Closing Costs, Refinancing, and Inefficiencies in the Mortgage Market

David Zhang∗
Harvard University

Job Market Paper
(Click here for latest version)

December 3, 2021

Abstract

In the US, mortgage borrowers who are slow to refinance cross-subsidize other borrowers. This effect is amplified when borrowers cover their closing costs by accepting a higher mortgage rate, as borrowers who are slow to refinance make the extra interest payments for a longer expected period of time. Is this cross-subsidization merely a transfer, or does it also lead to social deadweight losses by distorting borrower incentives? To answer this question, I construct a general equilibrium model of mortgage refinancing where borrowers with heterogeneous refinancing tendencies choose how much of their closing costs they want to add to the rate. I estimate this model using a newly constructed data set linking upfront closing cost choices and subsequent borrower behavior. I find significant cross-subsidization of mortgage closing costs to the extent that they are added to the rate, which approximately doubles the transfers between borrowers with different refinancing speeds. Minority borrowers are particularly affected as they pay 0.4-0.5% of the loan amount more in extra interest payments. Furthermore, borrowers who would otherwise not refinance become incentivized to do so only to receive more transfers, an effect that accounts for about one quarter of all US refinancing and generates deadweight losses due to administrative resource costs. Overall, I estimate a welfare loss of $365/mortgage (∼$2.9 billion per year) relative to the no cross-subsidization case. Consequently, alternative contract designs such as (i) adding closing costs to the balance of the loan, or (ii) making fixed-rate mortgages automatically refinancing can both 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 Matthew Curtis, Mark Egan, Jiacheng Feng, Xavier Gabaix, Daniel Green, Jun Ishii, Larry Katz, David Laibson, Frank Pinter, David Scharfstein, Jeremy Stein, Audrey Tiew, Boris Vallee, Jeffrey Wang, Paul Willen, and Ron Yang 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 their mortgages when interest rates fall.\(^1\) Less understood is the fact that this sluggishness interacts with the institutional feature that mortgage closing costs, which I define as the price of mortgage origination, are typically paid for through higher interest rates. Consequently, borrowers who are slow to refinance cross-subsidize the mortgage closing costs of other borrowers. This cross-subsidization has sizable consequences in terms of both transfers and economic efficiency through its distortion of borrower incentives. As a result, alternative mortgage contract designs can increase both equity and total welfare.

Mortgage originating lenders must cover their costs. They can do so in two ways. First, they can charge the borrower upfront, through upfront closing costs known as “points.”\(^2\) Second, they can raise the interest rate on the mortgage, holding fixed its principal balance and then recovering their costs from the secondary market.\(^3\) Borrowers can therefore choose to get a lower rate, higher upfront closing cost mortgage, or a higher rate, lower upfront closing cost mortgage. In my sample, more than 80% of closing costs are paid for through a higher mortgage interest rate. When borrowers add closing costs to their mortgage rate, they can stop paying the higher rate when they move or refinance. Therefore, borrowers who add closing costs to the rate of their mortgage and then actively refinance could end up paying less than what they added.

I estimate significant cross-subsidization of mortgage closing costs to the extent that they are added to the rate. Borrowers who refinance more actively can benefit from this cross-subsidization by choosing lower upfront closing cost mortgages and refinancing more

---


\(^2\) In the industry, each mortgage point refers to 1% of the loan amount that borrowers pay upfront.

\(^3\) Borrowers could also in principle pay their closing costs upfront and then add them to the principal balance and thus hold the interest rate fixed. In practice, this may be infeasible for many borrowers who face binding loan-to-value (LTV) and debt-to-income (DTI) constraints.
often than they otherwise would.\footnote{The extra refinancing comes from two mechanisms. First, actively refinancing borrowers become more likely to take out a mortgage with a higher rate and lower upfront closing costs, which mechanically carries a higher refinancing incentive. Second, actively refinancing borrowers are able to refinance more cheaply than they otherwise would by taking out a low upfront closing cost mortgage when they do refinance.} The magnitude of this effect is large: I find that approximately one quarter of US mortgage refinancing activity would not have occurred without this cross-subsidization of mortgage closing costs. Because mortgage refinancing involves administrative resources that could have been used for other economic activity, the extra refinancing that actively refinancing borrowers undertake solely to receive transfers generates deadweight losses from a social perspective. As an extreme example, an actively refinancing borrower may find it optimal to take a zero upfront closing cost mortgage and then refinance it whenever interest rates go down, even by 1/8th of a percentage point. Such a strategy is socially costly in terms of the administrative resources used for refinancing but is privately optimal for a borrower who is always able to refinance with zero hassle costs in my calibrated model even though it would not be privately optimal without cross-subsidization.

I begin the analysis by documenting five stylized facts about the mortgage market in Section 3 to provide reduced-form evidence of this cross-subsidization and to inform the model. First, almost all borrowers pay for most of their mortgage closing costs through a higher interest rate on their mortgage relative to mortgage-backed securities (MBS) yields. Second, many borrowers are slow to refinance. These two facts naturally lead to a third: there is large borrower heterogeneity in terms of how much they pay for the same amount of closing costs added to the interest rate, measured in terms of the ex post net present values (NPVs) of extra interest payments. Fourth, I find that this heterogeneity in ex post NPVs is predictable via ex ante demographics, which suggests a role for ex ante cross-subsidization. In particular, for my sample of mortgages originated in 2013, Black and Hispanic borrowers paid an extra 0.43\% and 0.48\%, respectively, of the loan amount more in ex post NPVs of extra interest payments controlling for the amount closing costs added to the rate. Fifth, I find evidence of selection of borrowers into upfront closing cost choices as well as substantial heterogeneity in borrower prepayment behavior among borrowers with the same upfront
To quantify the size of the cross-subsidy and study its ex ante welfare consequences, I develop a general equilibrium model that captures borrower heterogeneity in refinancing and moving tendencies while endogenizing borrower choices of upfront closing costs in Section 4. Since my novel source of cross-subsidization is about how borrowers who are slow to refinance effectively pay the closing costs of more actively refinancing borrowers, it is important for my model to capture heterogenous borrower refinancing behavior along with their general equilibrium effect on market prices. To do so, I embed the time and state dependence of borrower refinancing behavior described in Andersen et al. (2020) into a life-cycle model that gives welfare estimates interpretable in dollar-equivalent terms. A zero-profit condition pins down the supply side. As such, my model is able to quantify the equilibrium welfare implications of heterogenous borrower refinancing behavior in dollar terms, which is an independent contribution to the literature that has primarily studied this cross-subsidization in the reduced form.⁵

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 refinance, (ii) ex ante moving hazards, and (iii) discount factors. 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): a behavior not reconcilable with only a fixed hassle cost component and suggests a role for borrowers’ time-varying ability to refinance. Conditional on refinancing costs, borrowers’ ex ante moving expectations are identified from the correlation between their responses to the refinancing incentive and their subsequent moving decisions. The fact that borrowers who do not refinance despite facing a large incentive to do so are more likely to move shortly

---

⁵A contemporaneous paper, Fisher et al. (2021), also studies the equilibrium welfare implications of heterogenous refinancing types in the context of a structural model, but with risk-neutral consumers. A life-cycle model is able to capture the covariance between borrower refinancing savings and their marginal utility of consumption and is in some cases needed to obtain intermediate upfront closing cost choices under the market exchange rate between the mortgage interest rate and upfront closing costs.
thereafter suggests that they have heterogenous ex ante moving expectations that affect their refinancing decisions. Finally, conditional on borrower moving and refinancing types, their discount factors are identified from their choices of upfront closing costs.

I estimate the model using maximum likelihood on a newly constructed data set linking borrower upfront closing cost choices to their subsequent prepayment behavior in Section 5. This was made computationally feasible by the value function approximation approach that is novel to this literature. In particular, instead of computing the value function on a large discretized state space \( S \), as was done in Campbell and Cocco (2015) and Chen, Michaux, and Roussanov (2020), I approximate the value function \( V(S) \) using a sieve function \( \hat{V}(S) \).\(^6\)

The advantage of this approach is that it allows value functions on relatively large state spaces to be computed tractably.

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 zero hassle costs, a mortgage with a one percent upfront closing cost carries a 1.25% 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 0.26%. The intuitive reason for the larger cross-subsidization of low upfront closing cost mortgages is that, from the perspective of the lender, non-refinancing borrowers overpay for their mortgage closing costs when they add it to the rate because they keep paying the higher interest rate for longer, while actively refinancing borrowers underpay for their mortgage closing costs when they add it to the rate.

