X_i + \gamma Z_i + \xi_{l_{i,t} \times c_{i,t} \times t} + \epsilon_{i,t} \tag{2}$$

where as before X_i is a set of demographic and credit utilization variables including race (Black and Hispanic), gender (male and female), credit card revolver status, and quartiles of education; Z_i is a set of underwriting variables including categories of credit scores at origination, LTV, DTI, and log loan amount; $\xi_{l_{i,t} \times c_{i,t} \times t}$ is the lender by county by year fixed effects. I run three regressions of this form with the indicator variable $\mathbb{1}_{i,t}$ being equal to the amount of points paid, whether the mortgage was prepaid within five years, and whether the mortgage was originated by a borrower who failed to refinance despite facing a greater than or equal to 1.2% refinancing rate incentive.

Results are shown in Table 3. First, in terms of points, I find that borrowers with a larger loan amount pay more points, and that the correlation is small in terms of other borrower characteristics. The correlation between point choices and predicted prepayment behavior is also weak. For example, Black and Hispanic borrowers are significantly less likely to prepay their mortgage and more likely to be a non-refinancing borrower, but their choices of points are not statistically significantly different from zero compared to the other borrowers.[11]

Another way to examine selection is to look at how borrower choices of points relate to their moving and refinancing behavior. Points do predict moving and prepayment behavior in a statistically significant manner, which is indicative of some selection being important in this market. To do so, I run the the linear probability model on an indicator variable for moving or refinancing:

$$\mathbb{1}_{i,t}(\text{move/refi}) = \sum_{j=1}^{N} \beta_j \mathbb{1}(\psi_i = j) + \gamma Z_i + \xi_{l_{i,t} \times c_{i,t} \times t} + \epsilon_{i,t} \quad (3)$$

where $\mathbb{1}_{i,t}(\text{move/refi})$ is an indicator variable that is equal to either moving or refinancing; β_j are a set of coefficients on categories of points choices as represented by the indicator function $\mathbb{1}(\psi_i = j)$, and Z_i is a set of controls including the call option value of refinancing from Deng,

[11]Bhutta and Hizmo (2019) finds that minority borrowers tend to pay fewer points. The discrepancy in results can be explained by the fact that we focus on conforming mortgages rather than FHA mortgages used in Bhutta and Hizmo (2019), and is explored in more detail in Willen and Zhang (2023).

Quigley, and Van Order (2000), the spread of the mortgage interest rate at origination to the Freddie Mac Primary Market Survey Rate (spread at origination, or SATO) as well as its square, and the standard set of loan amount, credit score at origination (credit score), loan-to-value ratio (LTV), and debt-to-income ratio (DTI) controls. In particular, the call option value of refinancing is defined as:

$$Call\ Option_{i,k} = \frac{V_{i,m} - V_{i,r}}{V_{i,m}} \tag{4}$$

where

$$V_{i,m} = \sum_{s=1}^{TM_i - k_i} \frac{P_i}{(1+m_{it})^s} \tag{5}$$

$$V_{i,r} = \sum_{s=1}^{TM_i - k_i} \frac{P_i}{(1+c_i)^s} \tag{6}$$

and c_i is borrower i's mortgage rate at origination, TM_i is the mortgage term, k_i is the number of months already past, m_{it} is the Freddie Mac Primary Market Survey Rate, and P_i is the size of the current mortgage payment. The *Call Option* variable represents the potential interest rate savings from refinancing, which is positively correlated with refinancing behavior. Finally, $\xi_{l_{i,t} \times c_{i,t} \times t}$ represents lender by county by year fixed effects, and $\epsilon_{i,t}$ is the error term.

Figure 4 present the results. In particular, Figure 4a plots the predicted probabilities of moving by categories of points paid in intervals of width 1. It shows that, all else equal, the borrowers' moving hazard is decreasing in the amount of points that they pay, which is consistent with a selection story. Figure 4b shows the same pattern but for refinancing.

Table 2 shows the regression coefficients that underlie these results. The regression coefficients show a negative, monotone, and statistically significant relationship between the level of points paid and moving and refinancing probabilities. In terms of additional covariates, the *Call Option*, spread at origination *SATO*, and log of the loan amount are positively correlated with moving and refinancing.

The earlier analysis has focused on the differences between upfront closing cost choices among borrowers. A question remains about the level of upfront closing cost choices, which determines the extent to which borrowers pay their price of origination via the interest rate or upfront, and how much of the price of origination may be susceptible to cross-subsidization by borrower refinancing tendencies. I show that almost all borrowers pay for most of their mortgage closing costs through a higher interest rate on their mortgage relative to mortgage-backed securities yields, rather than upfront in Appendix Section A.4.

Overall, my motivating facts imply that a model of cross-subsidization by prepayment type has to take into account both the within-choice heterogeneity in prepayment behavior as well as the selection of borrowers into point choices by their ex ante prepayment expectation. My model accomplishes both of these tasks. In particular, by estimating a distribution of ex ante moving and refinancing types and how they correlate through borrower choices of points, it simultaneously incorporates both selection and within-choice borrower heterogeneity.

5 Model

The motivating facts in Section 4 show that the existence of significant refinancing inertia in the US mortgage market as well as selection of mortgage contracts by borrower prepayment types. Because borrower refinancing behavior is an important determinant of mortgage interest rates, an equilibrium model that incorporates the supply side (ie. mortgage interest rate) response to heterogeneity in refinancing behavior is needed to get at the welfare questions. I build such an equilibrium of mortgage choice that captures the heterogeneity in borrower refinancing behavior and allows me to assess its welfare implications in dollar terms.

On the demand side, following the state-of-the-art from Andersen et al. (2018), I estimate a distribution of borrower refinancing costs with two components: a fixed refinancing hassle cost and a time varying ability to refinance. In addition, borrowers differ by their moving probabilities and discount factors. These decisions are then embedded in a workhorse life-cycle model of mortgage choice from Campbell and Cocco (2015) and Chen, Michaux, and Roussanov (2020). A competitive supply side pins down mortgage interest rates at various levels of upfront closing costs and closes the model.

Calibration of the model shows evidence of large cross-subsidization of low upfront closing cost mortgages from slow to refinance borrowers. In addition, the fully estimated model allows me to measure the welfare implications of heterogeneity in borrower refinancing tendencies in equilibrium.

5.1 Setup

5.1.1 Demand side

On the demand side, households maximize non-housing consumption with time-separable utility with bequest motive for terminal wealth taking housing choice as exogenous:

$$\max \mathbb{E}_1 \sum_{t=1}^{T} \beta_i^{t-1} \frac{(C_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta_i^T b_i \frac{W_{i,T+1}^{1-\gamma}}{1-\gamma}, \tag{7}$$

where T is the terminal age, β_i the time discount factor, C_{it} the non-durable consumption, γ_i the coefficient of relative risk aversion, and $W_{i,T+1}$ the real terminal wealth.

In terms of exogenous state transitions, I assume that the risk-free rate r_{1t} follows the model of Cox, Ingersoll, and Ross (1985), which has a natural zero lower bound. I take inflation $\pi = 1.68\%$ as a constant equal to the average in my sample.[12] Real (log)labor income L_{it}, house price H_{it}, and changes in the mortgage interest rate at an average level of upfront closing costs $\Delta\bar{c}_t$ are modelled as a vector auto-regression (VAR) with the risk-free rate r_{1t} as an exogenous covariate, the details of which are described in Appendix A.6.1. Finally, moving is treated as an exogenous mortgage refinance at an average level of upfront

[12] Inflation expectations were stable over my sample period, and a constant term for inflation allows me to easily convert the nominal mortgage payment from the amortization table to real terms.

closing costs.

Mortgage payments follow a standard 30 year amortization schedule. In particular, the real mortgage payment under constant inflation is $P_{it}^M = \frac{1}{(1+\pi)^t} M_i \frac{c_{it}/12(1+c_{it}/12)^n}{(1+c_{it}/12)^n - 1}$. Note that the amortization is based on the current rate rather than the full history of rates, which increases the computational tractability of the model. I add a correction for the difference in amortization as an additional upfront payment to be made by the borrower during refinancing so as to be more numerically correct, but the error resulting from this issue is likely to be small for minor differences in rates.

In each period, households make a decision of whether to refinance along with a consumption and savings decision. In doing so, they face financial constraints in the sense that their savings $S_{it} \geq 0$. They make a real mortgage payment P_{it}^M and earn interest r_{1t} on savings minus inflation π_t, and so in non-refinancing periods their non-durable consumption C_{it} in real terms can be written as:

$$C_{it} = \exp(L_{it}) - P_{it}^M + (r_{1,t-1} - \pi_t)S_{it-1} - \Delta S_{it} \tag{8}$$

Where $\Delta S_{it} = S_{it} - S_{it-1}$ is the change in the borrower's savings. In order to refinance, borrowers need to pay a cost $\tilde{\kappa}_{it}$. I model the borrowers' refinancing cost $\tilde{\kappa}_{it}$ as:

$$\tilde{\kappa}_{it} = \begin{cases} \infty, \text{ with probability } 1 - p_i^a \\ \kappa_i, \text{ with probability } p_i^a \end{cases} \tag{9}$$

where p_i^a is the probability that a borrower is able to refinance in a particular time period. The inclusion of time- and state-varying refinancing costs is necessary to fit the data where borrowers do not immediately refinance when facing their cut-off, as described in Andersen et al. (2018) which uses a similar setup for capturing refinancing costs.

Furthermore, I require that the refinance must leave the borrower a loan-to-value (LTV) ratio of at most 95%, which is required by Freddie Mac[13] and captures the constraints to refinancing in periods of house price decline as described in Hurst, Keys, Seru, and Vavra (2016).

The full value function $V_{it}(c_{it}, S_{i,t-1}, \bar{c}_t, r_{1,t-1}, H_{it}, H_{i,t-1}, L_{it})$ is a function of the state variables interest rate on the mortgage c_{it}, last period savings $S_{i,t-1}$, the current market interest rate $\bar{c}_t$, last period's risk-free rate $r_{1,t-1}$, house price H_{it}, lagged house prices $H_{i,t-1}$, labor income L_{it}. Of these variables, c_{it}, S_{it} are endogencous in that they are influenced by the decision to refinance and borrower's consumption decision, while the other states are exogenous. In what follows I write the value function $\tilde{V}_{it}(c_{it}, S_{it}) = V_{it}(c_{it}, S_{it}, \bar{c}_t, r_{1,t-1}, H_{it}, H_{i,t-1}, L_{it})$ as a function of the endogenous variables only for brevity.

When first getting a mortgage, borrowers make a choice of mortgage interest rate c along with their associated upfront closing cost $\psi_{it}(c)$ to maximize their expected utility in the first period:

$$\mathbb{E}_1 U_{i1} = \max_{\Delta S_{i2}, c} \frac{(\exp(L_{i1}) - (\tilde{\kappa}_{i1} + \psi_{it}(c)M) - \Delta S_{i1})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_1 \tilde{V}_{i2}(c, S_{i1}) \tag{10}$$

In the following periods, borrowers make a mortgage payment $P^M(c_{it})$. And in periods where the borrower is able to refinance, their utility can be written as the maximum of what can be obtained by refinancing and not refinancing:

$$\mathbb{E}_t U^a_{it} = \max \begin{cases} \max_{\Delta S_{it}} \frac{(\exp(L_{it}) - P^M(c_{it}) + (r_{1,t-1} - \pi_t) S_{it-1} - \Delta S_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1}(c_{it}, S_{it}) \\ \max_{\Delta S_{it}, c} \frac{(\exp(L_{it}) - P^M(c_{it}) - (\tilde{\kappa}_{it} + \psi_{it}(c)M) + (r_{1,t-1} - \pi_t) S_{it-1} - \Delta S_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1}(c, S_{it}) \end{cases} \tag{11}$$

where the first line of Equation (11) corresponds to the borrower's utility from not refinancing and continuing to get the interest rate c_{it}, while the second line corresponds to the borrower's

[13]Freddie Mac's requirements for refinancing are described in https://sf.freddiemac.com/general/maximum-ltv-tltv-htltv-ratio-requirements-for-conforming-and-super-conforming-mortgages. Fannie Mae has a slightly looser LTV requirement of at most 97%: https://singlefamily.fanniemae.com/media/20786/display.

utility from refinancing to the rate c which affects the upfront closing cost they pay $\psi_{it}(c)$.

Similarly, the borrower's utility given that they are not able to refinance is:

$$\mathbb{E}_t U_{it}^{na} = \max_{\Delta S_{it}} \frac{(\exp(L_{it}) - P_{it}^M - (r_{1t} - \pi_t)S_{i,t-1} - \Delta S_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1}(c_{it}, S_{it}). \tag{12}$$

Finally, I model moving as an exogenous costless refinance to the new mortgage with an interest rate $\bar{c}_t$ that is associated with an average level of closing costs, which occurs with probability p_i^m for borrower i. Therefore, the borrower's utility upon moving is:

$$\mathbb{E}_t U_{it}^{m} = \max_{\Delta S_{it}} \frac{(\exp(L_{it}) - P_{it}^M - (r_{1t} - \pi_t)S_{i,t-1} - \Delta S_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1}(\bar{c}_t, S_{it}). \tag{13}$$

Combined, the value function of the borrower can be written as:

$$\mathbb{E}_t V_{it} = (1 - p_i^m)(p_i^a \mathbb{E}_t U_{it}^a + (1 - p_i^a)\mathbb{E}_t U_{it}^{na}) + p_i^m \mathbb{E}_t U_{it}^m. \tag{14}$$

5.1.2 Supply side

A supply side to the model is needed compute mortgage premia with counterfactual mortgage contract designs. I assume that the supply side is perfectly competitive and that lenders set the rate and upfront closing cost/points trade-off based on the MBS value of mortgages. That is, in equilibrium the relationship between the upfront closing costs paid as a fraction of the loan amount ψ_{it} for borrower i at time t and the mortgage interest rate c is pinned down by a zero profit condition:

$$\pi_{it}^l = \psi_{it} M + \phi_t(c) M - \bar{m}_t^l - m_i^l(M) = 0 \tag{15}$$

where π_{it}^l is lender profit from a originating loan to borrower i at time t, $\phi_t(c)$ is the MBS premium of the mortgage as a percent of the loan amount at the time of origination, and $\bar{m}_t^l$ is average marginal cost incurred by the lender for originating the loan, and $m_i^l(M)$ is the borrower and loan amount specific marginal cost incurred by the lender for originating the loan. Assuming that the marginal cost of loan origination $\bar{m}_t^l + m_i^l(M)$ does not vary by the borrower's choice of points, we have by re-arranging:

$$\psi_{it}(c) = \frac{\bar{m}_t^l + m_i^l(M)}{M} - \phi_t(c). \tag{16}$$

So that, all else equal, a mortgage with a higher interest rate c and MBS value $\phi_t(c)$ would require fewer upfront points ψ_{it}. In particular, my model implies that the MBS value of mortgages with a higher interest rate will be passed-through to borrowers in terms of lower upfront closing costs. This pass-through implication is approximately true in reality, as I show in Figure A.3.

The zero profit condition in Equation (16) requires an estimate of MBS prices $\phi_t(c)$. These prices incorporate heterogeneous borrower refinancing behavior in the current world, but not in counterfactuals without cross-subsidization between borrower refinancing types. Estimation of these counterfactual prices is therefore key to establishing the interest rate effect of heterogeneous borrower refinancing behavior.

I estimate the MBS value of mortgages $\phi_t(c)$ based on an standard expected NPV method where the cashflows from MBS are assumed to be discounted using the risk-free rate r_{1t} plus an option-adjusted spread (OAS) term that compensates for the the liquidity and prepayment risk. The OAS has been used and evaluated as a proxy for expected MBS returns in Gabaix, Krishnamurthy, and Vigneron (2007), Song and Zhu (2018), and Boyarchenko, Fuster, and Lucca (2019), and Diep, Eisfeldt, and Richardson (2021).[14] Under this setup, the MBS value of mortgages may be written as:

$$\phi_t(c)M = E_t \sum_{t'=t}^{t+T} \delta_{t'} q_{t'} [(1 - p_{t'}) P^M(c) + \hat{p}_{t'} B_{t'}^M] - M \tag{17}$$

[14] Another method of valuing MBS is via multivariate density estimation, as in Boudoukh, Whitelaw, Richardson, and Stanton (1997), but that does not allow me to get counterfactual prices under alternative prepayment behavior or with alternative mortgage contract designs.

where $p_{t'}$ is the prepayment probability of the borrower at time t', $q_{t'} = \prod_{j=t}^{t'-1}(1 - p_j)$ is the remaining proportion of borrowers who have not prepaid, $B^M_{t'}$ is the remaining principal the lender gets when a borrower prepays, the lender gets remaining principal $B^M_{t'}$, and $P^M(c)$ is the regular mortgage payment. The discount factor is based on the cumulative risk-free rate in period j, r_{jf}, plus an estimated OAS term that compensates for liquidity and prepayment risk:

$$\delta_{t'} = \frac{1}{\prod_{j=t}^{t'}(1 + r_{jf} + OAS)}. \tag{18}$$

Based on Equations 17 and (18), an estimate of the OAS combined with borrower refinancing behavior allows me to arrive at counterfactual MBS prices. To estimate the OAS, I use actual MBS prices combined with an empirical prepayment hazard function $\hat{p}_{t'}$ and its implied empirical cumulative remaining balance $\hat{q}_{t'} = \prod_{j=t}^{t'-1}(1 - \hat{p}_j)$. Details of the OAS estimation is shown in Appendix A.6.2.

The no cross-subsidization counterfactual, or the equilibrium without pooling of borrower prepayment types, is computed by: (i) computing the required lender payoff in each state as implied by the estimated OAS and $\hat{p}$, conditional on $\bar{c}_t$ and r_{ft} as state variables, and then (ii) finding the rate-point trade-off in separating equilibrium in each period via joint iteration, where each period represents one quarter of calendar time. The joint iteration is conducted as follows. In the last period, borrowers cannot refinance. In the second to last period, the lender creates a rate-and-upfront closing costs schedule based on the borrower's expected behavior in the last period and the required lender payoff, and then the borrower makes a refinancing decision conditional on their state and the lender's schedule, and so on.