A key advantage of my approach is that I am able to quantify the consequences of this cross-subsidization. As my second conclusion, I find that the cross-subsidization of mortgage closing costs generates large transfers between borrowers. I estimate that eliminating the

---

\(^6\)The use of a sieve approximation to conduct value function iteration is proven to be consistent in Arcidiacono et al. (2013) and has been applied in an empirical context in e.g. Keane and Wolpin (1997) and Barwick and Pathak (2015).
cross-subsidization of mortgage closing costs by requiring all borrowers to add their closing costs to the balance of the loan would reduce the average change in borrower utility due to cross-subsidization, measured in dollar terms, from $1301/mortgage to $647/mortgage.\footnote{Requiring mortgage closing costs to be paid upfront or added to the balance of the loan both eliminate the cross-subsidization. I chose to model it as the latter to avoid liquid savings constraints which are less flexible compared to the LTV or DTI requirements from the GSEs that can be updated.} Thus, approximately half of the cross-subsidization in the US mortgage market due to differences in prepayment tendencies can be attributed to the equilibrium consequences of adding mortgage closing costs to the rate. As my third conclusion, I show that the efficiency consequences of price distortions are large. In particular, I estimate a welfare loss of $365/mortgage, or around $2.9 billion per year assuming 8 million originations each year, relative to the no cross-subsidization benchmark.

Using the model, I conduct two counterfactual analyses in Section 6. 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 by approximately half and an increase in average borrower utility by $453/mortgage in dollar terms. Second, I study the case of automatically refinancing mortgages. I find a reduction in cross-subsidization by a similar magnitude and a bigger increase in average borrower utility of $1053/mortgage. 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.

Broadly speaking, my paper is about how the impact of heterogeneity in household refinancing costs can be amplified by financial contract design. While the earlier literature has emphasized that many households refinance “too little” from a private perspective, I show that this induces other households to refinance “too much” from a social perspective as a result of the prevalent mortgage contract design. I estimate the distribution of household refinancing costs and study the welfare impact of counterfactual contract designs that addresses both problems. This is motivated by the observation that it can be difficult to change household refinancing behavior (Johnson, Meier, and Toubia, 2018), and so evaluating the
welfare impacts of alternative financial contracts conditional on the existing distribution of household heterogeneity may be of both academic and policy interest.

My paper is also about how information frictions can lead to cross-subsidization and how the incentives generated by such cross-subsidization can lead to inefficiency. Without information frictions, it would be Pareto optimal to have complete markets for mortgage contracts under competitive equilibrium. With information frictions, actively refinancing borrowers may seek out contracts that carry more cross-subsidization and generate deadweight losses in the process. The fact that actively refinancing borrowers may select into contracts that are more heavily cross-subsidized but are “costlier” for the lender may be considered a form of adverse selection in the sense of Einav et al. (2013). As such, my findings have close parallels in the health insurance market, where it is well-known that adverse selection can lead to sub-optimal outcomes under competitive equilibrium and that contractual mandates can improve welfare. Finally, while my model is fully consistent with all borrowers being rational, if one instead views the slow to refinance borrowers who add closing costs to the rate 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).

My paper is primarily related to the literature on borrower heterogeneity in mortgage refinancing behavior. Many papers document and model the large borrower heterogeneity in refinancing behavior conditional on the interest rate savings available, including Deng, Quigley, and Van Order (2000), Stanton (1995), Agarwal, Rosen, and Yao (2016), Keys, Pope, and Pope (2016), Johnson, Meier, and Toubia (2018), Andersen et al. (2018), Beraja et al. (2018), Ambokar and Samaee (2019), and Gerardi, Willen, and Zhang (2021). A key contribution of my paper to this literature is that I study the equilibrium welfare conse-

---

8 Arrow and Debreu (1954).
quences of this heterogeneity while incorporating the effect of the cross-subsidization of the price of mortgage origination.

My paper also contributes to the literature on life-cycle models of mortgage choice. This includes Campbell and Cocco (2003), Mayer, Piskorski, and Tchisty (2013), Corbae and Quintin (2015), Campbell and Cocco (2015) Eichenbaum, Rebelo, and Wong (2018), Chen, Michaux, and Roussanov (2020), Campbell, Clara, and Cocco (2021) and Guren, Krishnamurthy, and McQuade (2021). 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 welfare.

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 this selection seriously and evaluates its welfare implications. Chari and Jagannathan (1989) study 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.\textsuperscript{10}

The rest of this paper is structured as follows. Section 2 presents background and data used in the study. Section 3 presents motivating facts. Section 4 presents my model and sim-

\textsuperscript{10}Another strand of literature on mortgage points concerns its role in mortgage discrimination: Bhutta and Hizmo (2019), Bartlett et al. (2019), and Zhang and Willen (2021).
ulation results. Section 5 presents estimation results. Section 6 describes the counterfactual analyses. Section 7 concludes.

2 Background and Data

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 set of options for rates and upfront closing costs from a price comparison website. It shows how borrowers might have the option of getting a 30-year, fixed-rate, mortgage at a 2.74% interest rate and $0 in upfront closing costs, or a mortgage with a 2.49% interest rate and $3,750 in upfront closing costs. Upfront closing costs are also often quoted in terms of points, where each point customarily represents 1% of the loan amount.

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

Note: Figure 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.

Focusing on the setting where lenders are selling the mortgages they originate on the secondary market, we can decompose lenders’ total origination revenue from making a loan
lender origination revenue = upfront closing costs + secondary marketing income(c)  \( (1) \)

where secondary marketing income(c) refers to the net income lenders derive from selling a loan with interest rate \( c \) on the secondary market, which can be alternatively described as the premium of the mortgage relative to par. Secondary marketing income tends to be higher for mortgages originated at higher interest rates, which allows lenders to charge lower upfront closing costs while maintaining the same revenue. In particular, in Appendix A.2 I find the pass-through of higher secondary marketing income to lower upfront closing costs to be nearly complete.

For market-level information on the rate and upfront closing cost trade-off, I obtain information on MBS TBA prices from Morgan Markets and on the rate and upfront closing cost menus from LoanSifter.\(^{11}\) The TBA market is a highly liquid market where most MBS are traded, and is described in more detail in Vickery and Wright (2013). Summary statistics and more detailed descriptions of the LoanSifter data are shown in Appendix A.1.3.

To illustrate what the secondary marketing income as a function of interest rates looks like on a given day, Figure 2 plots the MBS TBA prices from Morgan Markets, as a percentage of the loan amount at various interest rates, along with the extent of secondary marketing income indicated in brackets. It shows that 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.

\(^{11}\) These two data sets have also been used in Fuster, Lo, and Willen (2017) to study the time-varying price of mortgage intermediation.
Figure 2: Secondary marketing income as a function of interest rates

Note: Figure 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 revenue is the extent to which the secondary market value of the mortgage is above its principal balance.

For my loan-level analyses, I use two different matches of three data sets. The first data set is the 2013–2020 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. It contains information about interest rates, upfront closing costs in the form of points paid 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

---

12Mortgage lenders use rate-locking platforms such as Optimal Blue to assist their loan originators and mortgage brokers in offering rates to their clients. A rate is “locked” when a lender commits to originate a mortgage at a given rate. This data set has been used to study issues surrounding rates and points in Bhutta and Hizmo (2019) and in mortgage pricing in Bhutta, Fuster, and Hizmo (2020).
moves or refinances.\footnote{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.} It has been frequently used to study borrower refinancing behavior.\footnote{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).} Third, I use the 2013–2019 Home Mortgage Disclosure Act (HMDA) data to get at borrower demographics.

I construct two novel matches of these data sets, including a 2018–2019 Optimal Blue-HMDA match and a 2013–2021 Optimal Blue-HMDA-CRISM match, for my empirical analyses. 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. Details of the matching procedure as well as summary statistics can be found in the Appendix A.1.

3 Motivating facts

In this section, I present some facts that motivate my model. First, I show that almost all borrowers pay for most of their mortgage closing costs through a higher rate on their mortgage relative to mortgage-backed securities yields in Section 3.1. Second, I show that borrowers have heterogeneous refinancing tendencies in Section 3.2. Third, I show that the interaction of these two effects means 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 3.3. Fourth, I assess magnitude of this difference by demographic groups in Section 3.4. Fifth, I explore the correlation between upfront closing cost choice and refinancing types, which drives this cross-subsidization, in Section 3.5.

3.1 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),\textsuperscript{15} where the revenue that lenders generate from the secondary market \( y \) as a fraction of the mortgage balance \( M_{it} \) is given as:

\[
y_{it} = \frac{p_{it}^{TBA+payup}(c_{it} - gfees_{it}) - M_{it}}{M_{it}}
\]  

(2)

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 \( c_{it} - gfees_{it} \) where \( c_{it} \) is the interest rate on the mortgage and \( gfees_{it} \) 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.\textsuperscript{16}

\textsuperscript{15}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 \( gfees \) (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.

\textsuperscript{16}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.3, 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 3. The left panel in Figure 3a 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 2017.17

The right panel of Figure 3b shows that only a small fraction of lender revenue is paid as upfront closing costs, with an average of 19.5%. That is, even though most of the lender costs of origination are incurred upfront, 80.5% 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 that are prone to the kind of cross-subsidization I describe. Their interest rates are higher than the relevant MBS yields, which enables the lender to generate a majority of their revenue from secondary market sales rather than upfront closing costs.