Combined with the demand side, my model can be viewed as an equilibrium model of mortgage premia, in line with Campbell and Cocco (2015) and Campbell, Clara, and Cocco (2021), but with the addition of heterogenous borrower refinancing costs and endogenous upfront closing costs. A key assumption in these models is the perfectly competitive supply side. If the supply side were not perfectly competitive as is assumed here, my pricing results would still hold if lenders charged a constant markup across loans (i.e. so that constant revenue per loan in the counterfactual still holds).

5.2 Cross-subsidization by upfront closing cost choice: a calibration

Using the model, I illustrate the cross-subsidization of low upfront closing cost mortgages from the perspective of a quick to refinance borrower through a calibration. All of the analysis in this section is conducted for a calibrated borrower with parameters described in Table 4, where β, M, p^m are the median of the estimates from Section 6, and $p_i^a = 1, \kappa_i = 200$ are chosen to represent the behavior of an optimally refinancing borrower who is always able to refinance with a hassle cost of \$200.

Figure 5 illustrates this pricing impact of cross-subsidization by plotting the implied interest rates from the joint iteration of borrower and lender values in the dashed line. The market rate and upfront closing cost rate-off as implied by the model is shown in the solid line, and the empirical rate and upfront closing cost trade-off is presented in the dotted line. The close match between the two suggests that the supply side of the model, which is the previously described OAS model of MBS valuation, matches the average empirical rate and upfront closing cost well.

As Figure 5 shows, the interest rate trade-off is higher, and steeper, for the calibrated quick to refinance borrower in the no cross-subsidization counterfactual. This suggests that the market interest rate for low upfront closing cost mortgages is especially lower than in the no cross-subsidization case due to the presence of slow to refinance borrowers. In terms of numbers, I find that a mortgage with a one percent upfront closing cost would carry a 0.97% higher interest rate in the no cross-subsidization case relative to the existing market equilibrium, whereas the difference is only 0.21% for a mortgage with a four percent upfront closing cost.

Figure 6 presents the welfare implications of this calibration for the borrower, lender, and society. The calibrated quick to refinance borrower benefits from cross-subsidization, and would have to be paid 2.4% of the loan amount in liquid assets in the no cross-subsidization counterfactual in order to be indifferent from the current world. The lender, on the other land, loses 5.5% of the loan amount in profit in the current world relative to the no cross-subsidization counterfactual. Since the lender loses more than the borrower gains, cross-subsidization led to a social loss of 3.0% of the loan amount. This social loss comes from the excessive refinancing that the quick to refinance borrowers undertake at the expense of the slow to refinance borrowers in the market, which in the calibration is 1.74 times as frequent in expectation relative to the no cross-subsidization counterfactual.

6 Estimation

To estimate the model, I allow $p_i^a, \kappa_i, \beta_i, p_i^m, M_i$ to vary by individual, where p_i^a is the probability that an individual is available to refinance in a particular time period, κ_i is the individual's refinancing hassle cost when they do refinance, β_i is the discount factor, p_i^m is the individual's moving probability, and M_i is the individual's mortgage size. I fix the coefficient of risk aversion $\gamma = 2$, liquid savings at origination to \$50k, and a bequest motive of $b = 200$ in accordance with Campbell and Cocco (2015). To maintain comparability to the TBA market, I further restrict my analysis to 30 year purchase mortgages with a balance above \$150k, FICO above 680, and LTV below 85% following Fusari, Li, Liu, and Song (2020).

I first present the identification argument in Section 6.1, then estimation procedure in Section 6.2, then results in Section 6.3, some calibration based on my estimates in Section 5.2, and finally the implications of my estimates for transfers and welfare in Section 6.4.

6.1 Identification

Of the unknown parameters, the distribution of M_i is observed. I discuss the identification for the distribution of $p_i^a, \kappa_i, \beta_i, p_i^m$ as follows. First, the time-varying ability to refinance p_i^a and hassle costs κ_i are separately identified from borrower responses to the time series movement of the interest rate incentive. More specifically, if the only heterogeneity in borrower refinancing behavior were due to hassle costs, borrowers would refinance immediately when their refinancing cutoff is reached. This is rejected in the data as many borrowers wait long after the interest rate has fallen to their eventual refinancing rate, suggesting that a time-varying refinancing cost is at play. This line of reasoning is also used in Andersen et al. (2020).

Of the other parameters, ex ante moving probabilities p_i^m are identified from the interaction between the interest rate incentive and borrower refinancing behavior. In particular, borrowers who do not refinance when faced with a large interest rate incentive are more likely to subsequently move. This suggests that moving is not just an ex post shock and that there is heterogeneity in moving expectations ex ante. Finally, conditional on refinancing and moving probabilities, discount factors β_i are identified from borrower choices of upfront closing costs. In general, because upfront closing costs involve an initial outlay, they are more attractive to borrowers with a higher discount factor. The choices of borrowers who choose low upfront closing cost mortgages despite being unlikely to refinance or move are rationalized with a lower discount factor.

6.2 Parametrization

I estimate the distribution of the borrower types using mortgage performance data. More specifically, I use a Logit-Normal distribution[15] to model p_i^a, β_i, p_i^m, a Log-Normal distribution to model κ_i, and allow p_i^a, β_i to be correlated via a coefficient ρ. The precise parametrization

[15]The Logit-Normal distribution is the distribution generated by $Y = \frac{\exp(X)}{1+\exp(X)}$ with a normally distributed X. This formulation allows me to model observations that are between zero and one, as well as correlations between them, in closed form.

is as follows:

$$\begin{bmatrix} p_i^a \\ \beta_i \end{bmatrix} \sim Logit\left(MultivariateNormal \left(\begin{bmatrix} \mu_{p^a}(b,h) \\ \mu_\beta \end{bmatrix}, \begin{bmatrix} \sigma_{p^a}^2 & \rho\sigma_{p^a}\sigma_\beta \\ \rho\sigma_{p^a}\sigma_\beta & \sigma_\beta^2 \end{bmatrix} \right) \right) \tag{19}$$

$$p_i^m \sim Logit(Normal(\mu_{p^m}(b,h), \sigma_{p^m})) \tag{20}$$

$$\kappa_i \sim LogNormal(\mu_\kappa(b,h), \sigma_\kappa) \tag{21}$$

where $\mu_{p^a}(b,h), \mu_{p^m}(b,h), \mu_\kappa(b,h)$ can depend on a Black and Hispanic dummy represented by b and h, respectively. This gives me 15 parameters:

$$\theta = (\mu_{p^a}(0,0), \mu_{p^a}(1,0), \mu_{p^a}(0,1), \sigma_{p^a}, \mu_{p^m}(0,0), \mu_{p^m}(1,0),$$
$$\mu_{p^m}(0,1), \sigma_{p^m}, \mu_\kappa(0,0), \mu_\kappa(1,0), \mu_\kappa(0,1), \sigma_\kappa, \mu^\beta, \sigma_\beta, \rho)$$

to estimate. I focus on the correlation ρ between a borrower's probability of being able to refinance and their discount factor because variation in the distribution of κ is small. Intuitively, this is because when borrowers do refinance, they tend to do so for relatively low interest rate savings (ie. in the range of 1%), which would not be reconcilable with a high refinancing hassle cost κ. Therefore, time-varying ability to refinance appears more important in the data, and I also estimate its correlation with the borrowers' discount factors.

In the data, I observe borrowers' prepayment decisions which combines moving and refinancing.[16] I construct the likelihood based on prepayment decisions, which implicitly treats all non-model implied refinancing as a move. Therefore, the moving probability p_i^m in my model captures all exogenous prepayment. The likelihood function for a prepayment decision y_{jt} for loan j at time t given a set of parameters $x_i = \{p_i^a, \kappa_i, \beta_i, p_i^m, M_i\}$ is then:

$$l_{jt}(x_i) = (1 - y_{jt})^{1-p_{jt}(x_i)} y_{jt}^{p_{jt}(x_i)}. \tag{22}$$

[16] I also separately observe moving and refinancing decisions for a subset of prepayments.

Furthermore, at time $t = 0$, the likelihood of observing the borrower with 's choice of upfront closing costs ψ_{i0} that is equal to the optimal choice implied by the model of $\psi_0^*(x_i)$:[17]

$$l'_j(x_i) = \mathbb{1}(\psi_{i0} = \psi_0^*(x_i)). \tag{23}$$

To estimate the model, I simulate individuals with a grid for $x_i = \{p_i^a, \kappa_i, \beta_i, p_i^m, M_i\}$ based on a set of parameters θ, with $x_i \sim \mathcal{F}(\theta)$ where $\mathcal{F}(\theta)$ is the distribution of types from Equations (19) to (21). I then get their model implied optimal point choices ($\psi^*(x_i)$, in whole numbers from -2 to 2) and time-varying prepayment (i.e., refinancing and moving) decisions for each loan-time observation $p_{jt}(x_i)$, and search for the set of parameters that maximizes the likelihood of the data following the standard maximum likelihood formulation:

$$\mathcal{L} \propto \sum_j \log \left(\sum_{i=1}^{nsim} l'_j(x_i) \prod_{t=1}^{T_j} l_{j,t}(x_i) \right), x_i \sim \mathcal{F}(\theta), \tag{24}$$

where $nsim = 2000$ is the number of simulations used to compute the likelihood function.

6.3 Results

In this section I present my estimates for the distribution of borrower types in the population. The parameters and their standard errors are shown in Appendix Table 5, and I plot their distributions in the rest of this section.

Figure 7 presents the estimates on the distribution of refinancing types in the population. In the left panel in Figure 7a, results show that most borrowers have a low probability of being able to refinance in a particular month, with some variance. Mean able-to-refinance probability is 6.0% monthly, or 52% annualized. This is consistent with my stylized fact in Section 4.1 showing that around half of all borrowers fail to refinance following ten months of a relatively high refinancing incentive. In the right panel in Figure 7b, the results show

[17] Since I only observe points and not application fees prior to 2018, I assume a real application fee of \$2000 following Agarwal, Driscoll, and Laibson (2013).

that the implied hassle cost of refinancing for most borrowers is low. Taken together, the results suggest that most of the inaction in refinancing is due to a Calvo-style time-varying ability to refinance rather than hassle costs. The identification in the data is that borrowers who eventually refinance tend to do so at relatively low interest rate savings (for example, at around 1%), which implies a low hassle cost for refinancing for most borrowers despite a time-varying inability to do so.

Figure 8 presents my estimates for borrower discount factors and their correlation with their time-varying ability to refinance. Figure 8a plots the distribution of discount factors, which is above 0.9 for most borrowers, but there is a small group of borrowers with discount factors closer to 0.0. The discount factors are identified from borrower choices of upfront closing costs, and the existence of many borrowers with low refinancing/moving probabilities but nevertheless get higher interest rate, lower closing cost mortgages is rationalized in the model via borrower myopia. Figure 8b shows a strong correlation between the likelihood of being able to refinance and the discount factor. It is a scatterplot drawn from the multivariate Logit-Normal distribution of Equation (19). It shows that many borrowers with a probability of being able to refinance in a particular month of less than 5% also have a discount factor significantly lower than 0.9. On the other hand, borrowers with a probability of being able to refinance in a particular month of greater than or equal to 5% tend to have a discount factor above 0.95.

Finally, Figure 9 presents my estimates of the distribution of moving probabilities by borrower. Ex ante expectations of probabilities are identified from the joint interaction of refinancing hazards and the interest rate incentive to refinance. As Figure 9 shows, annualized moving probabilities are centered around 11% per year, with some groups of borrowers having a lower moving probability. Appendix Figure A.16 plots these distributions by the racial group of the borrower.

6.4 Implications for transfers and welfare

In this section I use my empirical estimates to examine the deviation of borrower behavior from the perfect information benchmark. Doing so allows me to reveal the transfers and efficiency consequences of heterogeneity in borrower refinancing behavior when interacted with the financial contract design of adding closing costs to the rate of the mortgage.

Figure 10 plots the differences in utility in the actual world versus the no perfect information, no cross-subsidization benchmark. I find an average welfare loss of $445 per mortgage, most of it borne by borrowers with a probability of being able to refinance of less than 5%. Given that there are around 8 million new mortgages being originated per year, the welfare loss from the closing cost channel of cross subsidization is around $3.6 billion per year. In addition, the average utility difference to the perfect information benchmark, in absolute dollar value terms, is $1339/borrower, suggesting an average difference in utility of 1% of the loan amount from slow to refinance borrowers to quick to refinance borrowers.[18] By comparison, the difference in utility from comparing the benchmark quick to refinance borrower as calibrated in Section 5.2 to a non-refinancing borrower that has $p_i^a = 0$ but are otherwise similar for a mortgage with zero upfront closing costs is 3.5% of the loan amount.

Figure 11 plots the welfare effects of the cross-subsidization by racial group. The welfare effects are -$1776 per households for Black borrowers, -$1448 per households for Hispanic borrowers, and -$366/borrower for other households. The welfare impact is negative for all racial groups in part due to the deadweight loss generated by the cross-subsidization of mortgage closing costs, but it is particularly strong for minorities.

To get at the excessive refinancing incentives generated by the cross-subsidization of mortgage closing costs, Figure 12 plots the differences in the expected number of refinances per new origination in the actual world versus the perfect information, no cross-subsidization benchmark. I find an average increase of 0.13 refinances per new purchase origination. My

[18] This difference in utility is approximated by doubling the average utility difference to the perfect information benchmark, or $2678/borrower, and dividing by the average loan size of $252,000.

model implies an average number of refinances per new purchase origination of 0.47. Therefore, it implies that 27.5% of the total US mortgage refinancing volume may be considered excessive relative to the perfect information benchmark.

7 Counterfactuals

I conduct two counterfactual analyses. First, I consider an alternative mortgage contract design where closing costs have to be added to the balance of the loan. The advantage of this design is that it eliminates the cross-subsidization of mortgage closing costs: all borrowers have to pay for their own price of mortgage origination. Second, I consider the case of automatically refinancing mortgages, which is a mortgage whose interest rate resets downwards automatically to a lower rate when the market rates falls by more than 1%. This contract has been discussed in Campbell (2006). In both of these cases, I compute the updated borrower and lender value functions, and I re-estimate the equilibrium using the same zero profit condition on the supply side. To avoid complications with multiple equilibria, I restrict myself to counterfactuals where upfront closing cost choices are fixed.

7.1 Adding closing cost to balance

First, I consider the utility changes of borrowers when they add their closing cost to the balance of the loan. That is, their new mortgage balance becomes $M' = M(1 + c^l(M))$, and their mortgage payment becomes:

$$P_{it}(M') = M' \frac{c_{it}/12(1 + c_{it}/12)^n}{(1 + c_{it}/12)^n - 1}. \tag{25}$$

In periods where borrowers are able to refinance, their utility can still be written as the maximum of what can be obtained by refinancing and not refinancing, except that refinancing increases the balance of the loan from M to M'. Hence, M becomes an endogenous state variable that we add to the model which affects the size of the mortgage payment $P_{it}(M')$.

The expected utility in periods where borrowers are able to refinance, $\tilde{U}^a_{i,t}$, is then:

$$\mathbb{E}_t \tilde{U}^a_{i,t} = \max \begin{cases} \max_{\Delta S_{it}} \frac{(\exp(L_{it}) - P_{it}(M) - (r_{1,t-1} - \pi_t) S_{i,t-1} - \Delta S_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1}(c_{it}, S_{it}, M), \text{ if no move/refi} \\ \max_{\Delta S_{it}} \frac{(\exp(L_{it}) - P_{it}(M') - \tilde{\kappa}_{it} - (r_{1,t-1} - \pi_t) S_{i,t-1} - \Delta S_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1}(c_{it}, S_{it}, M'), \text{ if refi} \end{cases} . \tag{26}$$

I simulate borrower utility and prepayment behavior under this counterfactual with borrower utility when they are able to refinance being described by Equation (26) instead of Equation (11). I then obtain the implied aggregate borrower behavior and lender values based on my estimated distribution of borrower types in Table 5, conditional on the paths of interest rates as estimated in Section A.6.1. Finally, I decrease the initial mortgage interest rate for all borrowers, holding fixed their prepayment behavior, until the zero profit condition in Equation (16) is satisfied on average, which is an equilibrium effect of this contract design that increases in borrower utility.

Results are shown in Figure 13a, with a significantly narrower range of utility differences relative to the perfect information benchmark. When closing costs are added to the balance of the mortgage, there are still gains from actively refinancing relative to not refinancing, albeit less than in the current world. This reduces the cross-subsidization between borrower types. In particular, the average utility difference to the perfect information benchmark, in absolute dollar value terms, falls by around half from \$1339/borrower in the current world to \$698/borrower in this counterfactual world. The same reduction in cross-subsidization can be inferred from Figure 13b, which plots the mean utility difference to the perfect information case, in dollar terms, by buckets of borrower refinancing ability.

In terms of total welfare, I find that on average consumer welfare relative to the perfect information benchmark rises from -\$446/borrower to \$110/borrower. Not only is the negative welfare impact of excessive refinancing eliminated in this contract design, but there is also a welfare gain due to the relaxation of financial constraints as closing costs can be added to the balance. In the current world, actively refinancing borrowers can only pre-commit to not undertaking costly refinancing activity by paying more in upfront closing costs, which is itself costly due to financial constraints. Otherwise, they would have to take a higher initial interest rate and refinance more which carries administrative resource costs. The addition of mortgage closing costs to the balance both eliminates the cross-subsidization of mortgage closing costs and resolves this commitment problem. As a result, it is able to simulatenously reduce transfers by borrowers with different refinancing tendencies and also increase total welfare.

Appendix Figure A.17 plots the counterfactual change in utility by racial group under the alternative contract design of adding all closing costs to the balance of the loan. All racial groups gain from this counterfactual, with Black borrowers gaining on average \$1566, Hispanic borrowers gaining \$1325, and other borrowers gaining \$472. The average welfare gain under this counterfactual is \$556.

7.2 Making mortgages automatically refinancing

Second, I consider a counterfactual where mortgages are automatically refinancing and are originated with zero upfront closing costs. In this case, I keep the same demand as in Section 5 but automatically change the mortgage interest rate from c to r whenever $c - r > 1$ conditional on the paths of interest rates as estimated in Section A.6.1. Furthermore, I eliminate the possibility of refinancing as that is no longer relevant. Finally, I increase the initial mortgage premia over the risk-free rate for all borrowers until the zero profit condition in Equation (16) is satisfied in the counterfactual, which is an equilibrium effect of this contract design that decreases borrower utility.