17https://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 3.62% of the loan amount, which is consistent with my estimate of 4.6% with LLPAs.
Figure 3: 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 3a plots histograms of estimated lender revenue which consists of the sum of upfront closing costs plus secondary marketing revenue. Figure 3b 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.2.

3.2 Heterogenous refinancing tendencies

It is well-known that some borrowers fail to refinance, while others are more likely to refinance when interest rates fall. This is also true in my Optimal Blue-HMDA-CRISM sample. In particular, Figure 4 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 4. Kaplan-Meier survival hazards are also used to

\[\text{Refer to additional references}\]

\[\text{Page 14}\]
illustrate borrower refinancing behavior in Andersen et al. (2018).

Figure 4 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.

Figure 4: 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 April 2021, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2020. The green line Figure 4 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 4 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% throughout 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.

3.3 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, Figure 5 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.\textsuperscript{19} 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%.

Figure 5: 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 April 2021, 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 5 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

\textsuperscript{19}The year 2013 was chosen because it is the earliest year in my sample.
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.

### 3.4 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:

\[
NPV_{i,t} = \beta X_i + \gamma Z_i + \xi_{\phi_i,t} \times t + \epsilon_{i,t}
\]  

(3)

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 6 and Table 1. 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 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 6: 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 1. 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 1: Regression on NPV of extra interest paid by demographic and borrower characteristics

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NPV of Extra Interest Paid</td>
</tr>
<tr>
<td>Black</td>
<td>0.434**</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.480***</td>
</tr>
<tr>
<td>Single male</td>
<td>-0.042</td>
</tr>
<tr>
<td>Single female</td>
<td>0.223*</td>
</tr>
<tr>
<td>First-time home buyer</td>
<td>0.078</td>
</tr>
<tr>
<td>Credit card revolver</td>
<td>0.091</td>
</tr>
<tr>
<td>1st quartile of education</td>
<td>0.101</td>
</tr>
<tr>
<td>2nd quartile of education</td>
<td>0.124</td>
</tr>
<tr>
<td>3rd quartile of education</td>
<td>0.098</td>
</tr>
<tr>
<td>Log(loan amount)</td>
<td>-0.363***</td>
</tr>
<tr>
<td>Credit Score controls</td>
<td>Yes</td>
</tr>
<tr>
<td>LTV controls</td>
<td>Yes</td>
</tr>
<tr>
<td>DTI control</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>7.918***</td>
</tr>
<tr>
<td>Observations</td>
<td>1275</td>
</tr>
<tr>
<td>φ by month FEs</td>
<td>Yes</td>
</tr>
</tbody>
</table>

robust t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

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 (2). The dependent variable is the NPV of extra interest paid from the closing costs that are added to the rate. Column (1) presents results by borrower demographic and credit revolver status, and Column (2) also controls for credit score, LTV, DTI, and loan amounts. 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. The constant term is omitted from the table. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.
3.5 Selection in choices of upfront closing costs

Finally, 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, the 2013–2021 Optimal Blue-HMDA-CRISM data contains only information on the points and not the application fee. To the extent that application fees are constant within lender, my lender by county by year fixed effects alleviates the effect of this 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 7 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 1.4%. 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.
Figure 7: 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 April 2021, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013-2020. Figure 7a 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 1.4%) and all borrowers who faced a Freddie Mac Survey Rate decrease of at least 1.4%. Figure 7b 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.

To make sure that the result of Figure 7 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 2. Indeed, while I find a positive correlation between non-refinancing borrowers and their payment of points, and a negative correlation between borrowers who prepay within five years and their choices of points, the magnitude of the difference is small at no more than 12 basis points. This analysis suggests that most of the heterogeneity between borrower prepayment behavior remains conditional on choices of upfront closing costs.
Table 2: Choices of points and refinancing/prepayment behavior

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Points</td>
<td>0.094***</td>
<td>-0.122***</td>
</tr>
<tr>
<td></td>
<td>(3.91)</td>
<td>(-3.94)</td>
</tr>
<tr>
<td>5-year prepayment</td>
<td></td>
<td>-0.122***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-3.94)</td>
</tr>
<tr>
<td>Log(loan amount)</td>
<td>0.121***</td>
<td>0.118***</td>
</tr>
<tr>
<td></td>
<td>(3.54)</td>
<td>(3.70)</td>
</tr>
<tr>
<td>Credit score controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>LTV controls</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>DTI control</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.419***</td>
<td>-1.290***</td>
</tr>
<tr>
<td></td>
<td>(-3.20)</td>
<td>(-3.25)</td>
</tr>
<tr>
<td>Observations</td>
<td>3935</td>
<td>3935</td>
</tr>
<tr>
<td>LenderXCountyXYear FEs</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust t statistics clustered by lender and county in parentheses.

* p < 0.05, ** p < 0.01, *** p < 0.001

Note: The data used in this figure is the Optimal Blue-HMDA-CRISM data from January 2013 to April 2021, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2020. Table 2 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 1.4%, and (2) borrowers who prepaid within five years. The sample for (1) is the set of borrowers whose mortgages originated before April 2016 where the Freddie Mac Survey Rate decreased at least 1.4% since origination. The sample for (2) is the set of borrowers whose mortgages originated before April 2016. Both regressions include lender by county by year fixed effects. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

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:

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

(4)
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 $1_{i,t}$ 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 1.4% refinancing rate incentive.

Results are shown in Table 3. First, in terms of points, I find some evidence that women and credit card revolvers pay fewer points, while first-time home buyers pay more. Higher credit score, higher LTV, and higher DTI borrowers pay fewer points, while higher loan amount borrowers pay more. The correlation between point choices and prepayment behavior is rather 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.  

Higher credit score borrowers are less likely to prepay, but they also pay fewer points. Higher LTV borrowers are more likely to prepay but pay fewer points.

\textsuperscript{20}Bhutta and Hizmo (2019) finds that minority borrowers tend to pay fewer points, but they use an FHA sample. The discrepancy in results can be explained by the fact that we focus on conforming mortgages rather than FHA mortgages.
Table 3: Borrower choices of points and their prepayment behavior by characteristics

<table>
<thead>
<tr>
<th></th>
<th>(1) Points</th>
<th>(2) 5-year prepayment</th>
<th>(3) Non-Refi Borrower</th>
</tr>
</thead>
<tbody>
<tr>
<td>Black</td>
<td>0.022 (0.21)</td>
<td>-0.129*** (-3.60)</td>
<td>0.229*** (6.28)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.022 (0.46)</td>
<td>-0.059* (-1.89)</td>
<td>0.074*** (3.38)</td>
</tr>
<tr>
<td>Single male</td>
<td>0.020 (0.66)</td>
<td>-0.000 (-0.01)</td>
<td>0.006 (0.34)</td>
</tr>
<tr>
<td>Single female</td>
<td>-0.019 (-0.51)</td>
<td>-0.022 (-1.01)</td>
<td>0.016 (0.72)</td>
</tr>
<tr>
<td>First-time home buyer</td>
<td>0.026 (0.47)</td>
<td>-0.017 (-0.54)</td>
<td>0.026 (0.96)</td>
</tr>
<tr>
<td>Credit card revolver</td>
<td>-0.041 (-0.89)</td>
<td>0.080** (2.37)</td>
<td>-0.022 (-0.58)</td>
</tr>
<tr>
<td>1st quartile of education</td>
<td>-0.051 (-1.18)</td>
<td>-0.039 (-0.99)</td>
<td>0.021 (1.14)</td>
</tr>
<tr>
<td>2nd quartile of education</td>
<td>-0.060 (-1.05)</td>
<td>-0.010 (-0.38)</td>
<td>-0.016 (-0.60)</td>
</tr>
<tr>
<td>3rd quartile of education</td>
<td>-0.019 (-0.41)</td>
<td>-0.007 (-0.19)</td>
<td>-0.031 (-1.10)</td>
</tr>
<tr>
<td>Log(loan amount)</td>
<td>0.093*** (2.83)</td>
<td>0.0763*** (3.96)</td>
<td>-0.140*** (-7.21)</td>
</tr>
<tr>
<td>Credit score controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>LTV controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>DTI control</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.069** (-2.41)</td>
<td>-0.437* (-1.95)</td>
<td>2.041*** (10.62)</td>
</tr>
<tr>
<td>Observations</td>
<td>3935</td>
<td>3935</td>
<td>3935</td>
</tr>
<tr>
<td>LenderXCountyXYear FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Robust t statistics clustered by lender and county in parentheses.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: The data used in this table is the Optimal Blue-HMDA-CRISM data from January 2013 to April 2021, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2019. This table regression results from estimation Equation (4). 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 facing a Freddie Mac Survey Rate decrease of at least 1.4%. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.
Another way to examine selection is to look at how borrower choices of points relate to their moving and refinancing behavior. Points do strongly predict moving and prepayment behavior, which is indicative of some selection being important. To do so, I run the the linear probability model on an indicator variable for moving or refinancing:

$$\mathbb{1}_{i,t} (\text{move/refi}) = \sum_{j=1}^{N} \beta_j \mathbb{1}(\psi_i = j) + \gamma Z_i + \xi_{i,t} \times c_{i,t} \times t + \epsilon_{i,t}$$  \hspace{1cm} (5)$$

where $\mathbb{1}_{i,t} (\text{move/refi})$ is an indicator variable that is equal to either moving or refinancing; $\beta_j$ 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, 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:

$$Call\ Option_{i,k} = \frac{V_{i,m} - V_{i,r}}{V_{i,m}}$$  \hspace{1cm} (6)$$

where

$$V_{i,m} = \sum_{s=1}^{TM_i - k_i} \frac{P_i}{(1 + m_{it})^s}$$  \hspace{1cm} (7)$$

$$V_{i,r} = \sum_{s=1}^{TM_i - k_i} \frac{P_i}{(1 + c_i)^s}$$  \hspace{1cm} (8)$$

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, $\xi_{i,t} \times c_{i,t} \times t$ represents lender by county by year fixed effects, and $\epsilon_{i,t}$ is the error term.