Results are shown in Figure 14. I terms of distribution, automatically refinancing mortgages also feature lower average utility difference to the perfect information benchmark compared to the current world. In particular, I find that this statistic falls from \$1339/mortgage to \$773/mortgage. Furthermore, the automatically refinancing mortgages counterfactual feature a greater welfare improvement relative to the current world compared to adding closing costs to the balance of the loan, at $1216/mortgage. This significant improvement is due to the resource cost savings of refinancing, and is concentrated among the actively refinancing borrowers as shown in Figure 14b. Appendix Figure A.18 plots the counterfactual change in utility by racial group under the alternative contract design of automatically refinancing mortgages, showing that all racial groups would on average increase their utility in this counterfactual.

Conceptually, there are two main channels through which automatically refinancing mortgages can increase total welfare. First, they can eliminate the excessive refinancing incentives from the cross-subsidization of mortgage closing costs. Second, they also generate resource savings by eliminating the administrative and hassle costs of refinancing. To the extent that automatically refinancing mortgages present real resource savings to the economy and enable a more efficient pass-through of monetary policy not modelled here, it may be an attractive contract design for policymakers to consider.

8 Conclusion

The broad lesson of my paper is that in markets for consumer financial products, seemingly small contractual details can have significant equity and efficiency implications. I illustrate this lesson quantitatively in the US mortgage market where borrowers typically choose to finance their closing costs through the rate. I show that this contractual feature exacerbates transfers between borrower refinancing types while also generating deadweight losses through incentivizing excessive origination. In terms of policy, my results suggest that two alternative mortgage contract designs—(1) adding closing costs to the balance of the loan and (2) having automatically refinancing mortgages—can simultaneously reduce inequality in the market and improve total consumer welfare.

References

Abel, Joshua, and Andreas Fuster. 2021. "How Do Mortgage Refinances Affect Debt, Default, and Spending? Evidence from HARP." *American Economic Journal: Macroeconomics* 13(2): 254–291.

Agarwal, Sumit, Itzhak Ben-David, and Vincent Yao. 2017. "Systematic Mistakes in the Mortgage Market and Lack of Financial Sophistication." *Journal of Financial Economics* 123(1): 42–58. ISSN 0304-405X.

Agarwal, Sumit, John C. Driscoll, and David I. Laibson. 2013. "Optimal Mortgage Refinancing: A Closed-Form Solution." *Journal of Money, Credit and Banking* 45(4): 591–622.

Agarwal, Sumit, Richard J. Rosen, and Vincent Yao. 2016. "Why Do Borrowers Make Mortgage Refinancing Mistakes?" *Management Science* 62(12): 3494–3509.

Ambokar, Sumedh, and Kian Samaee. 2019. "Inaction, Search Costs, and Market Power in the US Mortgage Market." *Working Paper*.

Amromin, Gene, Jennifer Huang, Clemens Sialm, and Edward Zhong. 2018. "Complex Mortgages." *Review of Finance* 22(6): 1975–2007.

Andersen, Steffen, John Y. Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai. 2018. "Sources of Inaction in Household Finance: Evidence from the Danish Mortgage Market." *Working Paper*.

Andersen, Steffen, John Y. Campbell, Kasper Meisner Nielsen, and Tarun Ramadorai. 2020. "Sources of Inaction in Household Finance: Evidence from the Danish Mortgage Market." *American Economic Review* 110(10): 3184–3230. doi:10.1257/aer.20180865.

Archer, Wayne R., and David C. Ling. 1993. "Pricing Mortgage-Backed Securities: Integrating Optimal Call and Empirical Models of Prepayment." *Real Estate Economics* 21(4): 373–404.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace. 2019. "Consumer-Lending Discrimination in the FinTech Era." *Working Paper.*

Belgibayeva, Adiya, Teresa Bono, Philippe Bracke, João Cocco, and Tommaso Majer. 2020. "When Discounted Rates End: The Cost of Taking Action in the Mortgage Market." *FCA Occasional Paper No. 54.*

Benetton, Matteo, Alessandro Gavazza, and Paolo Surico. 2020. "Inaction, Search Costs, and Market Power in the US Mortgage Market." *Working Paper.*

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra. 2018. "Regional Heterogeneity and the Refinancing Channel of Monetary Policy." *Quarterly Journal of Economics* 134(1): 109–183.

Berger, David, Konstantin Milbradt, Fabrice Tourre, and Joe Vavra. 2023. "Refinancing Frictions, Mortgage Pricing and Redistribution." *Working Paper.*

Bhutta, Neil, and Glenn B Canner. 2013. "Mortgage Market Conditions and Borrower Outcomes: Evidence from the 2012 HMDA data and Matched HMDA-Credit Record Data." *Federal Reserve Bulletin* 99(4): 1–58.

Bhutta, Neil, and Aurel Hizmo. 2019. "Do Minorities Pay More for Mortgages?" *Working Paper.*

Boudoukh, Jacob, Robert F Whitelaw, Matthew Richardson, and Richard Stanton. 1997. "Pricing mortgage-backed securities in a multifactor interest rate environment: A multivariate density estimation approach." *The Review of Financial Studies* 10(2): 405–446.

Boyarchenko, Nina, Andreas Fuster, and David O. Lucca. 2019. "Understanding Mortgage Spreads." *Review of Financial Studies* 32(10): 3799–3850.

Brueckner, Jan K. 1994. "Borrower Mobility, Adverse Selection, and Mortgage Points." *Journal of Financial Intermediation* 3(4): 416–441.

Campbell, John Y. 2006. "Household Finance, Presidential Address to the American Finance Association." *Journal of Finance* LXI(4): 1553–1604.

Campbell, John Y., Nuno Clara, and João F. Cocco. 2021. "Structuring Mortgages for Macroeconomic Stability." *Journal of Finance* 76: 2525–2576.

Campbell, John Y., and Joao F. Cocco. 2003. "Household Risk Management and Optimal Mortgage Choice." *Quarterly Journal of Economics* 118(4): 1449–1494.

Campbell, John Y., and Joao F. Cocco. 2015. "A Model of Mortgage Default." *Journal of Finance* 70(4): 1495–1554.

Chari, V. V., and Ravi Jagannathan. 1989. "Adverse Selection in a Model of Real Estate Lending." *Journal of Finance* 44(2): 499–508.

Chen, Hui, Michael Michaux, and Nikolai Roussanov. 2020. "Houses as ATMs: Mortgage Refinancing and Macroeconomic Uncertainty." *Journal of Finance* 75(1): 323–375.

Corbae, Dean, and Erwan Quintin. 2015. "Leverage and the Foreclosure Crisis." *Journal of Political Economy* 123(1): 1–65.

Cox, John C., Jonathan E. Ingersoll, and Stephen A. Ross. 1985. "A Theory of the Term Structure of Interest Rates." *Econometrica* 53(2): 385–407.

Cunningham, Chris, Kristopher Gerardi, and Lily Shen. 2021. "The Double Trigger for Mortgage Default: Evidence from the Fracking Boom." *Management Science* 67(6): 3943–3964.

Deng, Yongheng, John M. Quigley, and Robert Van Order. 2000. "Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options." *Econometrica* 68(2): 275–307.

Di Maggio, Marco, Amir Kermani, and Christopher J Palmer. 2020. "How Quantitative Easing works: Evidence on the Refinancing Channel." *Review of Economic Studies* 87(3): 1498–1528.

Diep, Peter, Andrea L Eisfeldt, and Scott Richardson. 2021. “The cross section of MBS returns.” *The Journal of Finance* 76(5): 2093–2151.

Eichenbaum, Martin, Sérgio Rebelo, and Arlene Wong. 2018. “State Dependent Effects of Monetary Policy: the Refinancing Channel.” CEPR Discussion Papers 13223. C.E.P.R. Discussion Papers.

Fisher, Jack, Alessandro Gavazza, Lu Liu, Tarun Ramadorai, and Jagdish Tripathy. 2022. “Refinancing Cross-Subsidies in the UK Mortgage Market.” *Working Paper*.

Fusari, Nicola, Wei Li, Haoyang Liu, and Zhaogang Song. 2020. “Asset pricing with cohort-based trading in mbs markets.” *FRB of New York Staff Report* (931).

Fuster, Andreas, Stephanie H. Lo, and Paul S. Willen. 2017. “The Time-Varying Price of Financial Intermediation in the Mortgage Market.” *Working paper*.

Gabaix, Xavier, Arvind Krishnamurthy, and Olivier Vigneron. 2007. “Limits of Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market.” *The Journal of Finance* 62(2): 557–595. doi:10.1111/j.1540-6261.2007.01217.x.

Gabaix, Xavier, and David Laibson. 2006. “Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets.” *Quarterly Journal of Economics*.

Gerardi, Kristopher, Paul Willen, and David Hao Zhang. 2021. “Prepayment, Race, and Monetary Policy.” *Working Paper*.

Glaeser, Edward L, and Charles G Nathanson. 2017. “An Extrapolative Model of House Price Dynamics.” *Journal of Financial Economics* 126(1): 147–170.

Green, Richard K., and Michael LaCour-Little. 1999. “Some Truths about Ostriches: Who Doesn’t Prepay Their Mortgages and Why They Don’t.” *Journal of Housing Economics* 8(3): 233–248.

Guren, Adam M, Arvind Krishnamurthy, and Timothy J McQuade. 2021. "Mortgage Design in an Equilibrium Model of the Housing Market." *Journal of Finance* 76(1): 113–168.

Hurst, Erik, Benjamin J. Keys, Amit Seru, and Joseph Vavra. 2016. "Regional Redistribution through the US Mortgage Market." *American Economic Review* 106(10): 2982–3028.

Johnson, Eric J, Stephan Meier, and Olivier Toubia. 2018. "What's the Catch? Suspicion of Bank Motives and Sluggish Refinancing." *Review of Financial Studies* 32(2): 467–495.

Keys, Benjamin J., Devin G. Pope, and Jaren C. Pope. 2016. "Failure to refinance." *Journal of Financial Economics* 122(3): 482–499.

Kladivko, Kamil. 2021. *Maximum Likelihood Estimation of the Cox-Ingersoll-Ross Process: the Matlab Implementation*. MATLAB Central File Exchange.

Lambie-Hanson, Lauren, and Carolina Reid. 2018. "Stuck in Subprime? Examining the Barriers to Refinancing Mortgage Debt." *Housing Policy Debate* 28(5): 770–796.

LeRoy, Stephen F. 1996. "Mortgage Valuation Under Optimal Prepayment." *Review of Financial Studies* 9(3): 817–844.

MacGee, James, and Yuxi Yao. 2022. "Accounting for the Rise in Mortgage Debt: Lower Inflation and Mortgage Innovations." *Working Paper*.

Mayer, Chris, Tomasz Piskorski, and Alexei Tchistyi. 2013. "The Inefficiency of Refinancing: Why Prepayment Penalties are Good for Risky Borrowers." *Journal of Financial Economics* 107(3): 694–714.

McConnell, John J., and Manoj Singh. 1994. "Rational Prepayments and the Valuation of Collateralized Mortgage Obligations." *Journal of Finance* 49(3): 891–921.

Schwartz, Eduardo S., and Walter N. Torous. 1989. "Prepayment and the Valuation of Mortgage-Backed Securities." *Journal of Finance* 44(2): 375–392.

Song, Zhaogang, and Haoxiang Zhu. 2018. "Mortgage Dollar Roll." *The Review of Financial Studies* 32(8): 2955–2996.

Stanton, Richard. 1995. "Rational Prepayment and the Valuation of Mortgage-Backed Securities." *Review of Financial Studies* 8(3): 677–708.

Stanton, Richard, and Nancy Wallace. 2003. "Mortgage Choice: What's the Point?" *Real Estate Economics* 26: 173–205.

Vickery, James I, and Joshua Wright. 2013. "TBA Trading and Liquidity in the Agency MBS Market." *Economic Policy Review* 19(1).

Willen, Paul S, and David Hao Zhang. 2023. "Testing for Discrimination in Menus." *Working Paper*.

Woodward, Susan E., and Robert E. Hall. 2012. "Diagnosing Consumer Confusion and Sub-Optimal Shopping Effort: Theory and Mortgage-Market Evidence." *American Economic Review* 102(7): 3249–3276.

Tables and Figures

Table 1: Summary statistics for the Optimal Blue-HMDA-CRISM sample

Panel A: Fixed Characteristics						
	All		Black		Hispanic	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Loan amount ($'000s)	252688.6	114694.2	231226.7	111223.1	237658.2	107874.4
Credit score	748.5	46.0	724.8	53.3	732.6	46.8
LTV (%)	79.8	15.0	84.5	14.6	81.6	14.4
DTI (%)	34.4	9.4	36.7	8.9	37.7	8.4
Interest rate	4.365	0.499	4.565	0.530	4.546	0.530
Points paid	0.006	0.932	-0.119	0.970	-0.093	0.948
First-time home buyer (d)	0.201	0.400	0.275	0.446	0.277	0.448
Single Female (d)	0.249	0.432	0.449	0.497	0.273	0.446
Single Male (d)	0.322	0.467	0.360	0.480	0.437	0.496
Credit Card Revolver (d)	0.110	0.313	0.132	0.339	0.094	0.292
# Observations	338,338		10,211		25,217	
Panel B: Time-Varying Characteristics						
Mark-to-market LTV (%)	67.9	16.7	71.7	15.5	69.2	16.3
Equifax Risk Score	770.3	70.7	743.5	86.6	752.0	75.5
Mark-to-market LTV >95 (d)	0.0068	0.0822	0.0135	0.1156	0.0104	0.1013
Rate gap	0.1618	0.7365	0.2653	0.7887	0.2826	0.7746
Moved (d)	0.0042	0.0646	0.0029	0.0534	0.0030	0.0550
Refied (d)	0.0093	0.0962	0.0071	0.0839	0.0081	0.0895
# Observations	13,192,408		342,089		863,323	

Notes: This table reports summary statistics from the Optimal Blue-HMDA-CRISM merged sample from January 2013 to December 2019, with performance until May 2022. Loan amount is expressed in thousands of dollars, origination costs are expressed in dollars, credit score is the borrower's Optimal Blue credit score at origination, and LTV, interest rate are expressed in percentage points. The label (d) denotes dummy variables. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

Table 2: Choices of points and refinancing/prepayment behavior

	(1) Moved		(2) Refi'ed	
-1.5% to -0.5% points	-0.046***	(-2.60)	-0.021	(-1.54)
-0.5% to 0.5% points	-0.110***	(-5.33)	-0.053***	(-3.93)
0.5% to 1.5% points	-0.120***	(-4.95)	-0.070***	(-4.99)
≥1.5% points	-0.141***	(-5.11)	-0.075***	(-4.33)
Call Option	0.986***	(13.01)	1.290***	(17.81)
SATO	0.025	(0.84)	-0.135***	(-3.87)
SATO Sq	-0.131***	(-6.46)	0.063*	(-2.00)
Log(loan amount)	0.204***	(18.99)	0.095***	(9.62)
Credit score controls	Yes		Yes	
LTV controls	Yes		Yes	
DTI control	Yes		Yes	
Constant	-1.940***	(-15.73)	-0.897***	(-6.88)
Observations	8529466		8529466	
LenderXCountyXYear FEs	Yes		Yes	

Robust t statistics clustered by lender and county in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Note: The data used in this table is the Optimal Blue-HMDA-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. This table regression results from estimation Equation (3). Column (1)'s dependent variable is an indicator variable for whether the borrower has moved in a given month multiplied by 100. Column (2)'s dependent variable is an indicator variable for whether the bororwer has refinanced in a given month multiplied by 100. The control variables include the *Call Option* variable of Deng, Quigley, and Van Order (2000) as described in the text, spread of the mortgage interest rate to the Freddie Mac rate at origination (SATO), log of the loan amount, as well as five categories of credit score, four categories of LTV, and a linear control for DTI. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

Table 3: Borrower choices of points and their prepayment behavior by characteristics

	(1)		(2)		(3)	
	Points		5-year prepayment		Non-Refi Borrower	
Black	0.0337	(0.81)	-0.120***	(-5.48)	0.152***	(7.20)
Hispanic	0.0445*	(1.91)	-0.0802***	(-8.43)	0.0872***	(10.64)
Single male	0.000181	(0.01)	-0.00327	(-0.45)	0.0156*	(1.80)
Single female	-0.0287*	(-1.71)	-0.0133*	(-1.84)	0.0181**	(2.18)
First-time home buyer	0.000776	(0.04)	-0.0340**	(-2.46)	0.0371***	(3.03)
Credit card revolver	-0.0287	(-1.60)	0.0225*	(1.81)	0.000864	(0.05)
1st quartile of education	0.00803	(0.40)	-0.00771	(-0.53)	0.0120	(1.02)
2nd quartile of education	-0.0170	(-0.86)	-0.00622	(-0.76)	-0.00266	(-0.29)
3rd quartile of education	0.00614	(0.56)	-0.00520	(-0.57)	0.00141	(0.18)
Log(loan amount)	0.0382**	(2.34)	0.111***	(9.97)	-0.164***	(-16.22)
Credit score controls	Yes		Yes		Yes	
LTV controls	Yes		Yes		Yes	
DTI control	Yes		Yes		Yes	
Constant	-0.414**	(-2.22)	-0.876***	(-6.53)	2.358***	(18.36)
Observations	25245		25245		25245	
LenderXCountyXYear FEs	Yes		Yes		Yes	

Robust t statistics clustered by lender and county in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Note: The data used in this table is the Optimal Blue-HMDA-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. This table regression results from estimation Equation (2). Column (1)'s dependent variable is the number of points paid, with outliers below -4 and above 4 being excluded from the analysis. Column (2)'s dependent variable is whether the borrower prepayed within five years of the mortgage being originated, conditional on the mortgage being originated before April 2016. Column (3)'s dependent variable is whether the borrower did not refinance or otherwise prepay within five years despite having faced a Freddie Mac Survey Rate decrease of at least 1.2%. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

Table 4: Parameters for an illustrative calibration of cross-subsidization from the perspective of a quick to refinance borrower

Parameter	Value
β_i	0.98
γ_i	2
M_i	\$223,784
p_i^m	0.074
κ_i	200
p_i^a	1
Initial liquid assets	\$50,000
Initial risk-free rate	1.0%
Initial mortgage rate	3.25%
Initial income	\$75,000
Initial house price	\$300,000

Note: These are parameters of the model estimated in Section 5. β refers to the discount factor, γ the coefficient of risk aversion, M the mortgage size, p^m the moving probability, κ_i the fixed component of refinancing costs, and p^a the time-varying ability of a borrower to refinance.

Table 5: Estimated model parameters and their standard errors

Parameter	Value	Standard Error
μ_{p^a}	-2.941	(0.244)
σ_{p^a}	0.879	(0.097)
μ^{β}	2.322	(1.034)
σ_{β}	3.950	(0.045)
ρ	0.956	(0.018)
μ_{p^m}	-2.103	(0.092)
σ_{p^m}	0.190	(0.039)
μ_{κ}	3.551	(0.051)
σ_{κ}	2.108	(0.023)
$\mu^b_{p^a}$	-0.626	(0.326)
$\mu^b_{p^m}$	-0.851	(0.253)
μ^b_{κ}	-0.132	(0.080)
$\mu^h_{p^a}$	-0.520	(0.200)
$\mu^h_{p^m}$	-0.655	(0.153)
μ^h_{κ}	0.059	(0.057)

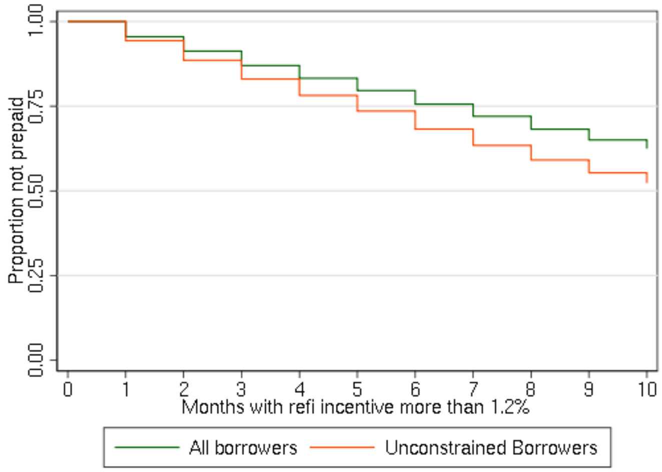
Note: These are parameters of the model estimated from maximum likelihood as in Equation (24). μ_{p^a} and σ_{p^a} refers to the mean and standard deviation of the Logit-Normal distribution of the probability that a borrower is able to refinance. μ_{β} and σ_{β} refers to the mean and standard deviation of the Logit-Normal distribution of the borrower's discount factors. ρ denotes the correlation between the borrower's ability to refinance and their discount factors. μ_{p^m} and σ_{p^m} refers to the mean and standard deviation of the Logit-Normal distribution of the probability that the borrower moves. μ_{κ} and σ_{κ} refers to location and scale parameter of the exponential distribution of the borrower's refinancing hassle costs. Standard errors are from the inverse Hessian.

Figure 1: Rate and upfront closing costs options in an example lender rate sheet

Rate	15 Day	30 Day	45 Day
3.500	4.043	4.213	4.303
3.625	2.910	3.080	3.180
3.750	2.104	2.274	2.364
3.875	1.649	1.829	1.919
4.000	0.917	1.097	1.187
4.125	0.238	0.408	0.508
4.250	(0.569)	(0.399)	(0.309)
4.375	(1.122)	(0.952)	(0.862)
4.500	(1.733)	(1.553)	(1.463)
4.625	(2.281)	(2.111)	(2.011)
4.750	(2.835)	(2.665)	(2.575)
4.875	(3.298)	(3.128)	(3.028)
5.000	(3.546)	(3.376)	(3.276)

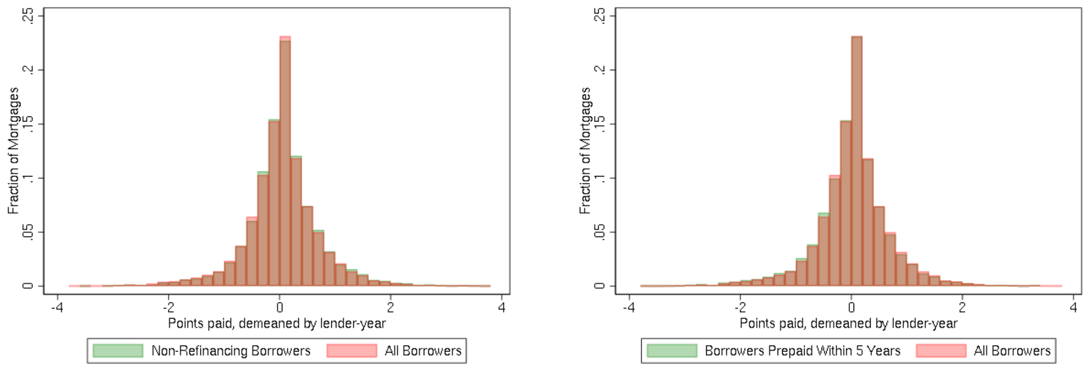
Note: Figure 1 shows a set of rate and upfront closing costs options available to borrowers from an example wholesale lender ratesheet. The first column indicates the rate, while the next three columns shows the amount of upfront closing costs, in the form of points/percentages of the loan amount, the borrower would have to pay to lock the rate for 15, 30, or 45 days, respectively. Negative points are also possible in order to cover the other upfront closing costs the borrowers might have to pay. Figure A.1 shows an example of how a price comparison website displayed the series of rate and upfront closing cost choices.

Figure 2: Kaplan-Meier survival hazards with months of interest rate incentive being greater than 1.2%



Note: The data used in this figure is the Optimal Blue-HMDA-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. The green line Figure 2 presents the Kaplan-Meier survival estimates of prepayment for mortgages with a refinancing incentive, here defined as a Freddie Mac survey rate decrease, of greater than or equal to 1.2%. The red line in Figure 2 shows the result of the same analysis among borrowers with an Equifax Risk Score that is above 700 and an estimated loan-to-value ratio of below 80% throught the sample, which is a group of borrowers who are unlikely to face supply-side constraints in refinancing. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

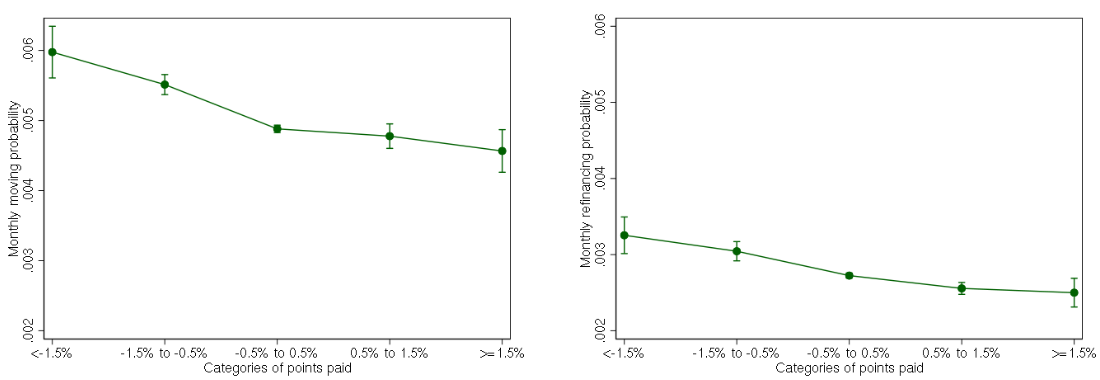
Figure 3: Points paid by borrower prepayment behavior



(a) Refinancing behavior (b) Prepayment behavior

Note: The data used in this figure is the Optimal Blue-HMDA-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. Figure 3a presents a histogram of borrower choices of points demeaned by lender by county by year groups, comparing between non-refinancing borrowers (defined as borrowers who did not refinance or otherwise prepay within five years despite facing a Freddie Mac Survey Rate decrease of at least 1.2%) and all borrowers who faced a Freddie Mac Survey Rate decrease of at least 1.2%. Figure 3b conducts the same analysis comparing borrowers who prepaid within five years versus all mortgages that have been originated for at least five years. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

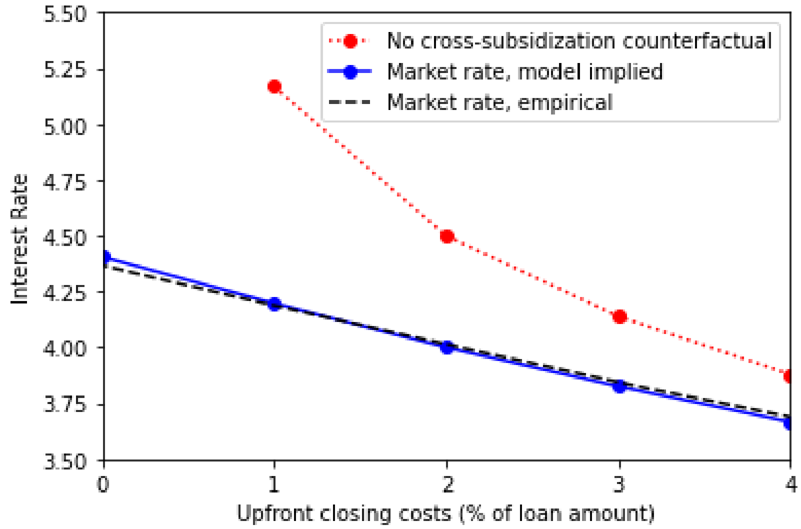
Figure 4: Moving/refinancing probability by points paid



(a) Moving probability by points (b) Refinancing probability by points

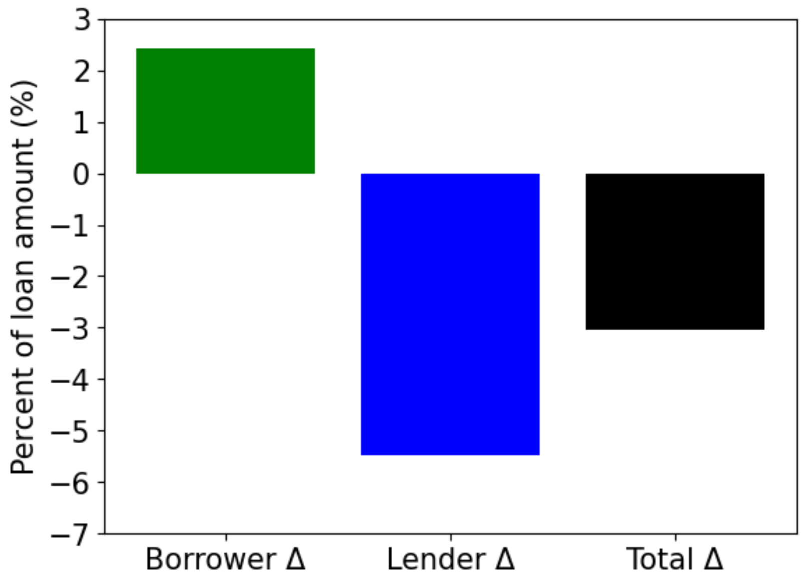
Note: The data used in this figure is the Optimal Blue-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data. Figure 4a presents the predicted probabilities in regressions of moving on control variables, while Figure 4b presents the predicted proabilities in regressions of refinancing on control variables. The regression estimates that these results were based on are presented in Table 2.

Figure 5: Market interest rate vs no cross-subsidization counterfactual interest rate for the calibrated quick to refinance borrower



Note: Figure 5 presents the equilibrium rate and upfront closing costs trade-off from the model and compares it to the empirical rate and upfront closing costs trade-off that I estimate from the data. The "Market rate, model implied" solid line refers to the equilibrium rate and closing cost trade-off given the logit prepayment hazard function and our estimated OAS. The "Market rate, empirical" dotted line was estimated using a regression of rate on upfront closing costs with ratesheet fixed effects using the LoanSifter data. Finally, the "No cross-subsidization counterfactual" dashed line refers to the model-implied equilibrium rate and closing cost trade-off in a world where the lender is pricing their mortgages for the calibrated quick to refinance borrower with perfect information on their type. This counterfactual was computed by jointly iterating on the borrower and lender's value functions.

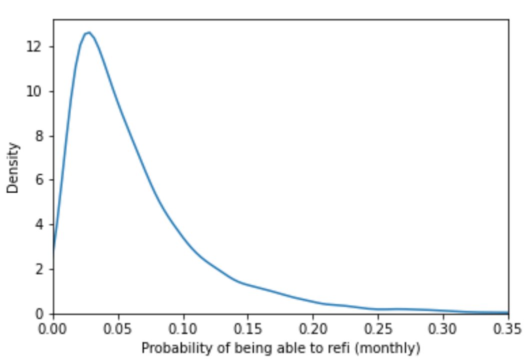
Figure 6: Welfare relative to no cross-subsidization counterfactual, calibrated quick to refinance borrower



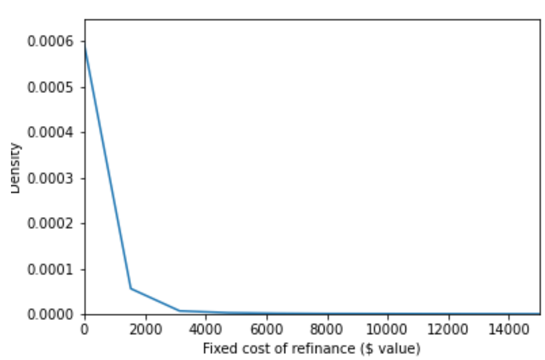
Note: Figure 6 plots (i) the upfront cash the calibrated quick to refinance borrower would have to receive to remain indifferent in the no cross-subsidization counterfactual, (ii) the upfront cash the lender's difference in profit from the quick to refinance borrower's loan between the current world and the no cross-subsidization counterfactual, and (iii) the sum of (i) and (ii). The results suggests that under the current system, the quick to refinance borrower gains 2.4% of loan amount in dollar terms, whereas lender loses 5.5% of the loan amount in profit, with a total social loss of 3.0% of the loan amount.

Figure 7: Distribution of borrower refinancing types

(a) Probability of being able to refi



(b) Hassle cost for refinancing

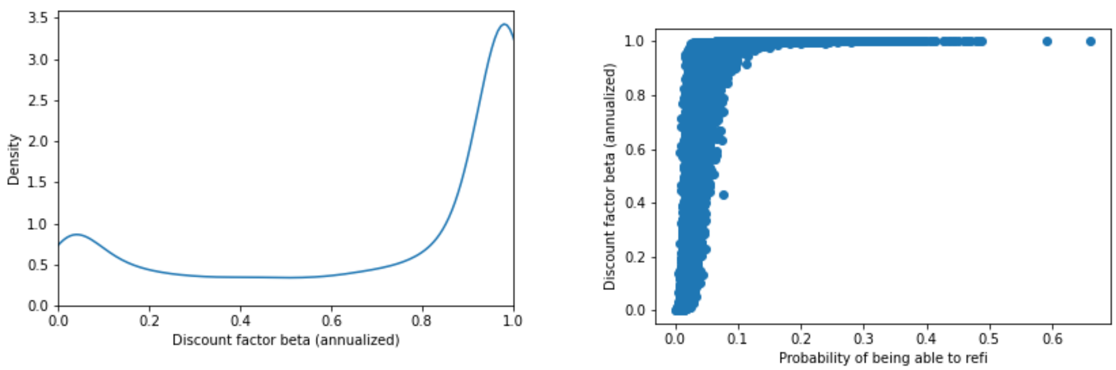


Note: Figure 7a plots the estimated density for the probability of being able to refinance coming from the marginal of the multivariate Logit-Normal distribution of Equation (19). Figure 7b plots the estimated density for the hassle cost of refinancing from the Log-Normal distribution of Equation (21). The distribution of borrower types from all racial groups are included.

Figure 8: Discount factor and its correlation with refinancing ability

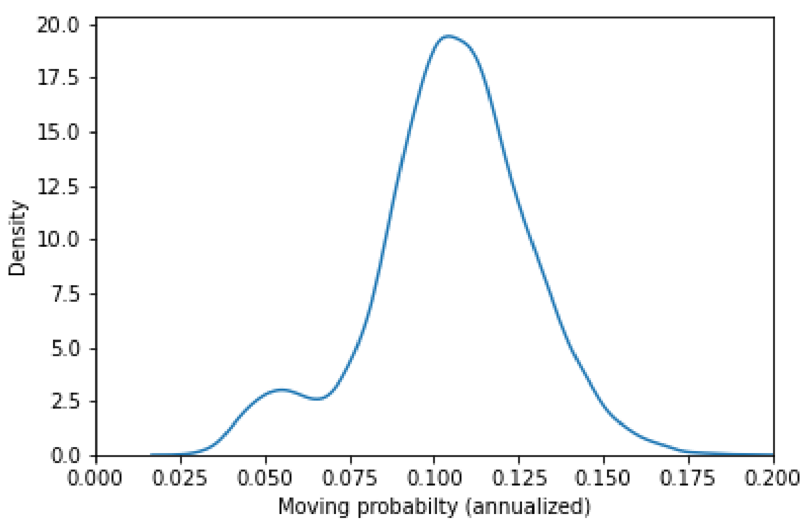
(a) Discount factor

(b) Scatter plot of the probability of being able to refi and discount factor



Note: Figure 8a plots the estimated density for the discount factor coming from the marginal of the multivariate logit-Normal distribution of Equation (19). Figure 8b plots a scatter plot with simulated draws of p_i^a in the x-axis and β_i in the y-axis from the multivariate logit-Normal distribution of Equation (19) across all racial groups.

Figure 9: Moving probability

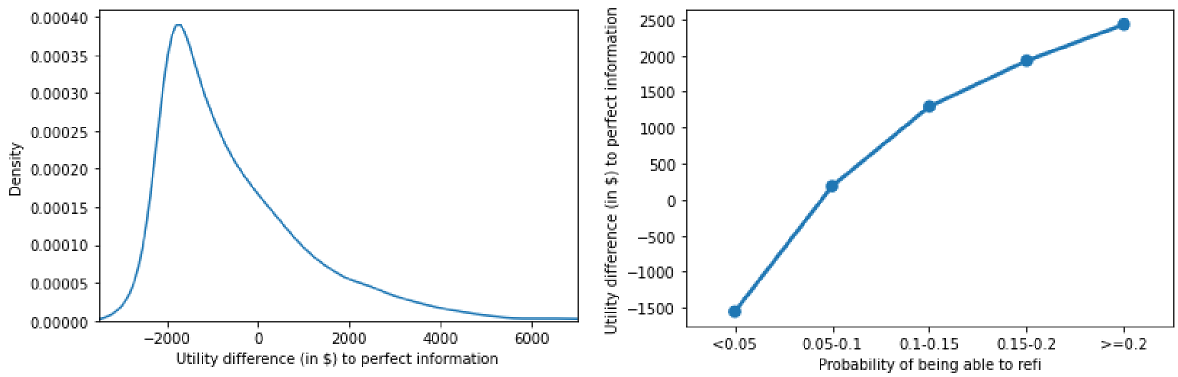


Note: Figure 9 plots the estimated density of moving probabilities across borrower types from the logit-Normal distribution of Equation (20) across all racial groups.