Figure 8 and Table 4 present the results. In particular, Figure 8a 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 8b shows the same pattern but for refinancing. In general, borrowers who pay more points are less likely to move and refinance.

**Figure 8: Moving/refinancing probability by points paid**

![Graph (a) Moving probability by points](image1)
![Graph (b) Refinancing probability by points](image2)

Note: The data used in this figure is the Optimal Blue-CRISM data from January 2013 to April 2021, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2020. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data. Figure 8a presents the predicted probabilities in regressions of moving on control variables, while Figure 8b presents the predicted probabilities in regressions of refinancing on control variables. The regression estimates that these results were based on are presented in Table 4.

Table 4 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 control variables, the *Call Option*, spread at origination *SATO*, and log of the loan amount are positively correlated with moving and refinancing.
Table 4: Choices of points and refinancing/prepayment behavior

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

Robust t statistics clustered by lender and county in parentheses.

* p<0.05, ** p<0.01, *** p<0.001

Note: The data used in this table is the Optimal Blue-HMDA-CRISM data from January 2013 to April 2021, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2020. This table regression results from estimation Equation (5). 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 bororver 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.

These patterns 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.

4 Model

4.1 Setup

I construct a general equilibrium model of mortgage choice. On the demand side, the model
rationalizes the heterogeneity in borrower refinancing behavior by combining the time and
state varying refinancing costs from Andersen et al. (2018) with a lifecycle 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. The model allows me to measure the welfare implications of
heterogeneity in borrower refinancing behavior in dollar terms, which is an independent
contribution to the literature.

4.1.1 Demand side

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

$$\max \mathbb{E}_t \sum_{t=1}^{T} \beta_t^{t-1} \left( \frac{C_{it}^{1-\gamma_i}}{1 - \gamma_i} \right) + \beta_i^{T} b_i \frac{W_{i,T+1}^{1-\gamma}}{1 - \gamma},$$

where $T$ is the terminal age, $\beta_i$ the time discount factor, $C_{it}$ the non-durable consumption,
$\gamma_i$ 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 $r_{it}$ 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.\(^{21}\) Real (log)labor income \( L_{it} \), house price \( H_{it} \), and the average mortgage rate \( \bar{c}_t \) 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.4.1. Finally, moving is treated as an exogenous mortgage refinance at an average level of upfront closing costs.

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 \( P^M_{it} \) and earn interest \( r_{1t} \) on savings minus inflation \( \pi_t \), and so in non-refinancing periods their non-durable consumption \( C_{it} \) in real terms can be written as:

\[
C_{it} = \exp(L_{it}) - P^M_{it} + (r_{1,t-1} - \pi_t)S_{i,t-1} + \Delta S_{it}
\]

Where \( \Delta S_{i,t} = S_{i,t} - S_{i,t-1} \) is the change in the borrower’s savings. In order to refinance, borrowers need to pay a cost \( \bar{\kappa}_{it} \). I model the borrowers’ refinancing cost \( \bar{\kappa}_{it} \) as:

\[
\bar{\kappa}_{it} = \begin{cases} 
\infty, & \text{with probability } 1 - p^a_i \\
\kappa_i, & \text{with probability } p^a_i 
\end{cases}
\]

where \( p^a_i \) 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.

\( ^{21} \)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. In particular, the real mortgage payment under constant inflation is \( P^M_{it} = \frac{1}{1+12} M_i \frac{c_{it}/12}{(1+c_{it}/12)^n-1} \). Note that because \( M_i \) is fixed, this formula does not incorporate the slight differences in the speed of principal paydown as borrowers refinance to mortgages with different interest rates. This feature is standard for the literature and the error resulting from it is likely small for minor differences in rates.
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\textsuperscript{22} and captures the constraints to refinancing in periods of house price decline as described in Hurst et al. (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 endogenous 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 $\tilde{V}_{it}(c_{it}, S_{i,t-1}) = V_{it}(c_{it}, S_{i,t-1}, \bar{c}_t, r_{1,t-1}, H_{it}, H_{i,t-1}, L_{it})$ as a function of the endogenous variables only for brevity.

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:

$$E_t V_{it} = \max \left\{ \max_{\Delta S_{it}} (\exp(L_{it}) - P_{it}^M + (r_{1,t-1} - \pi_t)S_{i,t-1} - \Delta S_{it})^{1-\gamma_i} + \beta E_t \tilde{V}_{i,t+1}(c_{it}, S_{it}) \right\}$$

where the first line of Equation (12) 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 utility from refinancing to the rate $c$ which affects the upfront closing cost they pay $\psi_t(c)$.

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

$$E_t V_{it}^{na} = \max_{\Delta S_{it}} (\exp(L_{it}) - P_{it}^M - (r_{it} - \pi_t)S_{i,t-1} - \Delta S_{it})^{1-\gamma_i} + \beta E_t \tilde{V}_{i,t+1}(c_{it}, S_{it}).$$

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

\textsuperscript{22}Freddie Mac’s requirements for refinancing are described in https://sf.freddiemac.com/general/maximum-ltv-tiltv-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.
probability $p_i^m$ for borrower $i$. Therefore, the borrower’s utility upon moving is:

$$
\mathbb{E}_t U_{i,t}^m = \max_{\Delta S_{it}, \psi} \frac{(\exp(L_{it}) - P_{it}^M - (r_{it} - \pi_{it})S_{i,t-1} - \Delta S_{it})^{1-\gamma_i}}{1-\gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1}(\bar{c}_i, S_{it}). \tag{14}
$$

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

$$
\mathbb{E}_t V_i = (1 - p_i^m)(p_i^a \mathbb{E}_t U_{i,t}^a + (1 - p_i^a)\mathbb{E}_t U_{i,t}^{na}) + p_i^m \mathbb{E}_t U_{i,t}^m. \tag{15}
$$

### 4.1.2 Supply side

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 $\psi_{it}$ for borrower $i$ at time $t$ and the mortgage interest rate $c$ is pinned down by a zero profit condition:

$$
\pi^l_{it} = \psi_{it}M + \phi_t(c)M - \bar{m}_{it}^l - m_{it}(M) = 0 \tag{16}
$$

where $\pi^l_{it}$ 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 $\bar{m}^l_{it}$ is average marginal cost incurred by the lender for originating the loan, and $m^l_{it}(M)$ 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 $\bar{m}^l_{it} + m^l_{it}(M)$ does not vary by the borrower’s choice of points, we have by re-arranging:

$$
\psi_t(c) = \left( \frac{\bar{m}^l_{it} + m^l_{it}(M)}{M} - \phi_t(c) \right). \tag{17}
$$

So that, all else equal, a mortgage with a higher interest rate $c$ and MBS value $\phi_t(c)$ would require fewer upfront points $\psi_t$. 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 is approximately true in reality, as I show in Figure A.1.

To close the model, I estimate the MBS value of mortgages \( \phi_t(c) \) based on an 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 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).\(^{23}\) More specifically, given an empirical prepayment hazard function \( \hat{p}_t \). When a borrower prepays, the lender gets remaining principal \( B^M_t \). Otherwise, they get a payment \( \tilde{P}^M_t \).\(^{24}\) The MBS premium of the mortgage, in dollar value terms, is then:

\[
\phi_t(c)M = E_1 \sum_{t=1}^{T} \delta_t [(1 - \hat{p}_t)\tilde{P}^M_t(c) + \hat{p}_t B^M_t] - M
\]

where 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:

\[
\delta_t = \frac{1}{\prod_{j=1}^{t} (1 + r_{jf} + OAS)}.
\]

Such that, conditional on empirical prepayment hazards \( \hat{p}_t(M) \), the OAS is the only free parameter in the supply side model. In particular, with the model of \( \phi_t(c) \), the mortgage interest rate at an average level of upfront closing costs \( \bar{c}_t \) and the level of the risk-free rate \( r_{1t} \) pins down \( \bar{m}_t^l + m_t^l(M) \) exactly and allows me to recover the mortgage interest rate and upfront closing cost trade-off for all levels of upfront closing costs and with counterfactual cash flows (ie. the no cross-subsidization case, or with alternative mortgage contract designs).

\(^{23}\) Another method of valuing MBS is via multivariate density estimation, as in Boudoukh et al. (1997), but that does not allow me to get counterfactual prices under alternative prepayment behavior or with alternative mortgage contract designs.

\(^{24}\) \( \tilde{P}^M_t \) is the nominal version of the real mortgage payment used in the demand model.
while holding $\bar{m}_t^l + m_t^l(M)$ as fixed. Time-varying changes in the refinancing incentive is captured as exogenous movements in $\bar{c}_t$ and rationalized in the model as a combination of changing risk-free rate and $\bar{m}_t^l$. Details of the OAS estimation is shown in Appendix A.4.2.

Combined with the demand side, my model can be viewed as a general equilibrium model of mortgage premia, in line with Campbell and Cocco (2015), but with the addition of endogenous upfront closing costs. A key assumption in this model is the perfectly competitive supply side. If the supply side were not perfectly competitive as is assumed here, my counterfactual results would still hold if lenders charge a constant markup across loans but should be interpreted in terms of consumer welfare instead of social welfare.

4.1.3 Computation

I solve the household life-cycle model using a value function approximation approach that is novel to this literature. In particular, instead of discretizing a state space $S$, I approximate:

$$V(S) \approx \hat{V}(S)$$

(20)

where $\hat{V}(S)$ is estimated using a Ridge regression on a fully interacted third order polynomial expansion of all the state variables, where the ridge parameter is chosen via cross-validation. The use of a sieve approximation to conduct value function iteration is proven to be consistent in Arcidiacono et al. (2013) and has been applied in other empirical contexts.\textsuperscript{25} The advantage of this approach is that it allows value functions on relatively large state spaces to be computed tractably.

5 Estimation

To estimate the model, I allow $p_i^a, \kappa_i, \beta, p_i^m, M_i$ to vary by individual, where $p_i^a$ is the probability that an individual is available to refinance in a particular time period, $\kappa_i$ is the

\textsuperscript{25}See, e.g., Keane and Wolpin (1997) and Barwick and Pathak (2015).
individual’s refinancing hassle cost when they do refinance, $\beta_i$ is the discount factor, $p^m_i$ 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).

I first present the identification argument in Section 5.1, then estimation procedure in Section 5.2, then results in Section 5.3, some calibration based on my estimates in Section 5.4, and finally the implications of my estimates for transfers and welfare in Section 5.5.

## 5.1 Identification

Of the unknown parameters, the distribution of $M_i$ is observed. I discuss the identification for the distribution of $p^a_i, \kappa_i, \beta_i, p^m_i$ as follows. First, the time-varying ability to refinance $p^a_i$ and hassle costs $\kappa_i$ 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 $p^m_i$ 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 $\beta_i$ 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.

5.2 Parametrization

I estimate the distribution of the borrower types using mortgage performance data. More specifically, I use a Logit-Normal distribution\(^{26}\) to model \(p^a_i, \beta_i, p^m_i\), a Log-Normal distribution to model \(\kappa_i\), and allow \(p^a_i, \beta_i\) to be correlated via a coefficient \(\rho\). The precise parametrization is as follows:

\[
\begin{bmatrix}
p^a_i \\
\beta_i
\end{bmatrix} \sim \text{Logit} \left( \text{MultivariateNormal} \left( \begin{bmatrix}
\mu_{p^a} \\
\mu_{\beta}
\end{bmatrix}, \begin{bmatrix}
\sigma^2_{p^a} & \rho \sigma_{p^a} \sigma_{\beta} \\
\rho \sigma_{p^a} \sigma_{\beta} & \sigma^2_{\beta}
\end{bmatrix} \right) \right) \quad (21)
\]

\[p^m_i \sim \text{Logit}(\text{Normal}(\mu_{p^m}, \sigma_{p^m})) \quad (22)\]

\[\kappa_i \sim \text{LogNormal}(\mu_{\kappa}, \sigma_{\kappa}) \quad (23)\]

which gives me 9 parameters \(\theta = (\mu_{p^a}, \sigma_{p^a}, \mu^\beta, \sigma_{\beta}, \rho, \mu_{p^m}, \sigma_{p^m}, \mu_{\kappa}, \sigma_{\kappa})\) to estimate. I focus on the correlation \(\rho\) between a borrower’s probability of being able to refinance and their discount factor because variation in the distribution of \(\kappa\) 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 \(\kappa\). 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.\(^{27}\) I construct the likelihood based on prepayment decisions, which implicitly treats all non-model implied refinancing as a move. Therefore, the moving probability \(p^m_i\) in my model captures all exogenous prepayment. The likelihood function for a prepayment decision

\(^{26}\)The Logit-Normal distribution is the distribution generated by \(Y = \frac{\exp(X)}{1 + \exp(X)}\) for 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.

\(^{27}\)I also separately observe moving and refinancing decisions for a subset of prepayments.
$y_{jt}$ for loan $j$ at time $t$ given a set of parameters $x_i = \{p_i^n, \kappa_i, \beta_i, p_i^m, M_i\}$ is then:

$$l_{jt}(x_i) = (1 - y_{jt})^{1 - p_{jt}(x_i)} y_{jt}^{p_{jt}(x_i)}. \quad (24)$$

Furthermore, at time $t = 0$, the likelihood of observing the borrower with $i$’s choice of upfront closing costs $\psi_i$ is:28

$$l_j'(x_i) = 1(\psi_i = \psi^*(x_i)). \quad (25)$$

To estimate the model, I simulate individuals with a grid for $x_i = \{p_i^n, \kappa_i, \beta_i, p_i^m, M_i\}$ based on a set of parameters $\theta$, with $x_i \sim F(\theta)$ where $F(\theta)$ is the distribution of types from Equations (21) to (23). 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:

$$L \propto \sum_{j} \log \left( \sum_{i=1}^{nsim} l_j'(x_i) \prod_{t=1}^{T_j} l_{jt}(x_i) \right), x_i \sim F(\theta), \quad (26)$$

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

### 5.3 Results

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

---

28Since 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).
Table 5: Estimated hyper-parameters and their standard errors

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_p$</td>
<td>-3.054</td>
<td>(0.195)</td>
</tr>
<tr>
<td>$\sigma_p$</td>
<td>0.919</td>
<td>(0.068)</td>
</tr>
<tr>
<td>$\mu_\beta$</td>
<td>2.428</td>
<td>(0.795)</td>
</tr>
<tr>
<td>$\sigma_\beta$</td>
<td>4.400</td>
<td>(0.031)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.989</td>
<td>(0.001)</td>
</tr>
<tr>
<td>$\mu_p^m$</td>
<td>-2.021</td>
<td>(0.090)</td>
</tr>
<tr>
<td>$\sigma_p^m$</td>
<td>0.078</td>
<td>(0.037)</td>
</tr>
<tr>
<td>$\mu_\kappa$</td>
<td>3.912</td>
<td>(0.038)</td>
</tr>
<tr>
<td>$\sigma_\kappa$</td>
<td>1.900</td>
<td>(0.016)</td>
</tr>
</tbody>
</table>

Note: These are parameters of the model estimated from maximum likelihood as in Equation (26). $\mu_p$ and $\sigma_p$ refers to the mean and standard deviation of the Logit-Normal distribution of the probability that a borrower is able to refinance. $\mu_\beta$ and $\sigma_\beta$ refers to the mean and standard deviation of the Logit-Normal distribution of the borrower’s discount factors. $\rho$ denotes the correlation between the borrower’s ability to refinance and their discount factors. $\mu_p^m$ and $\sigma_p^m$ refers to the mean and standard deviation of the Logit-Normal distribution of the probability that the borrower moves. $\mu_\kappa$ and $\sigma_\kappa$ 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 9 presents the estimates on the distribution of refinancing types in the population. In the left panel in Figure 9a, 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 6.2% monthly, or 54% annualized. This is consistent with my stylized fact in Section 3.2 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 9b, the results show 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 9: Distribution of borrower refinancing types

(a) Probability of being able to refi  (b) Hassle cost for refinancing

Note: Figure 9a plots the estimated density for the probability of being able to refinance coming from the marginal of the multivariate Logit-Normal distribution of Equation (21). Figure 9b plots the estimated density for the hassle cost of refinancing from the Log-Normal distribution of Equation (23).