Figure 10: Differences in utility in the actual world versus the perfect information benchmark

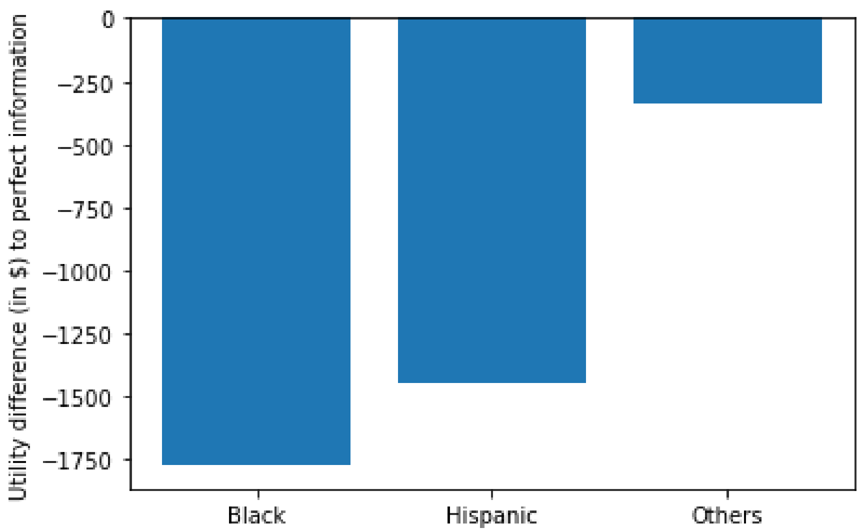
(a) Raw Density

(b) By borrower refinancing ability



Note: Figure 10a plots the estimated density of the difference in utility, in terms of upfront dollar savings, that would make borrowers indifferent between the existing system and what they would otherwise obtain in the perfect information case.

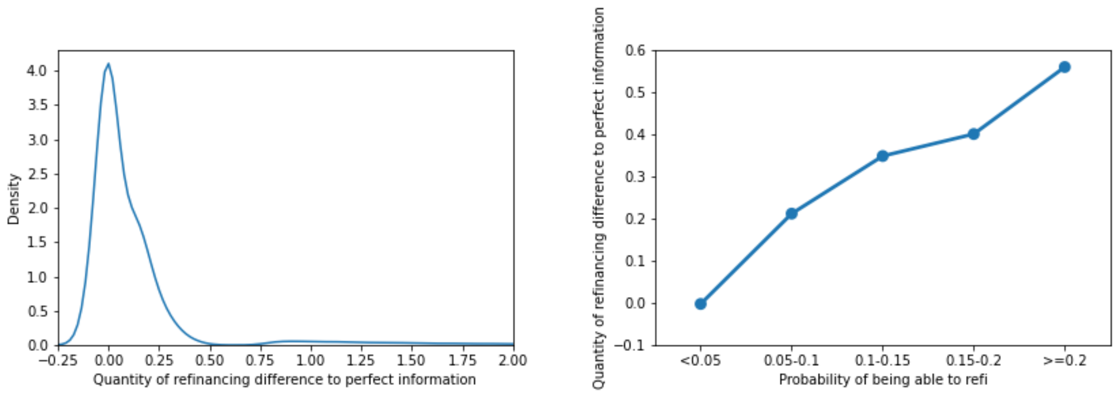
Figure 11: Welfare effects of cross-subsidization by racial group



Note: Figure 11 plots the average difference in utility due to the cross-subsidization by racial group. Utility is expressed in terms of the upfront dollar savings that would make borrowers indifferent between the existing system and what they would otherwise obtain in the perfect information case.

Figure 12: Differences in the expected number of refinances in the actual world versus the perfect information benchmark

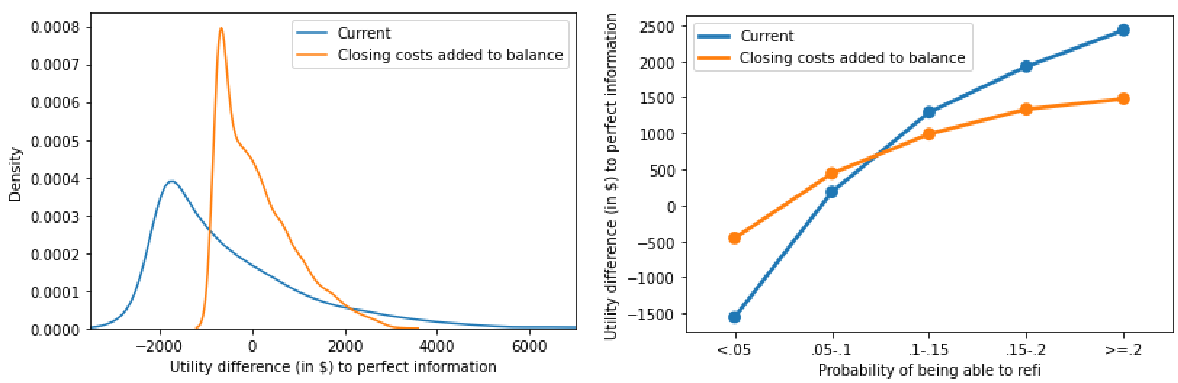
(a) Raw Density (b) By borrower refinancing ability



Note: Figure 12 plots the estimated density of the difference in the quantity of refinancing per new origination between the current system and the perfect information world where lenders price the rate and upfront closing cost trade-off with full knowledge of borrower parameters and borrowers optimizing accordingly.

Figure 13: Counterfactual utility from adding cost to balance

(a) Distribution (b) By borrower refinancing ability

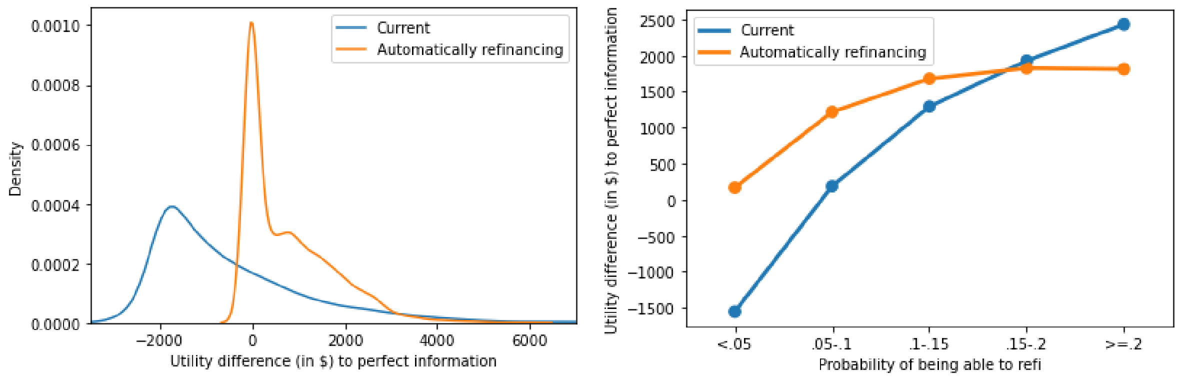


Note: Figure 13a plots the estimated density of the difference in utility, in terms of upfront dollar savings, that would make borrowers indifferent between the existing system and what they would otherwise obtain in the perfect information case.

Figure 14: Counterfactual utility from automatically refinancing

(a) Distribution

(b) By borrower refinancing ability



Note: Figure 14a plots the estimated density of the difference in utility, in terms of upfront dollar savings, that would make borrowers indifferent between the existing system and what they would otherwise obtain in the perfect information case, for the automatically refinancing counterfactual (in orange) as compared to the current system (in blue, reproduced from Figure 10).

Appendix

This appendix supplements the empirical analysis of Zhang (2023). Below is a list of the sections contained in this appendix.

Table of Contents

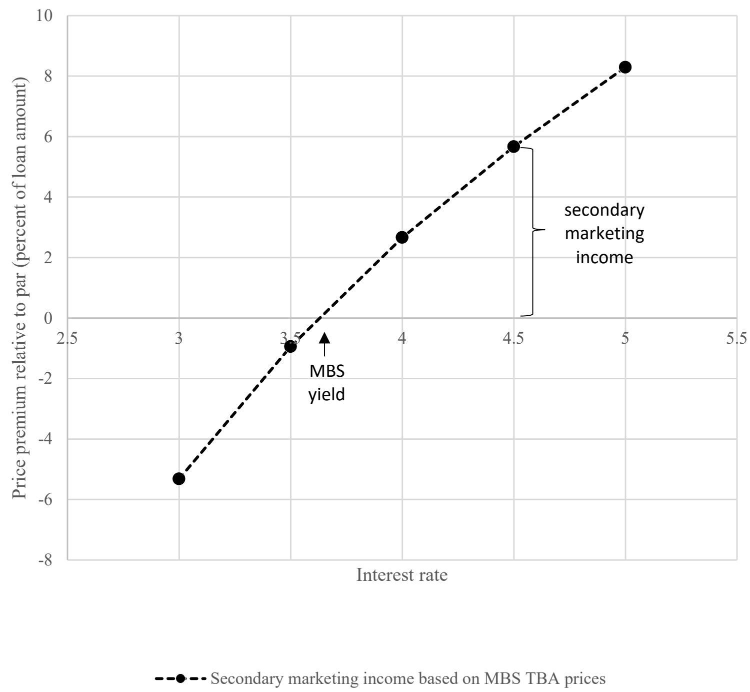
A.1 Additional Background About Rate and Upfront Closing Costs

Figure A.1: Rate and upfront closing costs trade-offs facing mortgage borrowers

Lender	Rate	Upfront costs	Mo. payment
Commonwealth Mortgage A Division Of Newfed Mortgage Corp. NMLS #1881 4.8 152 reviews	2.490% 30 year fixed refinance	$3,750 Points: 1.5	$987
Commonwealth Mortgage A Division Of Newfed Mortgage Corp. NMLS #1881 4.8 152 reviews	2.615% 30 year fixed refinance	$1,563 Points: 0.625	$1,003
Commonwealth Mortgage A Division Of Newfed Mortgage Corp. NMLS #1881 4.8 152 reviews	2.740% 30 year fixed refinance	$0 Points: 0	$1,019

Note: Figure A.1 shows a screenshot obtained by the author from Bankrate.com for a $250,000 refinancing mortgage on September 18, 2021. It shows how a borrower may choose to pay 0 points for a 2.740% interest rate mortgage, 0.626 points for a 2.615% interest rate mortgage, or 1.5 points for a 2.490% interest rate mortgage.

Figure A.2: Secondary marketing income as a function of interest rates



Note: Figure A.2 plots the FNMA MBS TBA prices on January 2, 2014 expressed as a percentage point premium/discount over the loan amount on the y-axis for a variety of coupon rates on the x-axis. Secondary marketing income is the extent to which the secondary market value of the mortgage is above its principal balance.

A.2 Data Construction and Summary Statistics

A.2.1 Optimal Blue-HMDA sample

I constructed the Optimal Blue-HMDA sample by merging the Optimal Blue rate locks from 2018–2019 with the public HMDA data. Because Optimal Blue contains a lender identifier number but no lender names, the merge proceeds in two steps: (1) an initial match based on loan characteristics, and (2) a second filtering based on a correspondence between the lender identifier in Optimal Blue and an anonymized version of HMDA lender IDs implied by the first step.

The initial match was made using loan amount, rate, year, loan type, loan purpose, loan term, ZIP code (with all ZIP codes corresponding to an HMDA census tract included), and up to a 5% difference in LTV with all matches kept in the data set. Then, for the second step I impose the requirement that the lender identifier in Optimal Blue is matched to an anonymized version of HMDA lender ID at least 10% of the time.[1] Overall, this two-step procedure uniquely matches 1,186,906 out of 2,318,940 locks for 30-year, conforming fixed-rate mortgages, implying a match rate of 51%. The match rate is comparable to a 66% "lock pull-through rate," which is the percent of rate locks that turn into originated loans, that I understand to be reasonable based on industry sources.

In terms of variable definitions, I construct a Black dummy equal to one if the mortgage has a HMDA-derived race variable of "Black or African American." The Hispanic dummy is equal to one if the mortgage has a HMDA derived ethnicity variable of "Hispanic or Latino." The Single Male and Single Female dummies are inferred from the HMDA-derived gender. Summary statistics for these samples are shown in the table below.

[1] The 10% requirement was set purposefully low to include cases where the Optimal Blue lender ID may not correspond to a HMDA reporter for example in the case of correspondent lending. It is sufficient to reduce the percent of matches that are non-unique from 49.6% to 3.9%.

Table A.1: Summary statistics for the 2018–2019 Optimal Blue-HMDA sample

	All		Black		Hispanic	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Loan amount ($'000s)	256695.6	117785.7	242574.6	117351.2	243938.2	112333.0
Origination cost ($)	1516.0	1807.2	1657.6	2062.3	1849.0	1969.4
Total loan cost ($)	3902.6	2362.4	4222.6	2713.2	4487.1	2547.2
LTV (%)	747.9	44.5	728.7	47.3	732.7	45.5
DTI (%)	80.4	15.0	84.9	13.5	82.6	14.7
Interest rate	34.973	9.681	37.363	8.849	38.239	8.600
Points paid	4.544	0.579	4.692	0.612	4.674	0.603
First-time home buyer (d)	0.307	0.461	0.395	0.489	0.387	0.487
Single Female (d)	0.252	0.434	0.436	0.496	0.268	0.443
Single Male (d)	0.330	0.470	0.356	0.479	0.441	0.497
# Observations	1,041,807		42,793		92,598	

Notes: This table reports summary statistics from the 2018–2019 Optimal Blue-HMDA merged sample. Loan amount is expressed in thousands of dollars, origination costs are expressed in dollars, credit score is the borrower's Optimal Blue credit score at origination, and LTV, interest rate are expressed in percentage points. The label (d) denotes dummy variables.

A.2.2 Optimal Blue-HMDA-CRISM sample

I also construct a merge between Optimal Blue, HMDA, and CRISM data sets for mortgages originated between 2013–2019, with loan performance until May 2022. The CRISM data set is an anonymous credit file match from Equifax consumer credit database to Black Knight's Mcdash loan-level Mortgage Data set. My Optimal Blue-HMDA-CRISM sample was constructed by joining together three merges, (i) the 2018–2019 Optimal Blue and HMDA merge described in Section A.2.1, (ii) a 2013–2017 Optimal Blue and HMDA merge, and (iii) the 2013–2019 Optimal Blue and CRISM merge.

Similar to the 2018-2019 Optimal Blue and HMDA merge, the 2013–2017 Optimal Blue and HMDA merge was also conducted in two steps, with an initial step based on loan characteristics, and a second step based on a correspondence between the Optimal Blue lender ID and an anonymized HMDA lender ID. A separate merge was conducted because the data fields in 2013–2017 HMDA are different than those in 2018–2019 HMDA: the interest rate, loan term, and LTV fields were not available, while loan amount was given in finer detail.

The first step for the 2013–2017 Optimal Blue to HMDA match was made using loan amount, year, loan type, loan purpose, occupancy, ZIP code (with all ZIP codes corresponding to an HMDA census tract included) with all matches kept in the data set. Then, for the second step I impose the requirement that the lender identifier in Optimal Blue is matched to an HMDA respondent ID at least 10% of the time.[2] Overall, this two-step procedure uniquely matches 1,382,057 out of 2,563,550 locks for 30-year, conforming fixed-rate mortgages, implying a match rate between locks to originated mortgages of 54%. The match rate is again comparable to a 66% "lock pull-through rate," which I understand to be reasonable based on industry sources.

The 2013–2019 Optimal Blue to CRISM match was made in one step. The variables used for matching are the loan amount, ZIP code, month of origination (which I require to lie within the date of the lock and the date of the lock plus the lock term), loan type, loan term, loan purpose, Equifax Risk Score (within 20 points of the Optimal Blue credit score), LTV (within 5%), and the rate. The more detailed loan-level information enabled the match to proceed despite not having lender information. Overall, I uniquely matched 617,058 out of 5,269,107 locks for 30-year, conforming fixed-rate mortgages, implying a match rate between locks to originated mortgages in the CRISM data set of 12%. The lower match rate is reasonable because neither the CRISM data nor the Optimal Blue data covers all

[2]The 10% requirement was set purposefully low to include cases where the Optimal Blue lender ID may not correspond to an HMDA reporter for example in the case of correspondent lending. It is sufficient to reduce the percent of matches that are non-unique from 75.2% to 11.8%.

US mortgage originations, so the overlap between the two must be smaller than the overlap between Optimal Blue and HMDA as the HMDA does provide essentially complete coverage of all US mortgage originations.

Combining the three merges, I get an Optimal Blue-HMDA-CRISM sample with 360,291 loans. In terms of variable definitions, I construct a Black dummy equal to one if the mortgage has a 2018–2019 HMDA derived race variable of "Black or African American." The Hispanic dummy is equal to one if the mortgage has a HMDA derived ethnicity variable of "Hispanic or Latino." In the case of 2013–2017 HMDA, these dummies are defined using the algorithm of Bhutta and Canner (2013). The Single Male and Single Female dummies are inferred from the 2018–2019 HMDA derived gender or the applicant gender when no co-applicant is present in the case of 2013–2017 HMDA. Finally, the Credit Card Revolver dummy is set equal to 1 if the primary borrower on the mortgage has a credit card balance of greater than or equal to $10,000 at the time of origination while also having a credit card utilization of greater than 40%.

Summary statistics on this sample is shown in Table 1.

A.2.3 The LoanSifter data

The LoanSifter data contains information about rate and upfront closing cost (i.e., points) trade-offs in rate sheets, which are prices that loan originators and mortgage brokers can offer to clients in locking the loan. Because these are actual available prices within a lender, they allow me to observe the rate and point menus that borrowers face. The sample period runs from September 9, 2009 to December 31, 2014 and consists of rate sheets from a sample of lenders from 50 metropolitan areas. Rate sheets observations are at the lender-day level, and in rare cases where a lender issues more than one rate sheet on a given day the observations with the best prices are kept. Linear interpolation was used to estimate the rate at various levels of points, following Fuster, Lo, and Willen (2017). To compare the rate and points menus in the lender rate sheets to the MBS TBA prices, I focus on rate sheets for conforming, 30-year, fixed-rate mortgages with a loan-to-value ratio of 80% and a loan amount of greater than or equal to $300k.

Summary statistics for this data are shown in Table A.2.

Table A.2: Summary statistics for the LoanSifter data

Year	No. of Lenders	Rate at -2 points	Rate at 0 points	Rate at 2 points	N lender-days obs
2009	93	5.42	5.01	4.65	3923
2010	93	5.10	4.70	4.44	16025
2011	83	4.82	4.46	4.25	16589
2012	86	4.07	3.67	3.41	18105
2013	126	4.42	4.07	3.80	19993
2014	103	4.52	4.21	3.97	19446

Note: This table contains information on the number of distinct lenders, mean rate at 0 points, mean rate at 2 points, and number of distinct lender-day observations by year. The data set comes from LoanSifter. The interest rates at 0 points and at 2 points are estimated through linear interpolation for lenders that do not offer mortgages at exactly those points.

A.3 When are closing costs added to the rate?

This paper focuses on the cross-subsidization of mortgage closing costs to the extent that they are added to the rate of the mortgage. I refer to mortgages with closing costs "added to the rate" as mortgages with a high enough interest rate c such that secondary marketing income(c) in Equation (1) is positive.[3] While intuitive, this definition is most sensible in a world in which lenders pass through their secondary marketing income as lower upfront closing costs to borrowers, for example in a model with a perfectly competitive supply side. Otherwise, the positive secondary marketing income may reflect not only closing costs added to the rate but also an additional cost that only some borrowers pay. Empirically, my analysis of US

[3]This turns out to be true for most mortgages, as I show in Section A.4.2.

mortgage pricing finds this pass-through to be nearly complete which makes my definition sensible.

To assess this pass-through, I examine how the secondary marketing income-interest rate trade-off matches the retail interest rate and upfront closing costs trade-off in the cross-section, with results in Figure A.3. I use data LoanSifter matched with MBS TBA pricing data from 2009Q3 to 2014. Following the methodology of Fuster, Lo, and Willen (2017), which estimates the price of intermediation as the premium of the mortgage over par on the secondary market, I estimate (i) the secondary marketing revenue generated by lenders in the secondary market as implied by MBS TBA prices, and (ii) the sum of the revenue generated by lenders in the secondary market and the upfront closing costs they charge in the form of points, for borrowers with a \$300k conforming mortgage, 700 LoanSifter credit score, 80% LTV, and 30% DTI.

Then, with the interest rate spread to the Freddie Mac Primary Mortgage Market Survey (PMMS) rate[4] rounded to the nearest 1/8th $\tilde{c}$, I run a linear regressions of the form:

$$\phi_{ijt} = \sum_{l=1}^{N} \gamma_l \mathbb{1}(c = c_l) + \xi_{jt} + \epsilon_{ijt}, \tag{27}$$

where c_l are the categorical variables of interest rate spread rounded to the nearest 1/8th, ξ_{jt} are lender-day fixed effects, and ϵ_{ijt} is the error term. ϕ_{ijt} is either the secondary marketing revenue generated the lender or sum of the revenue generated by lenders in the secondary market and the upfront closing costs, both expressed as a percentage of the loan amount.

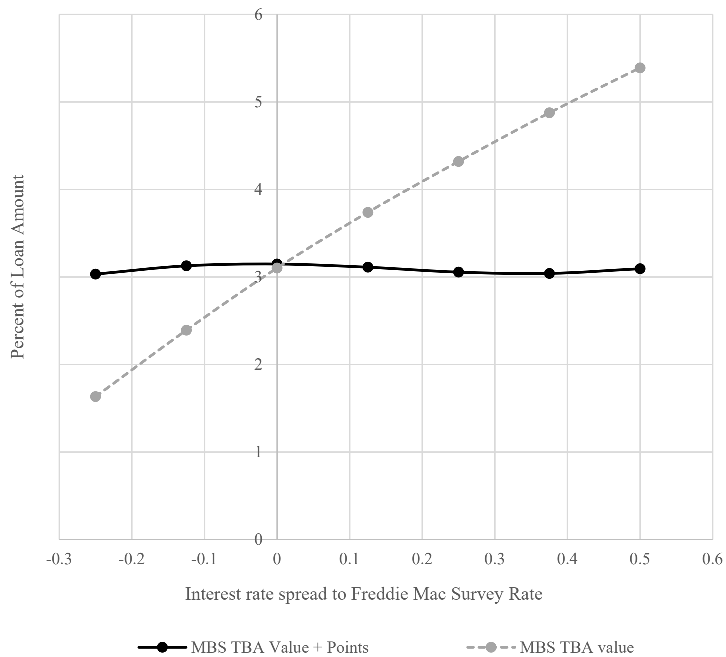
Results are presented in Figure A.3, which shows that mortgages that are originated at a higher spread to the Freddie Mac Survey rate tend to command higher valuations in the secondary market but generate almost exactly the same lender total income. This suggests that higher secondary marketing income is almost entirely passed through to consumers in the form of lower upfront lender fees/points.[5] Given the near complete pass-through

[4]The Freddie Mac Primary Mortgage Market Survey rate is obtained from https://fred.stlouisfed.org/series/MORTGAGE30US.

[5]The same patterns also exist in the time series, as I illustrate in Appendix Figure A.4. In Figure A.4,

of secondary marketing income to primary market upfront closing costs on average, it is economically meaningful to say that mortgages with positive secondary marketing income have a part of their upfront closing costs "added to the rate" which is then subject to cross-subsidization.

Figure A.3: Secondary marketing income and total lender revenues



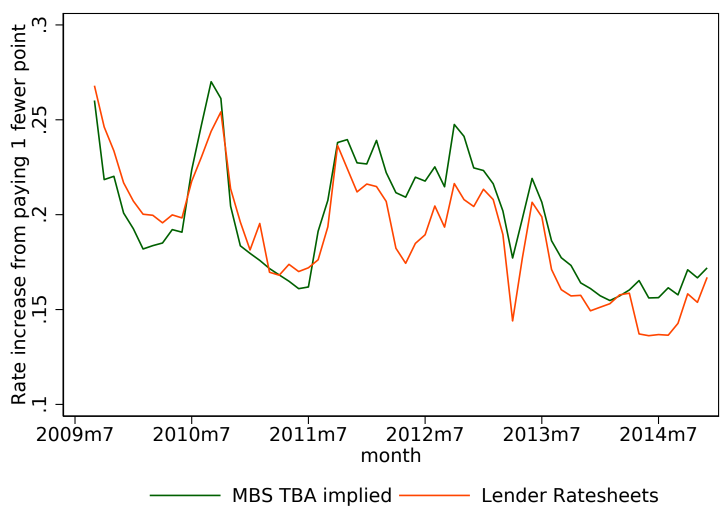
Note: Figure A.3 presents estimates from a linear regression of (i) the estimated secondary marketing revenue as implied by MBS TBA prices and (ii) the sum of estimated secondary marketing revenue as implied by MBS TBA prices and upfront closing costs in the form of points on categorical variables of eighths of rate spreads with lender-day fixed-effects based on Equation (27). The grey dotted line plots the predicted values from the regression with estimated secondary marketing revenue as the regressor. The black solid line plots the predicted values from the same regression on the sum of estimated secondary marketing revenue and upfront closing costs in the form of points.

In addition to cross-section, I also examine the relationship between the rate and upfront closing cost trade-off in the time series in Figure A.4. Using the LoanSifter data, I estimate the rate increase from paying 1 less point (i.e., 1% of the loan amount less) in upfront closing

there is some evidence that in more recent years the interest rate is slightly lower on low upfront closing cost mortgages than what would be implied by secondary marketing income, perhaps suggesting a role for markups. I abstract from markups that vary by points in this paper as the magnitude of the cross-subsidization I study is significantly larger than the differences shown in Figure A.4.

costs as the interest rate increase from going from a mortgage with 1 point in upfront closing costs to a mortgage with 0 points within each lender rate sheet. To get the corresponding exchange rate in the MBS TBA data, I take the mortgage rate at 0 points (net of the g-fees or the price of GSE guarantee) and compute the increase in rate that would imply a 1% increase in the MBS TBA value of the mortgage, with interpolated values for coupon rates in between eighths. I then take the mean of the exchange rate implied by the LoanSifter data and the MBS TBA data by month, with results plotted in Figure A.4.

Figure A.4: The interest rate increase from paying 1 less point in upfront closing cost over time, lender ratesheets (green) versus MBS TBA implied (red)



Note: Figure A.4 presents estimates from taking monthly means of (i) the required increase in rate to make the mortgage value increase by 1% of the loan amount in the MBS TBA data (ii) the increase in rate going from 0 points in lender rate sheet to 1 point in lender rate sheet in terms of upfront closing costs paid. The data used is Morgan Markets for MBS TBA prices and LoanSifter for rate sheets. MBS TBA values are linearly interpolated in between eighths of interest rates and LoanSifter rates are linearly interpolated to arrive at the rate at 0 and 1 point in upfront closing costs.

Figure A.4 shows that the exchange rate implied by the the LoanSifter data and the MBS TBA data are fairly close to each other, with the MBS TBA implied exchange rate being slightly larger near the end of the sample. This is consistent with near complete pass-through of secondary marketing revenue to upfront closing costs, with a small discount to lower closing cost mortgages in the retail market as compared to the secondary market near the end of the sample.

A.4 Additional motivating facts

In this section, I present some additional stylized facts that illustrate the existence of cross-subsidization of mortgage closing costs and its sizable distributional implications. First, I show in Section A.4.2 that almost all borrowers pay for most of their mortgage closing costs through a higher interest rate on their mortgage relative to mortgage-backed securities yields, rather than upfront. Second, I show that heterogenous borrower prepayment tendencies implies different borrowers with the same closing costs added to the rate end up with very different net present values (NPVs) of their extra interest rate payments, ex post, in Section A.4.3. Third, I assess magnitude of this difference by demographic groups in Section A.4.4.

A.4.1 Regression of choices of points as predicted by ex-post prepayment behavior

Table A.3: Choices of points as it relates to refinancing/prepayment behavior

	(1) Points		(2) Points	
Non-refi borrower	0.0659***	(5.32)		
5-year prepayment			-0.0841***	(-6.30)
Log(loan amount)	0.0511***	(2.71)	0.0497***	(2.73)
Credit score controls	Yes		Yes	
LTV controls	Yes		Yes	
DTI control	Yes		Yes	
Constant	-0.600***	(-2.83)	-0.519**	(-2.59)
Observations	25245		25245	
LenderXCountyXYear FEs	Yes		Yes	

Robust t statistics clustered by lender and county in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Note: The data used in this figure is the Optimal Blue-HMDA-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. The sample for (1) and (2) is further restricted to the set of borrowers whose mortgages originated before April 2016 and where the Freddie Mac Survey Rate decreased at least 1.2% since origination. Table A.3 presents OLS estimates of borrower choices of points on (1) an indicator variable for non-refinancing borrowers, defined as borrowers who did not refinance or otherwise prepay within five years despite facing a Freddie Mac Survey Rate decrease of at least 1.2%, and (2) borrowers who prepaid within five years.

A.4.2 Prevalence of mortgages with closing costs added to the rate

When borrowers take out a mortgage, they have a choice between adding closing costs to the rate of the mortgage or paying them upfront. In this section I assess the extent to which mortgage closing costs are added to the rate using the 2018–2019 Optimal Blue-HMDA data. The 2018–2019 HMDA data contains information about the upfront closing costs paid by the borrower in the form of loan origination costs, and the match to Optimal Blue data enables me to obtain information on when the rate was locked which then allows me to estimate the revenue that lenders generate from the secondary market.

I estimate the extent to which mortgage closing costs are added to the rate based on Equation (1), which breaks down lenders' total revenue from origination as the sum of upfront closing costs and secondary marketing income. The secondary marketing component of lender revenues is estimated following the procedure of Fuster, Lo, and Willen (2017),[6] where the revenue that lenders generate from the secondary market y as a fraction of the mortgage balance M_{it} is given as:

$$y_{it} = \frac{p_{it}^{TBA+payup}(c_{it} - gfees_t) - M_{it}}{M_{it}} \tag{28}$$

where $p_{it}^{TBA+payup}$ is the estimated value of the mortgage on the secondary market based on TBA prices plus "payups," for a coupon rate $c_{it} - gfees_t$ where c_{it} is the interest rate on the mortgage and $gfees_t$ is the price of the government guarantee. Payups are additional amounts that investors pay for an MBS relative to the TBA price for mortgages that have particularly favorable prepayment risk. Low-balance mortgages, for example, are less likely to be prepaid and hence tend to be more valuable in the secondary market. As a result, I add the payups based on mortgage size to the MBS TBA price.[7]

[6] The methodology of Fuster, Lo, and Willen (2017) for estimating secondary marketing income involves estimating the premium of an originated mortgage relative to par from MBS TBA prices by subtracting g-fees (the cost of GSE guarantee) from the mortgage interest rate and then using that as the coupon rate, the value of which is then derived using linear interpolation on reported MBS TBA prices between (i) coupons and (ii) trading days.

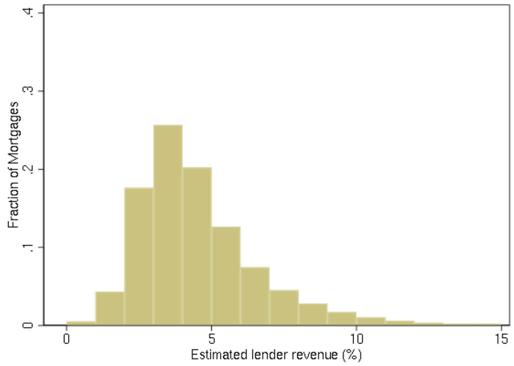
[7] A drawback of this approach of estimating secondary marketing income is that it excludes both the impact of the revenue generated from the sale of mortgage servicing rights and the fees paid to servicers from coupon payments. Fuster, Lo, and Willen (2017) argue that the two effects may approximately cancel each other out. Without explicit data on the value of mortgage servicing rights, I also compute a lower bound on the estimated lender revenues by looking at the MBS value of the net interest rate paid to investors by assuming counterfactually that mortgage servicing rights are worth zero. This lower bound is presented in Appendix Figure A.13, which still shows that the vast majority of mortgages have their closing costs paid for through the rate.

The results of my analysis are shown in Figure A.5. The left panel in Figure A.6a shows that lenders make on average 4.6% of the mortgage balance as revenue for each mortgage they originate. This revenue compensates the lender for their costs. First, lenders need to pay for the upfront costs of mortgage insurance, also called loan-level price adjustments (LLPAs) by Fannie Mae and Freddie Mac. Second, lenders pay for loan originator compensation, which can be 1–2% of the loan amount. Third, lenders pay for the underwriting and processing costs associated with the origination. Relative to these expenses, the portion that is attributable to accounting profits are low: the Mortgage Bankers' Association (MBA) reports an average production profit of 0.14% of the loan amount in 2018 and 0.31% of the loan amount in 2017.[8]

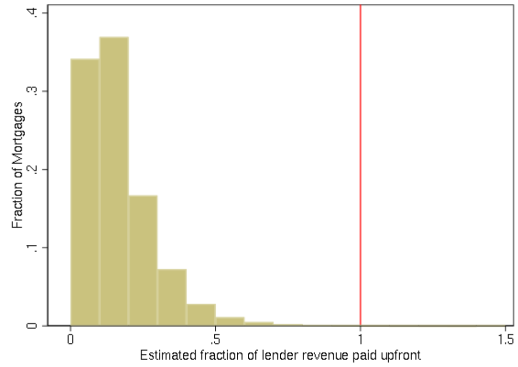
The right panel of Figure A.5b shows that only a small fraction of lender revenue is paid as upfront closing costs, with an average of 17.4%. That is, even though most of the lender costs of origination are incurred upfront, 82.6% of the price of origination is added to the rate of the mortgage and paid over time primarily by immobile and inactively refinancing borrowers. Hence, almost all mortgages being originated in the US can be considered "low upfront closing cost" mortgages whose price of mortgage origination are prone to cross-subsidization between borrowers with different refinancing speeds.

[8]https://www.mba.org/2019-press-releases/april/independent-mortgage-bankers-production-volume-and-profits-down-in-2018. MBA also reports that average net production revenues in 2018 (excluding LLPAs) are 3.47% of the loan amount, which is consistent with my estimate of 4.6% with LLPAs.

Figure A.5: Lender revenue and percentage paid as upfront closing costs



(a) Estimated lender revenue



(b) Fraction of lender revenue paid upfront

Note: The data used in this figure is the 2018–2019 Optimal Blue-HMDA data for 30-year, fixed-rate, conforming, primary residence mortgages originated. The data contains information on rates and upfront closing costs paid and was linked to MBS TBA data following Fuster, Lo, and Willen (2017) to estimated secondary marketing revenue. Figure A.6a plots histograms of estimated lender revenue which consists of the sum of upfront closing costs plus secondary marketing revenue. Figure A.5b then plots histograms of the fraction of lender revenue that is paid upfront.

Conceptually, the empirical observation that lenders make most of their income from secondary marketing revenue is best characterized as closing costs being added to the rate if higher secondary marketing revenue is passed through to consumers as lower upfront closing costs. I present evidence that this is true in Section A.3.

Table A.4: Total loan costs and loan balance

	(1)	(2)	(3)
	All	Purchase	Refi
Loan amount in dollars	0.00504***	0.00640***	0.00132***
	(14.38)	(18.61)	(3.05)
Constant	2595.5***	2378.4***	3172.8***
	(28.24)	(23.93)	(30.40)
Observations	1154560	899391	255169

Robust t statistics clustered by lender and county in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Note: The data used in this figure is the 2018-2019 Optimal Blue-HMDA data, for 30-year, fixed-rate, conforming, primary residence mortgages.