Figure 10 presents my estimates for borrower discount factors and their correlation with their time-varying ability to refinance. Figure 10a 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 10b 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 (21). 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.
Figure 10: 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 10a plots the estimated density for the discount factor coming from the marginal of the multivariate logit-Normal distribution of Equation (21). Figure 10b plots a scatter plot with simulated draws of $p_i^a$ in the $x$-axis and $\beta_i$ in the $y$-axis from the multivariate logit-Normal distribution of Equation (21).

Finally, Figure 11 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 11 shows, annualized moving probabilities are centered around 11% per year, with a range between 9–14%.
5.4 Cross-subsidization by upfront closing cost choice: a calibration

Using the model, I illustrate the cross-subsidization between borrowers who differ by the manner through which their mortgage closing costs are financed. First, I show in Section 5.4.1 that, all else equal, actively refinancing borrowers tend to benefit from getting mortgages with lower upfront closing cost, while non-refinancing borrowers benefit from getting mortgages with higher upfront closing cost. Section 5.4.2 shows that optimally refinancing borrowers refinance more when they get lower upfront closing cost mortgages. Section 5.4.3 shows that low upfront closing cost mortgages are cross-subsidized for optimally refinancing borrowers from a pricing perspective. Finally, Section 5.4.4 summarizes the economic intuition of the cross-subsidization from a transfer and efficiency perspective.

All of the analysis in this section is conducted for a borrower with the simulated parameters described in Table 6, where $\beta, M, p^m$ are the median of the estimates, $OAS$ is as
estimated, and $p^a, \kappa_i$ are chosen to represent the behavior of an actively refinancing borrower and a non-refinancing borrower. However, I note that these results are not overly sensitive to the choice of parameters or even the model in general: in Appendix A.5 I show that essentially the same results can be obtained by using the model of Agarwal, Driscoll, and Laibson (2013) with Brownian motion interest rates. The same general results emerge regardless of the precise model specification.\footnote{The results for non-refinancing borrowers are somewhat sensitive to their discount factor and initial liquid assets. Their optimal strategy under the set of parameters in Table 6 is to pay closing costs upfront, which is not true if their discount factors $\beta$ are very low or if their initial liquid assets are low. The results for the actively refinancing borrower are more robust to these parameter changes because their optimal strategy is to get a low upfront closing cost mortgage, which is even more preferable with a lower $\beta$ and low initial liquid assets.}

Table 6: Parameters for an illustrative calibration of cross-subsidization

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.92</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>2</td>
</tr>
<tr>
<td>$M$</td>
<td>$$223,784$</td>
</tr>
<tr>
<td>$p^m$</td>
<td>0.12</td>
</tr>
<tr>
<td>$p^a$</td>
<td>${0, 1}$</td>
</tr>
<tr>
<td>$\kappa_i$</td>
<td>0</td>
</tr>
<tr>
<td>Initial liquid assets</td>
<td>$$50,000$</td>
</tr>
<tr>
<td>Initial risk-free rate</td>
<td>0.80%</td>
</tr>
<tr>
<td>OAS</td>
<td>0.22%</td>
</tr>
</tbody>
</table>

Note: These are parameters of the model estimated in Section 4. $\beta$ refers to the discount factor, $\gamma$ the coefficient of risk aversion, $M$ the mortgage size, $p^m$ the moving probability, $\kappa_i$ the fixed component of refinancing costs, and $p^a$ the time-varying ability of a borrower to refinance.

5.4.1 Borrower value by upfront closing cost choice

I present the results on borrower value by upfront closing cost choice in Figure 12. In particular, for the set of borrowers with parameters described in Table 6, I plot the borrower’s
utility when they always choose a given upfront closing cost, in terms of the equivalent increase in liquid assets that a non-refinancing borrower \((p^a = 0)\) would have to receive upfront to obtain the same utility as an actively refinancing borrower \((p^a = 1)\) with upfront closing cost equal to 5% of the loan amount.

Figure 12: Utility by closing cost choice

(a) Levels  
(b) Gain from active refinancing

Note: These figures represent the upfront cash a borrower would have to receive to obtain the same utility as a non-refinancing borrower \((p^a = 0)\) with closing costs equal to 5% of the loan amount. These results assume a market rate and interest rate trade-off of -0.17% in rate per point of upfront closing costs paid.

As Figure 12a shows, an actively refinancing borrower benefits from choosing a low upfront closing cost mortgage. In particular, they gain 4.1% of the loan amount in terms of value by choosing a zero upfront closing cost mortgage, relative to a non-refinancing borrower paying a 5% upfront closing cost. On the other hand, the non-refinancing borrower benefits from paying more in upfront closing cost. They would lose -0.5% of the loan amount if they were to choose a zero upfront closing cost mortgage. The reason for this difference is that the market interest rate and upfront closing cost trade-off is the same for everyone, while non-refinancing borrowers pay their higher interest rate for longer and thus effectively “over-pay” for their closing cost when they choose low upfront closing cost mortgages.

In addition, Figure 12b shows the difference in expected utility between actively refinancing and not refinancing in terms of the utility gain from refinancing measured in terms of equivalent initial liquid asset value. It shows that actively refinancing borrowers gain 4.7%
of the loan amount relative to non-refinancing borrowers, which is their “refi advantage,” if they always choose no upfront closing cost mortgages. On the other hand, the advantage is only 0.9% of the loan amount with high upfront closing cost mortgages. Since most mortgages are originated with low upfront closing costs (as shown in Figure 3b), the financing of closing costs through the interest rate of the mortgage exacerbates the inequality between actively refinancing and non-refinancing borrowers.

5.4.2 Optimal refinancing strategy by upfront closing costs

Next, I examine the source of the actively refinancing borrower’s advantage from getting a low upfront closing cost mortgage. In general, the advantage comes from an increase in the number of refinances: by getting a lower upfront closing cost mortgage and refinancing whenever interest rates fall, actively refinancing borrowers are able to gain a utility advantage. This is illustrated in Figure 13.

Figure 13: Active refinancing strategy by upfront closing costs

(a) Refi cutoff

(b) Expected number of refines

![Graphs showing active refinancing strategy by upfront closing costs](image)

Note: These results assume a market rate and interest rate trade-off of -0.17% in rate per point of upfront closing cost paid. They look at the refinancing strategy of an actively refinancing borrower ($p^a = 1$) in terms of the minimum interest rate decrease from initial to make refinancing optimal (Figure 13a) and the expected number of refines per each new mortgage taken out by a borrower (Figure 13b).

In particular, Figure 13a shows that, for an actively refinancing borrower, the optimally refinancing rate cut-off is much lower when the borrower gets a low upfront closing cost
mortgage. This is because the expected interest rate savings outweigh the upfront closing costs paid. In turn, this leads to more refinancing than otherwise, as shown in Figure 13b. As the next Section 5.4.3 shows, this is only profitable for the optimally refinancing borrower due to the cross-subsidization of low upfront fee mortgages.

5.4.3 Equilibrium interest rates and cross-subsidization

Figure 14 illustrates the cross-subsidization of low upfront closing cost mortgages. In particular, I compute the equilibrium rate for optimally refinancing borrowers in the model under perfect information by iterating the borrower and lender problem jointly using backward induction, where the supply side condition implied by Equation (17) from the last period with the borrower’s model-implied prepayment hazards are used as the rate and upfront closing cost trade-off that borrowers face in the following period. This essentially allows the lender to price on all borrower characteristics, thus eliminating cross-subsidization.

I find that the interest rate trade-off is higher, and steeper, for actively refinancing borrowers in this no cross-subsidization world. This suggests that the market interest rate for low upfront closing cost mortgages is especially lower than the no cross-subsidization case for actively refinancing borrowers. In terms of numbers, I find that a mortgage with a one percent upfront closing cost would carry a 1.25% higher interest rate in the no cross-subsidization case relative to the existing market equilibrium, whereas the difference is only 0.26% for a mortgage with a four percent upfront closing cost.\footnote{The effect of the presence of inactively refinancing borrowers in reducing the interest rate on low upfront closing cost mortgages has some parallel in Handel (2013), where high switching cost consumers help stabilize the market for health insurance.}
Figure 14: No cross-subsidization equilibrium interest rate by refinancing behavior

Note: Figure 14 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. “Equilibrium Rate, Only Actively Refinancing Borrowers” refers to the model-implied equilibrium rate and closing cost trade-off in a world where the lender is pricing their mortgages for the actively refinancing borrowers with perfect information on their type. The “Equilibrium Rate, Empirically Refinancing Borrowers” refers to the equilibrium rate and closing cost trade-off given a logit prepayment hazard function and our estimated OAS. Finally, the “Empirical Rate” was estimated using LoanSifter data by computing average trade-off at each level of points.

Indeed, low upfront closing cost mortgages are only favorable for actively refinancing borrowers because of this cross-subsidization. This is illustrated in Figure 15, which plots the utility of borrowers by choice of upfront closing costs in period $t = 1$. In particular, it shows that the actively refinancing borrower would not gain from getting low upfront closing cost mortgages in the case where they were by themselves in the market, without cross-subsidization from the non-refinancing borrowers. Hence, in the model, the cross-subsidization is strong enough to induce actively refinancing borrowers to choose lower closing cost mortgages and refinancing/“churn” excessively.
Figure 15: No cross-subsidization utility by upfront closing cost choice for actively refinancing borrowers

Note: Figure 15 presents the borrower utility, measured in terms of cash equivalent value, by upfront closing cost choice for an activity refinancing borrower $p^a = 1$ in the perfect information case where mortgage rates at each level of closing costs satisfy the zero profit condition in Equation (17) on the supply side.

5.4.4 Economic intuition on transfers and inefficiencies

I showcase the economic intuition behind these results in Figure 16, 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 16a. For actively refinancing borrowers, their effective price of mortgage origination is shifted downwards from the social cost, as illustrated in Figure 16b.
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 16b.

Figure 16: Deadweight loss from cross-subsidization of the price of mortgage refinancing

(a) Non-refinancing borrower

(b) Actively refinancing borrower

Note: Figure 16 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 16a 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 16b 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.

Figure 16 may also be interpreted in terms of price elasticities. Because non-refinancing borrowers’ quantity of mortgage origination are less price elastic, the effect of their cross-subsidization involves less of a change in behavior compared to the actively refinancing borrowers that receives the cross-subsidization. Therefore, to the extent that information frictions coupled with the design of financial contracts introduce economic distortions, they are mostly due to the changes in the incentives faced by actively refinancing borrowers.
5.5 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 17 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 0.12 refinances per new origination. Assuming there are around 8 million new mortgages each year, this accounts for around 960,000 mortgage refinances a year being “excessive” due to actively refinancing borrowers paying lower upfront closing costs than otherwise. Given that about half of new mortgages being originated are for a refinance, my model suggests that approximately one quarter of all US mortgage refinancing is excessive relative to a no cross-subsidization benchmark.

Figure 17: Differences in the expected number of refinances in the actual world versus the perfect information benchmark

![Figure 17](image)

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

Note: Figure 17a 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 18 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 $365 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 $2.9 billion per year.

Figure 18: Differences in utility in the actual world versus the perfect information benchmark

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

Note: Figure 18a 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.

6 Counterfactuals

I conduct two counterfactual analyses. In both 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.

6.1 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 $M' = M(1 + c(M))$, and their mortgage payment becomes:

$$P_{it}(M') = M' \frac{c_{it}/12(1 + c_{it}/12)^n}{(1 + c_{it}/12)^n - 1}. \quad (27)$$
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, $\tilde{U}_{i,t}^a$, is then:

$$\mathbb{E}_t \tilde{U}_{i,t}^a = \max \left\{ \begin{array}{ll}
\max_{\Delta S_{it}} \left( \exp(L_{it}) - P_{it}(M) - \frac{(r_{1,t-1} - \pi_t)S_{i,t-1} - \Delta S_{it}}{1 - \gamma_i} \right)^{1 - \gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1} \right) & \text{if no move/refi} \\
\max_{\Delta S_{it}, \psi} \left( \exp(L_{it}) - P_{it}(M') - \frac{(r_{1,t-1} - \pi_t)S_{i,t-1} - \Delta S_{it}}{1 - \gamma_i} \right)^{1 - \gamma_i} + \beta \mathbb{E}_t \tilde{V}_{i,t+1} & \text{if refi} 
\end{array} \right.$$

(28)

I simulate counterfactual borrower utility and behavior under this counterfactual with borrower utility when they are able to refinance being described by Equation (28) instead of Equation (12). I then obtain the implied aggregate borrower behavior based on my estimated distribution of borrower types in Table 5. Finally, I decrease the initial mortgage premia over the risk-free rate for all borrowers until the zero profit condition in Equation (17) is satisfied in the counterfactual, which is a general equilibrium effect of this contract design that increases in borrower utility.

Results are shown in Figure 19a, 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 $1301/$mortgage in the current world to $648/$mortgage in this counterfactual world. The same reduction in cross-subsidization can be inferred from Figure 19b, 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 -$365/mortgage to $88/mortgage. 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.

6.2 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 4 but automatically change the mortgage interest rate from $c$ to $r$ whenever $c - r > 1$. 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 (17) is satisfied in the counterfactual, which is a general equilibrium effect of this contract design that decreases borrower utility.

Results are shown in Figure 20. In 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 $1301/mortgage to $668/mortgage. Furthermore, automatically refinancing mortgages feature a greater welfare improvement compared to adding closing costs to the balance of the loan, at $688/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 20b.

Figure 20: Counterfactual utility from automatically refinancing

(a) Distribution

(b) By borrower refinancing ability

Note: Figure 20a 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 18).

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.

7 Conclusion

In this paper I have demonstrated a novel source of cross-subsidization in the US mortgage market: one in which non-refinancing borrowers pay for the actively refinancing borrowers’ closing costs. This mechanism exacerbates transfers between borrower types while also generating deadweight losses through excessive origination by actively refinancing borrowers. In terms of policy, my results suggest that two alternative mortgage contract designs—(1) adding the price of mortgage origination to the balance of the loan and (2) having automatically refinancing mortgages—can both reduce inequality in the market and improve total consumer welfare.
References


59


Appendix

This appendix supplements the empirical analysis of Zhang (2021). Below is a list of the sections contained in this appendix.

Table of Contents

A.1 Data Construction and Summary Statistics 2
  A.1.1 Optimal Blue-HMDA sample ........................................ 2
  A.1.2 Optimal Blue-HMDA-CRISM sample ............................... 3
  A.1.3 The LoanSifter data ................................................. 6

A.2 When are closing costs added to the rate? 7

A.3 Robustness check on the proportion of closing costs paid upfront 12

A.4 Model details 12
  A.4.1 Exogenous states .................................................... 12
  A.4.2 OAS ................................................................. 14
  A.4.3 Sanity check on model ............................................. 17

A.5 ADL 18
  A.5.1 Implications of market pricing of low upfront closing cost mortgages . 18
  A.5.2 Counterfactual pricing of low upfront closing cost mortgages ....... 20
A.1 Data Construction and Summary Statistics

A.1.1 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. 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.

\[\text{The 10% requirement was set purposefully low to include cases where the Optimal Blue lender ID may not correspond to a HMDA reporter for example in the case of correspondent lending. It is sufficient to reduce the percent of matches that are non-unique from 49.6% to 3.9%.}\]
Table A.1: Summary statistics for the 2018–2019 Optimal Blue-HMDA sample

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>25th Pctile</th>
<th>Median</th>
<th>75th Pctile</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan amount ($’000s)</td>
<td>256.7</td>
<td>117.8</td>
<td>166.3</td>
<td>240.0</td>
<td>333.8</td>
<td>1186906</td>
</tr>
<tr>
<td>Origination cost ($)</td>
<td>1818.7</td>
<td>1643.6</td>
<td>995.0</td>
<td>1370.0</td>
<td>2155.8</td>
<td>1154700</td>
</tr>
<tr>
<td>Credit Score</td>
<td>747.9</td>
<td>44.5</td>
<td>717</td>
<td>755</td>
<td>784</td>
<td>1186906</td>
</tr>
<tr>
<td>LTV (%)</td>
<td>80.3</td>
<td>15.0</td>
<td>75</td>
<td>80</td>
<td>95</td>
<td>1186906</td>
</tr>
<tr>
<td>DTI (%)</td>
<td>35.0</td>
<td>9.7</td>
<td>28.2</td>
<td>36.2</td>
<td>42.9</td>
<td>1171555</td>
</tr>
<tr>
<td>Interest rate (%)</td>
<td>4.54</td>
<td>0.58</td>
<td>4</td>
<td>4.625</td>
<td>4.875</td>
<td>1186906</td>
</tr>
<tr>
<td>First-time Home Buyer (d)</td>
<td>0.307</td>
<td>0.461</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1186551</td>
</tr>
<tr>
<td>Black (d)</td>
<td>0.041</td>
<td>0.199</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1071773</td>
</tr>
<tr>
<td>Hispanic (d)</td>
<td>0.096</td>
<td>0.294</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1063925</td>
</tr>
<tr>
<td>Single Female (d)</td>
<td>0.252</td>
<td>0.434</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1140692</td>
</tr>
<tr>
<td>Single Male (d)</td>
<td>0.330</td>
<td>0.470</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1140692</td>
</tr>
</tbody>
</table>

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.1.2 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 April 2021. 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.1.1, (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. 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 US mortgage originations, so the overlap between the two must be smaller than the overlap

---

2The 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%.
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 are as follows:
Table A.2: Summary statistics for the Optimal Blue-HMDA-CRISM sample