Table A.5: Upfront origination costs and loan balance

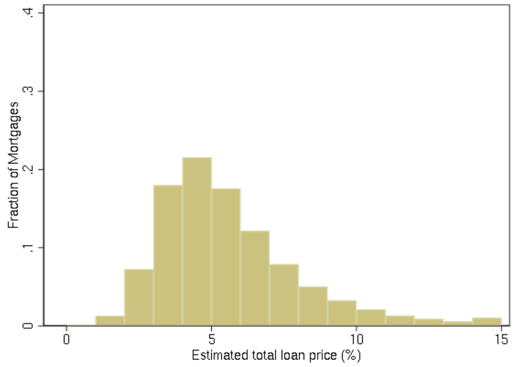
	(1)	(2)	(3)
	All	Purchase	Refi
Loan amount in dollars	0.00146***	0.00191***	-0.000156
	(6.01)	(8.31)	(-0.42)
Constant	1132.4***	984.6***	1702.0***
	(19.32)	(18.02)	(17.88)
Observations	1154695	899504	255191

Robust t statistics clustered by lender and county in parentheses.

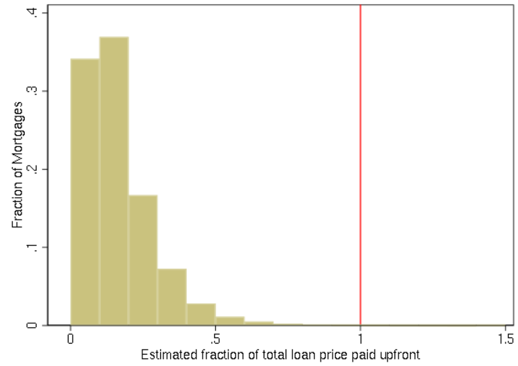
* p<0.1, ** p<0.05, *** p<0.01

Note: The data used in this figure is the 2018-2019 Optimal Blue-HMDA data, for 30-year, fixed-rate, conforming, primary residence mortgages.

Figure A.6: Lender revenue and percentage paid as upfront closing costs



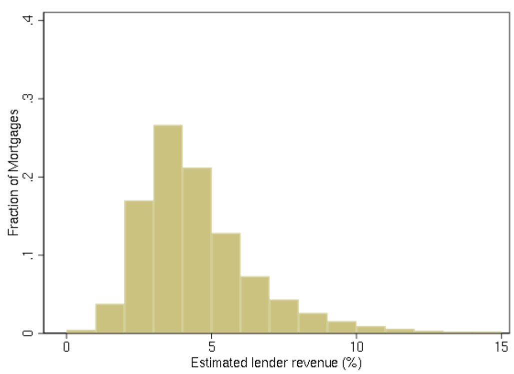
(a) Estimated lender revenue



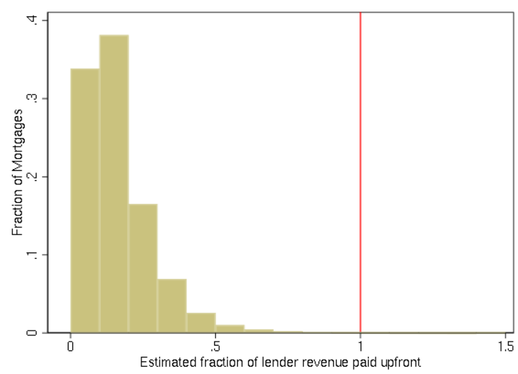
(b) Fraction of lender revenue paid upfront

Note: The data used in this figure is the 2018–2019 Optimal Blue-HMDA data for 30-year, fixed-rate, conforming, primary residence mortgages originated. The data contains information on rates and upfront closing costs paid and was linked to MBS TBA data following Fuster, Lo, and Willen (2017) to estimated secondary marketing revenue. Figure A.6a plots histograms of estimated lender revenue which consists of the sum of upfront closing costs plus secondary marketing revenue. Figure A.5b then plots histograms of the fraction of lender revenue that is paid upfront.

Figure A.7: Lender revenue and percentage paid as upfront closing costs

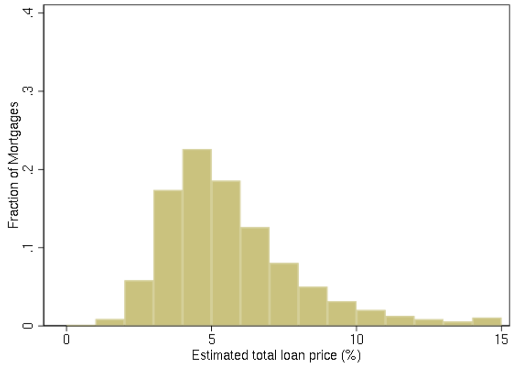


(a) Estimated lender revenue

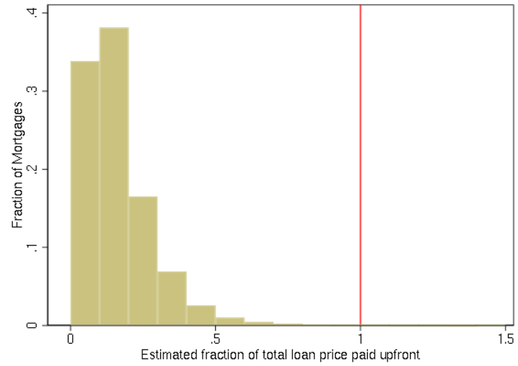


(b) Fraction of lender revenue paid upfront

Figure A.8: Total revenue and percentage paid as upfront closing costs, purchase

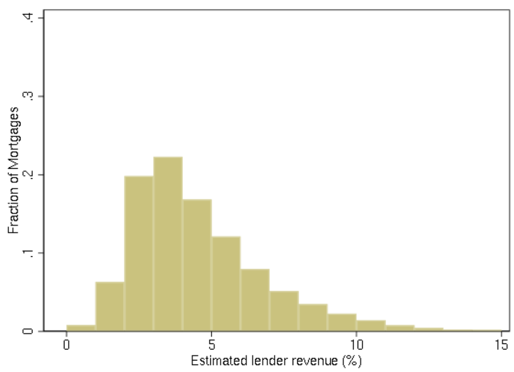


(a) Estimated lender revenue

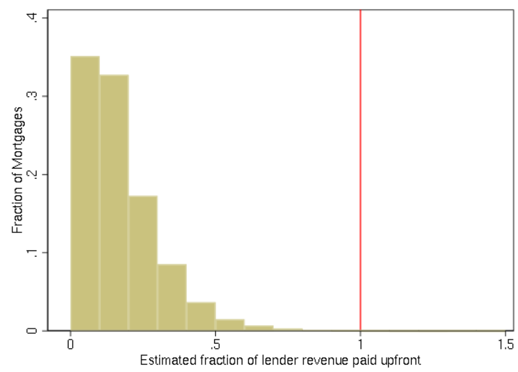


(b) Fraction of lender revenue paid upfront

Figure A.9: Lender revenue and percentage paid as upfront closing costs

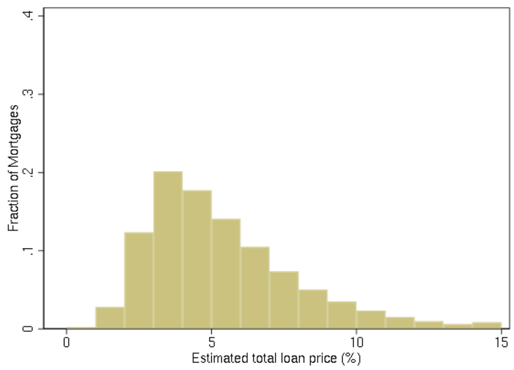


(a) Estimated lender revenue

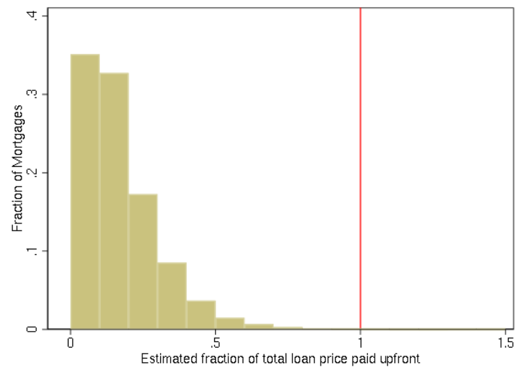


(b) Fraction of lender revenue paid upfront

Figure A.10: Total revenue and percentage paid as upfront closing costs, refi



(a) Estimated lender revenue



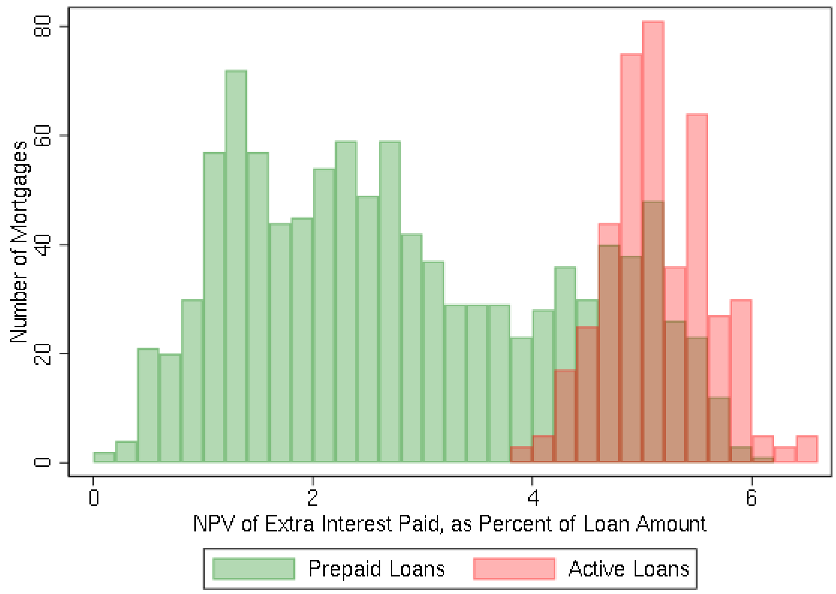
(b) Fraction of lender revenue paid upfront

A.4.3 Cross-subsidization of closing costs added to the rate

The interaction of heterogeneity in refinancing tendencies and closing costs added to the rate implies a cross-subsidization of mortgage closing costs. To illustrate this in my data, Figure A.11 looks at borrowers with similar amounts of closing costs added to the rate (between 4.75-5.25%) in 2013 in my Optimal Blue-HMDA-CRISM sample and compares the NPV of the extra interest rate they paid as a percentage of their loan amount.[9] Due to differences in prepayment behavior, I find large differences in how much borrowers end up paying for the 4.75-5.25% in closing costs they added to the rate, ranging from close to 0% to more than 6%.

[9] The year 2013 was chosen because it is the earliest year in my sample.

Figure A.11: NPV of extra interest paid, 2013 mortgages with 4.75–5.25% of the loan amount in closing costs added to the rate



Note: The data used in this figure is the Optimal Blue-HMDA-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013. The sample was further limited to mortgages with a secondary marketing revenue of 4.75–5.25% of the loan amount, as estimated based on MBS TBA prices following Fuster, Lo, and Willen (2017). The rate increase relative to a mortgage with 0% secondary marketing revenue (i.e., at par) is estimated as the difference between the mortgage interest rate net of the fee for government guarantee (gfees) minus MBS yields. The NPV of the extra monthly payment resulting from this difference, assuming a discount rate equal to the 10-year Treasury rate at the time of the rate lock, is then plotted in the histogram for loans that have prepaid (in green) and for loans that are still active (in red). CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

The reason for the variance in outcomes in Figure A.11 is that, when the closing costs are added to the rate of the mortgage, lenders can only recover their closing costs over time through a higher interest rate payment. The principal balance of the mortgage remains unchanged. Therefore, borrowers who prepay earlier end up paying less, while borrowers who prepay later end up paying more. The transfers and deadweight losses studied in this paper come from the extent to which that borrowers who actively refinance pay less for their closing costs in expectation and receive cross-subsidization from other borrowers.

A.4.4 The predictability of cross-subsidization by demographics

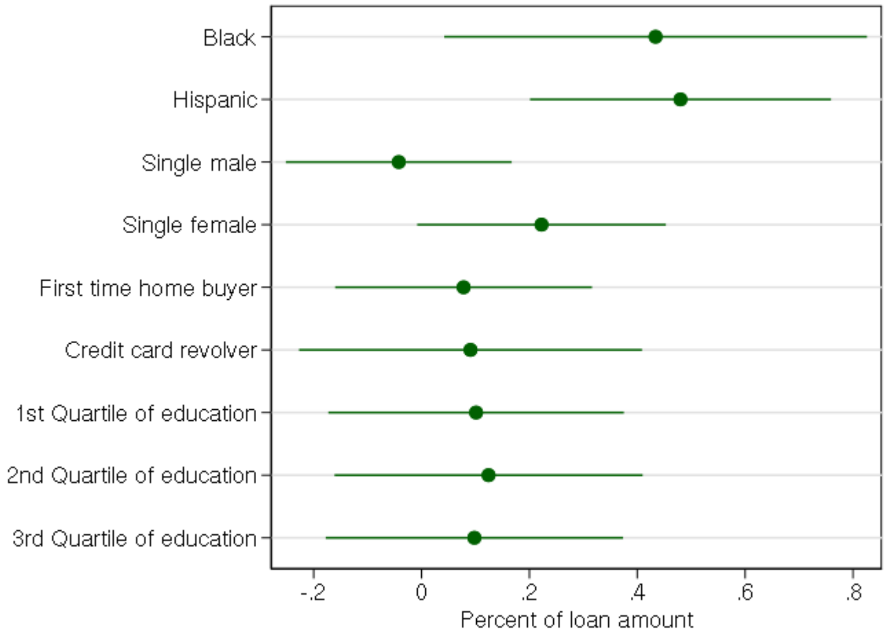
Next, I examine the extent of this ex-post cross-subsidization by demographics. To do so, I run the regression on loan level data in my Optimal Blue-HMDA-CRISM sample:

$$NPV_{i,t} = \beta X_i + \gamma Z_i + \xi_{\phi_{i,t} \times t} + \epsilon_{i,t} \tag{29}$$

where $NPV_{i,t}$ is the NPV of extra interest paid for their closing costs that are added to the rate over the observed life of the mortgage; X_i is a set of demographic and credit utilization variables including race (Black, Hispanic), gender (male and female), credit card revolver status, and quartiles of education; Z_i is a set of control variables including categories of credit scores at origination, LTV, DTI, and log loan amount; $\xi_{\phi_{i,t} \times t}$ is the amount of closing costs added to the rate by time fixed effects.

The results of this analysis are shown in Figure A.12 and Table A.6. I find that Black and Hispanic borrowers paid an extra 0.5% of the loan amount for their closing costs added to the rate relative to other borrowers. For a $300,000 loan, the magnitude of this cross-subsidization is about $1500 per loan. Furthermore, single-applicant female borrowers paid an extra 0.24% of the loan amount for their closing costs added to the rate. A limitation of this analysis is that does not take into account the potentially unexpected decline in interest rate during this period, so a model is needed to get at the welfare effects ex ante.

Figure A.12: NPV of extra interest paid by demographic and borrower characteristics



Note: The data used in this figure is the Optimal Blue-HMDA-CRISM data from January 2013 to December 2013, for 30-year, fixed-rate, conforming, primary-residence mortgages originated in 2013. The graph plots regression coefficients from Column (2) of Table A.6. In particular, it shows that Black, Hispanic and single-applicant female borrowers pay more for their closing costs added to the rate than other borrowers. Other characteristics, such as single-applicant male borrowers, first-time home buyers, credit card revolvers (defined as someone with a more than 60% credit utilization and $10,000 in debt at the time of getting a mortgage), and quartiles by education are not statistically different from zero at the 5% level. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

Table A.6: Regression on NPV of extra interest paid by demographic and borrower characteristics

	(1)	
	NPV of Extra Interest Paid	
Black	0.434***	(2.17)
Hispanic	0.480***	(3.38)
Single male	-0.042	(-0.40)
Single female	0.223**	(1.89)
First-time home buyer	0.078	(0.64)
Credit card revolver	0.091	(0.56)
1st quartile of education	0.101	(0.72)
2nd quartile of education	0.124	(0.85)
3rd quartile of education	0.098	(0.70)
Log(loan amount)	-0.363***	(-2.92)
Credit Score controls	Yes	
LTV controls	Yes	
DTI control	Yes	
Constant	7.918***	(4.85)
Observations	1275	
ϕ by month FEs	Yes	

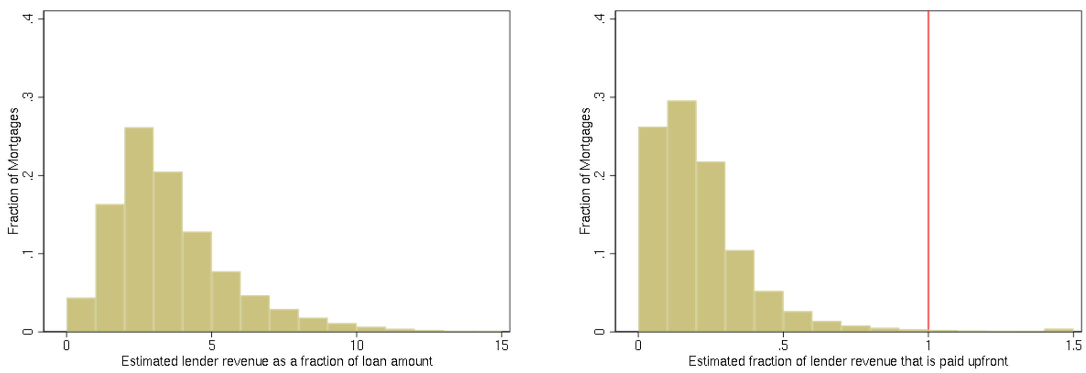
robust t statistics in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Note: The data used in this table is the Optimal Blue-HMDA-CRISM data from January 2013 to December 2013, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013. This table contains regression results from estimating Equation (28). The dependent variable is the NPV of extra interest paid from the closing costs that are added to the rate. I include ϕ by month fixed effects, where ϕ refers to the amount of closing costs added to the rate rounded to the nearest percent of the loan amount. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

A.5 Robustness check on the proportion of closing costs paid upfront

Figure A.13: Lender revenue and percent paid as upfront closing costs, net of mortgage servicing revenue



(a) Estimated lender revenue (b) Fraction of lender revenue paid upfront

Note: The data used in this figure is the Optimal Blue data for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2018-2019 matched to the 2018–2019 HMDA data. This data contains information on rates and upfront closing costs paid, and was linked to MBS TBA data to estimate secondary marketing revenue. A further 25 basis points was subtracted from the coupon rate for mortgage servicing. Figure A.6a plots histograms of estimated lender revenue which consists of the sum of upfront closing costs plus secondary marketing revenue. Figure A.13b then plots histograms of the fraction of lender revenue that is paid upfront.

A.6 Model details

A.6.1 Exogenous states

The risk-free rate follows the Cox, Ingersoll, and Ross (1985) model which has a natural zero lower bound:

$$dr_{1t} = a(b - r_{1t})dt + \sigma\sqrt{r_{1t}}dW_t. \tag{30}$$

I estimate the evolution of exogenous states in the model via maximum likelihood[10] using

[10]The program was based on Kladivko (2021), with some modifications to obtain standard errors.

the three-month Treasury bill data from January 1987 to January 2021.[11] The results for the risk-free rate are as follows:

Table A.7: Estimation of the CIR model of interest rates

Parameter	Estimate	Standard Error
a	0.0910	0.0506
b	1.2649	0.7209
σ	0.4930	0.0175

Note: This table contains estimates from fitting the Cox, Ingersoll, and Ross (1985) model on the three-month Treasury bill data from January 1987 to January 2021. Estimation proceeds via the maximum likelihood, and standard errors are obtained from the inverse Hessian.

I model the average mortgage rate $\bar{c}_t$, changes in log real house prices ΔH_t, and changes in log real personal income ΔL_t and as a vector autoregression (VAR) with r_{1t} as an exogenous dependent variable. I use two lags in the VAR, with the constraint that the matrix of coefficients on first lag is identity and on the second lag is positive only for the house price coefficient to reduce dimensionality.[12] More specifically, with $\boldsymbol{s_t} = \begin{bmatrix} \bar{c}_t \\ 100 * \Delta H_t \\ 100 * \Delta L_t \end{bmatrix}$, the VAR equation is as follows:

$$\boldsymbol{s_t} = \boldsymbol{\mu} + r_{1t}\boldsymbol{\beta_{r_{1t}}} + \Phi_1 \boldsymbol{s'_{t-1}} + \Phi_2 \Delta H_{t-1} + \boldsymbol{e_t}, \tag{31}$$

where $\boldsymbol{e_t} \sim N(0, \hat{\boldsymbol{\Sigma}}_{\boldsymbol{s}})$ and $\boldsymbol{\mu}, \boldsymbol{\beta_{r_{1t}}}, \Phi_2$ are the coefficients to be estimated. In terms of the state variables, data on $\bar{c}_t$ is obtained as the Primary Mortgage Market Survey (PMMS) rate,[13]

[11] Board of Governors of the Federal Reserve System (US), 3-Month Treasury Bill Secondary Market Rate [TB3MS], retrieved from FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/TB3MS.

[12] The second lag on the house price variable is added to capture momentum and mean reversion as in Glaeser and Nathanson (2017).

[13] Freddie Mac, 30-Year Fixed Rate Mortgage Average in the United States [MORTGAGE30US], retrieved from FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/MORTGAGE30US.

H_t is obtained from the Case-Shiller National House Price Index,[14] and L_t is obtained from the US Personal Income[15] divided by the US population.[16] Furthermore, H_t and L_t are converted to real terms using the Consumer Price Index for All Urban Consumers.[17] The results of the VAR estimation are as follows:

Table A.8: VAR estimates of state transitions

Parameter	$\boldsymbol{\mu}$	$\boldsymbol{\beta}_{\boldsymbol{r_{1t}}}$	$\boldsymbol{\Phi_1}$			$\boldsymbol{\Phi_2}$	$\hat{\boldsymbol{\Sigma}}_{\boldsymbol{s}}$		
$\bar{c}_t$	.093 (.051)	.024 (.010)	.972 (.012)	0	0	0	.050		
$100 * \Delta H_t$	.051 (.028)	-.008 (.007)	0	1.060 (.047)	0	-.286 (.047)	.009	.126	
$100 * \Delta L_t$	.182 (.079)	-.007 (.021)	0	0	-.232 (.053)	0	-.006	.041	1.030

Note: This table contains estimates from fitting a constrained VAR described in Equation (31). Data on mean mortgage rates $\bar{c}_t$ is obtained from the Primary Mortgage Market Survey (PMMS), data on house prices H_t are taken from the Case-Shiller index, and data on personal income Y_t are taken as the ratio of US aggregate personal income divided by the US population. House prices and income are divided by the CPI for urban consumers and then transformed into log differences.

The estimates from Tables A.7 and A.8 are then used to simulate the transitions of the exogenous states in my model in Section 5.

A.6.2 OAS

An empirical model of prepayment behavior combined with my model of interest rates is needed to estimate the OAS in Section 5.1.2. For my empirical model of prepayment, I use my panel data to estimate a logit regression of an indicator variable for borrower prepayment on the spread of the mortgage interest rate to the Freddit Mac survey rate at origination (SATO) as well as categories of the interest rate incentive defined as the current mortgage

[14] S&P Dow Jones Indices LLC, S&P/Case-Shiller U.S. National Home Price Index [CSUSHPINSA], retrieved from FRED, Federal Reserve Bank of St. Louis;,https://fred.stlouisfed.org/series/CSUSHPINSA.

[15] U.S. Bureau of Economic Analysis, Personal Income [PI], retrieved from FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/PI

[16] U.S. Bureau of Economic Analysis, Population [POPTHM], retrieved from FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/POPTHM.

[17] U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org/series/CPIAUCSL.

interest rate minus the Freddit Mac survey rate. To maintain comparability to the TBA market from which I derive the market exchange rate between the interest rate and upfront closing costs, I further restrict my analysis to 30 year purchase mortgages with a balance above \$150k, FICO above 680, and LTV below 85% following Fusari et al. (2020). Results of this regression are shown in Table A.9, which is used for my model of $\hat{p}_{t'}$ as in Equation (17).

Table A.9: Logit model of prepayment

	(1)	
	Logit	
prepaid		
init_t	7.446***	(16.59)
init_t_sq	-4.169***	(-12.32)
sato	0.121	(0.62)
sato_sq	-0.765***	(-2.88)
refi_ratediff_gt0	0.348***	(4.55)
refi_ratediff_gtp25	0.345***	(4.08)
refi_ratediff_gtp5	0.599***	(8.31)
refi_ratediff_gtp75	0.322***	(4.69)
refi_ratediff_gt1	0.538***	(5.63)
refi_ratediff_gt1p25	0.144	(1.09)
burnout	-0.0549*	(-1.94)
burnout_sq	0.00182	(1.45)
Constant	-8.264***	(-54.48)
Observations	267603	

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The data used in this regression is the Optimal Blue-HMDA-CRISM data from January 2013 to May 2022, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. The sample is further restricted to "TBA likely" mortgages defined as mortgages with a loan amount of at least $150k, loan-to-value ratio less than or equal to 85%, and FICO at origination greater than or equal to 680. The independent variable is an indicator variable for whether the borrower prepaid their mortgage in a given month. The dependent variables include the spread of the mortgage interest rate to the Freddie Mac survey rate at origination (SATO) and its square, as well as categories of rate incentive (the current spread of the mortgage interest rate to the Freddie Mac survey rate). CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

Using the prepayment model from Table A.9 and the interest rate model of Section A.6.1, with the risk-free rate r_{tf} being given as the implied 10 year rate under the Cox, Ingersoll, and Ross (1985) model, I estimate a $O\hat{A}S = 0.22\%$ by minimizing the equally-weighted difference between the observed MBS TBA price for the nearest two coupons above and below the Freddie Mac survey rate - gfees - servicing fees with the implied NPV given by Equation (17). The MBS TBA price is inclusive of the new production pay-up for a coupon (with data from Morgan Markets). The gfee is assumed to be 0.42% and servicing fee 0.25% following Fuster, Lo, and Willen (2017).

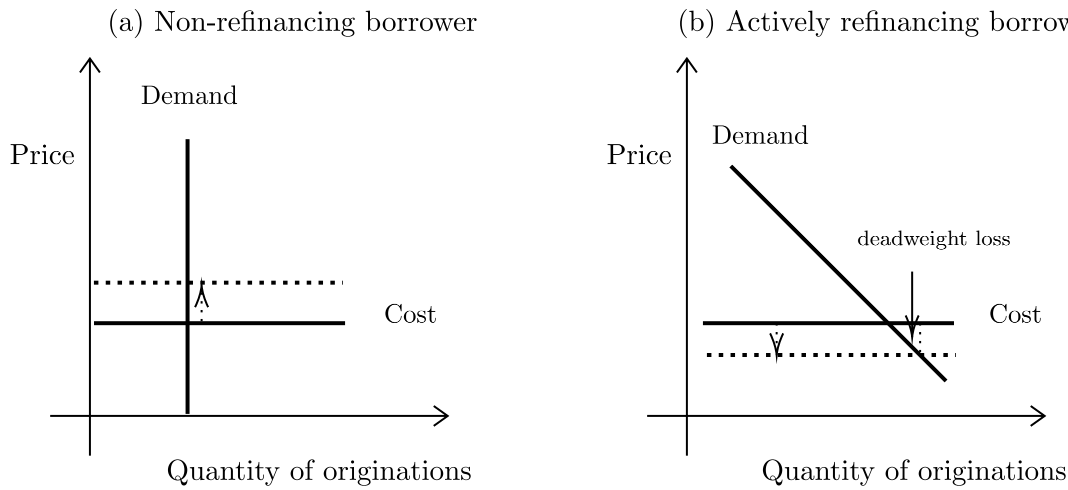
A.6.3 Economic intuition on transfers and inefficiencies

I showcase the economic intuition behind these results in Figure A.14, where I plot illustrative demand curves for mortgage originations for a non-refinancing borrower and an actively refinancing borrower. The demand curve for a non-refinancing borrower is vertical, representing that their quantity of upfront closing is fixed and due to exogenous factors (e.g., moving). The demand curve for an actively refinancing borrower is downward sloping in the price, representing the fact that an actively refinancing borrower would refinance more if the price of originations is lower, as the interest rate savings from refinancing become higher than the price of a new origination.

The social marginal cost of mortgage origination is represented as a solid horizontal line. For non-refinancing borrowers, the price they face is this cost shifted upwards as the cost of origination gets added to the rate and they end up paying more for each origination, which is illustrated in Figure A.14a. For actively refinancing borrowers, their effective price of mortgage origination is shifted downwards from the social cost, as illustrated in Figure A.14b. An important distinction between the two panels is in the change of borrower behavior. To the extent that actively refinancing borrowers originate more mortgages than they otherwise would due to this cross-subsidization, they introduce a social deadweight loss represented by the triangle indicated by the arrow in Figure A.14b.

Figure A.14 may also be interpreted in terms of price elasticities. To the extent that non-refinancing borrowers' quantity of mortgage origination are less price elastic, the effect of their cross-subsidization involves less of a change in behavior. Therefore, the economic distortions in the model mostly attributed to the changes in the incentives faced by the actively refinancing borrowers who refinance excessively.

Figure A.14: Deadweight loss from cross-subsidization of the price of mortgage refinancing



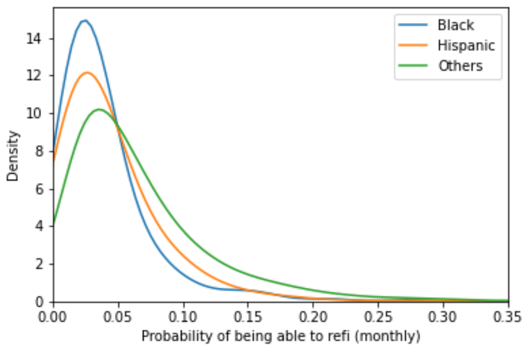
Note: Figure A.14 presents intuition on how cross-subsidization can generate welfare loss in my setting. In both panels, the quantity of originations is plotted on the x-axis and the price of origination on the y-axis, where the price of origination should be interpreted as the dollar value equivalent of the minimum of the borrowers' utility loss from paying either upfront closing costs or higher interest rates when given a set of choices. The left panel in Figure A.14a shows the demand for mortgage originations for a non-refinancing borrower as a vertical line, and that an increase in the effective cost of originations (from solid to dashed line) leads them to pay more for originations but does not change their behavior. On the other hand, the right panel in Figure A.14b shows that an active refinancing borrower by nature of their optimization activity does change their quantity of originations with the cross-subsidized price (from dashed to solid line), which allows them to receive transfers but also generates welfare losses in the form of excessive refinancing.

A.7 Estimates by race

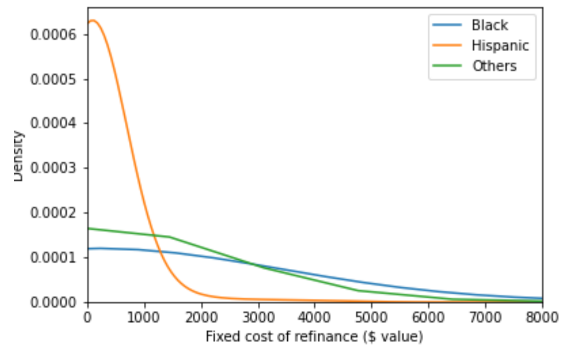
In the main text of the paper, many results were aggregated across borrower racial groups. This Appendix section presents some estimates by race.

Figure A.15: Distribution of borrower refinancing types by race

(a) Probability of being able to refi

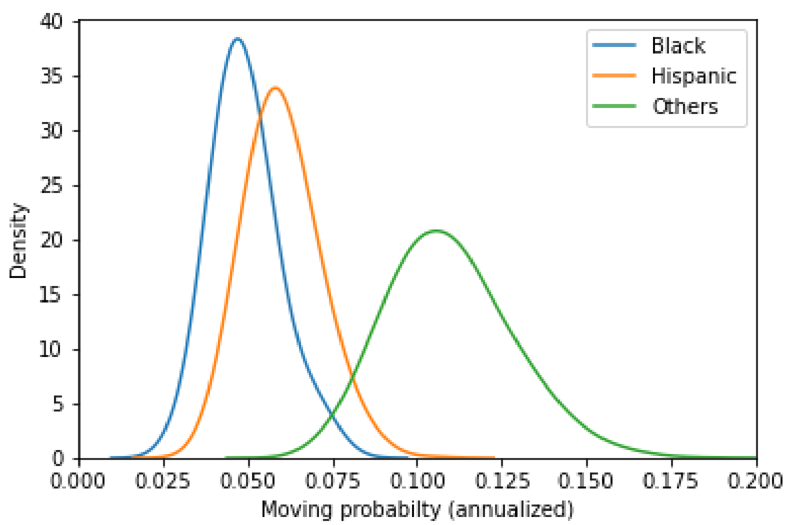


(b) Hassle cost for refinancing



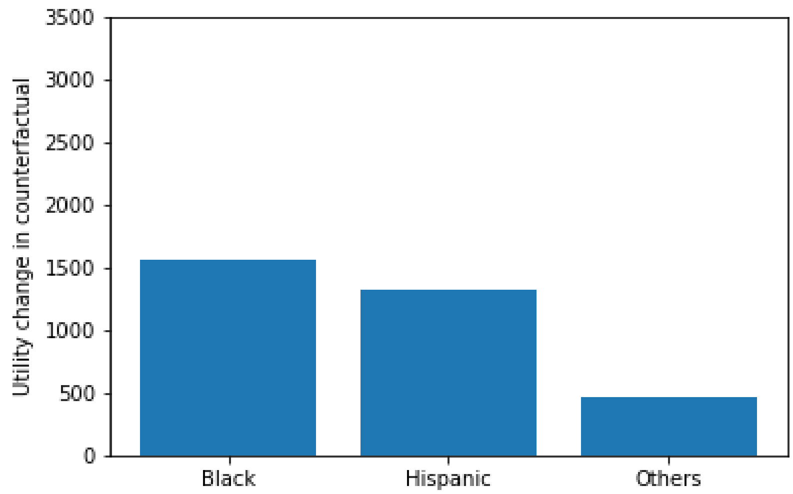
Note: Figure A.15 plots the estimated density for the probability of being able to refinance coming from the marginal of the multivariate Logit-Normal distribution of Equation (19). Figure 7b plots the estimated density for the hassle cost of refinancing from the Log-Normal distribution of Equation (21). The densities are separately plotted by racial group of the household.

Figure A.16: Moving probability



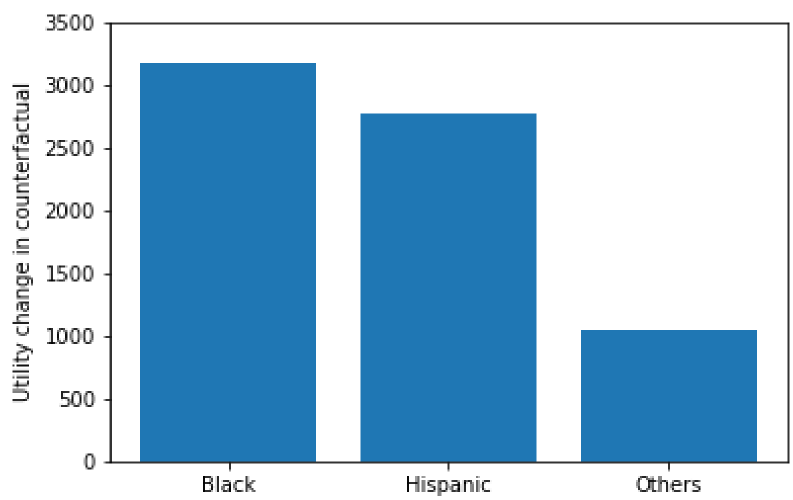
Note: Figure A.16 plots the estimated density of moving probabilities across borrower types from the logit-Normal distribution of Equation (20). The densities are separately plotted by racial group of the household.

Figure A.17: Counterfactual change in utility from adding closing costs to balance of the loan, by racial group



Note: Figure 11 plots the average difference in utility under the counterfactual contract design of adding all closing costs to the balance of the loan. Utility is expressed in terms of the upfront dollar savings that would make borrowers indifferent between the existing system and what they would otherwise obtain in the adding closing costs to the balance of the loan counterfactual.

Figure A.18: Counterfactual change in utility from automatically refinancing, by racial group



Note: Figure A.18 plots the average difference in utility under the counterfactual contract design of automatically refinancing mortgages. Utility is expressed in terms of the upfront dollar savings that would make borrowers indifferent between the existing system and what they would otherwise obtain in the adding closing costs to the balance of the loan counterfactual.