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>25th Pctile</th>
<th>Median</th>
<th>75th Pctile</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan amount ($'000s)</td>
<td>252.7</td>
<td>114.7</td>
<td>166.2</td>
<td>234.0</td>
<td>325.5</td>
<td>360291</td>
</tr>
<tr>
<td>Credit score</td>
<td>748.5</td>
<td>46.0</td>
<td>717.0</td>
<td>757.0</td>
<td>786.0</td>
<td>360291</td>
</tr>
<tr>
<td>LTV (%)</td>
<td>79.8</td>
<td>15.0</td>
<td>75.0</td>
<td>80.0</td>
<td>92.0</td>
<td>360291</td>
</tr>
<tr>
<td>DTI (%)</td>
<td>34.4</td>
<td>9.4</td>
<td>27.8</td>
<td>35.6</td>
<td>42.0</td>
<td>360291</td>
</tr>
<tr>
<td>First-time home buyer (d)</td>
<td>0.200</td>
<td>0.400</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>351955</td>
</tr>
<tr>
<td>Black (d)</td>
<td>0.030</td>
<td>0.171</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>340665</td>
</tr>
<tr>
<td>Hispanic (d)</td>
<td>0.076</td>
<td>0.265</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>340665</td>
</tr>
<tr>
<td>Single Female (d)</td>
<td>0.249</td>
<td>0.433</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>346222</td>
</tr>
<tr>
<td>Single Male (d)</td>
<td>0.322</td>
<td>0.467</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>346222</td>
</tr>
<tr>
<td>Credit Card Revolver (d)</td>
<td>0.110</td>
<td>0.313</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>346222</td>
</tr>
</tbody>
</table>

Notes: This table reports summary statistics from the Optimal Blue-HMDA-CRISM 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. CRISM data is attributed to Equifax Credit Risks Insight Servicing and Black Knight McDash Data.

A.1.3 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.3.

Table A.3: Summary statistics for the LoanSifter data

<table>
<thead>
<tr>
<th>Year</th>
<th>No. of Lenders</th>
<th>Rate at 0 points</th>
<th>Rate at 2 points</th>
<th>N lender-days obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>93</td>
<td>5.01</td>
<td>5.42</td>
<td>3923</td>
</tr>
<tr>
<td>2010</td>
<td>93</td>
<td>4.70</td>
<td>5.10</td>
<td>16025</td>
</tr>
<tr>
<td>2011</td>
<td>83</td>
<td>4.46</td>
<td>4.82</td>
<td>16589</td>
</tr>
<tr>
<td>2012</td>
<td>86</td>
<td>3.67</td>
<td>4.07</td>
<td>18105</td>
</tr>
<tr>
<td>2013</td>
<td>126</td>
<td>4.07</td>
<td>4.42</td>
<td>19993</td>
</tr>
<tr>
<td>2014</td>
<td>103</td>
<td>4.21</td>
<td>4.52</td>
<td>19446</td>
</tr>
</tbody>
</table>

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.2 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. While intuitive, this definition is most sensible in a world in

\footnote{This turns out to be true for most mortgages, as I show in Section 3.1.}
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 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.1. 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 \(\bar{c}\), I run a linear regressions of the form:

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

where \(c_l\) are the categorical variables of interest rate spread rounded to the nearest 1/8th, \(\xi_{jt}\) are lender-day fixed effects, and \(\epsilon_{ijt}\) is the error term. \(\phi_{ijt}\) 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.1, which shows that mortgages that are originated at

\(^4\)The Freddie Mac Primary Mortgage Market Survey rate is obtained from https://fred.stlouisfed.org/series/MORTGAGE30US.
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.\textsuperscript{5} Given the near complete pass-through 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.

\textsuperscript{5}The same patterns also exist in the time series, as I illustrate in Appendix Figure A.2. In Figure A.2, 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.2.
Figure A.1: Secondary marketing income and total lender revenues

![Graph showing secondary marketing income and total lender revenues](image)

Note: Figure A.1 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 (29). 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.2. 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 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.2.
Figure A.2: 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.2 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.2 shows that the exchange rate implied by 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.3 Robustness check on the proportion of closing costs paid upfront

Figure A.3: 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 3a plots histograms of estimated lender revenue which consists of the sum of upfront closing costs plus secondary marketing revenue. Figure A.3b then plots histograms of the fraction of lender revenue that is paid upfront.

A.4 Model details

A.4.1 Exogenous states

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

\[ dr_{1t} = a(b - r_{1t})dt + \sigma \sqrt{r_{1t}}dW_t. \]  

I estimate the evolution of exogenous states in the model via maximum likelihood\(^6\) using

---

\(^6\)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. The results for the risk-free rate are as follows:

Table A.4: Estimation of the CIR model of interest rates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.0910</td>
<td>0.0506</td>
</tr>
<tr>
<td>b</td>
<td>1.2649</td>
<td>0.7209</td>
</tr>
<tr>
<td>σ</td>
<td>0.4930</td>
<td>0.0175</td>
</tr>
</tbody>
</table>

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 $\Delta H_t$, and changes in log real personal income $\Delta L_t$ 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. More specifically, with $s_t = \begin{bmatrix} \bar{c}_t \\ 100 \times \Delta H_t \\ 100 \times \Delta L_t \end{bmatrix}$, the VAR equation is as follows:

$$s_t = \mu + r_{1t} \beta_{r_{1t}} + \Phi_1 s_{t-1}^t + \Phi_2 \Delta H_{t-1} + e_t,$$

where $e_t \sim N(0, \hat{\Sigma}_e)$ and $\mu, \beta_{r_{1t}}, \Phi_2$ 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)...

---

7 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.

8 The second lag on the house price variable is added to capture momentum and mean reversion as in Glaeser and Nathanson (2017).
rate,\(^9\) \(H_t\) is obtained from the Case-Shiller National House Price Index,\(^{10}\) and \(L_t\) is obtained from the US Personal Income\(^{11}\) divided by the US population.\(^{12}\) Furthermore, \(H_t\) and \(L_t\) are converted to real terms using the Consumer Price Index for All Urban Consumers.\(^{13}\) The results of the VAR estimation are as follows:

Table A.5: VAR estimates of state transitions

<table>
<thead>
<tr>
<th>Parameter</th>
<th>(\mu)</th>
<th>(\beta_{rt})</th>
<th>(\Phi_1)</th>
<th>(\Phi_2)</th>
<th>(\hat{\Sigma}_s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\bar{c}_t)</td>
<td>.093 (.051)</td>
<td>.024 (.010)</td>
<td>.972 (.012)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>100 * (\Delta H_t)</td>
<td>.051 (.028)</td>
<td>-.008 (.007)</td>
<td>0</td>
<td>1.060 (.047)</td>
<td>0</td>
</tr>
<tr>
<td>100 * (\Delta L_t)</td>
<td>.182 (.079)</td>
<td>-.007 (.021)</td>
<td>0</td>
<td>0</td>
<td>.232 (.053)</td>
</tr>
</tbody>
</table>

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.4 and A.5 are then used to simulate the transitions of the exogenous states in my model in Section 4.

A.4.2 OAS

An empirical model of prepayment behavior combined with my model of interest rates is needed to estimate the OAS in Section 4.1.2. 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 Freddie Mac survey rate at origination

\(^9\)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.

\(^{10}\)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.

\(^{11}\)U.S. Bureau of Economic Analysis, Personal Income [PI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PI.

\(^{12}\)U.S. Bureau of Economic Analysis, Population [POPTHM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/POPTHM.

\(^{13}\)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.
(SATO) as well as categories of the interest rate incentive defined as the current mortgage interest rate minus the Freddie Mac survey rate. 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 et al. (2020). Results of this regression are shown in Table A.6, which is used for my model of $\hat{p}_t$ as in Equation (18).

Table A.6: Logit model of prepayment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prepaid</td>
</tr>
<tr>
<td>SATO</td>
<td>-0.538***</td>
</tr>
<tr>
<td>SATO Sq</td>
<td>-0.325***</td>
</tr>
<tr>
<td>Rate Incentive $\geq$ 0%</td>
<td>0.482***</td>
</tr>
<tr>
<td>Rate Incentive $\geq$ 0.5%</td>
<td>1.061***</td>
</tr>
<tr>
<td>Rate Incentive $\geq$ 1%</td>
<td>0.768***</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.281***</td>
</tr>
<tr>
<td>Observations</td>
<td>4081108</td>
</tr>
</tbody>
</table>

$t$ statistics adjusted for clusters at the lender by county level 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 April 2021, for 30-year, fixed-rate, conforming, primary residence mortgages originated in 2013–2020. 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.6 and the interest rate model of Section A.4.1, with the risk-free rate being given as the implied 10 year rate under the Cox, Ingersoll, and Ross (1985) model, I estimate a $OAS = 0.22\%$ 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 (18). 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.4.3 Sanity check on model

Table A.7: Regression of model-implied optimal upfront closing cost choices by borrower characteristics

<table>
<thead>
<tr>
<th></th>
<th>optimal_points</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>beta</td>
<td>7.560***</td>
<td>(2.168)</td>
<td></td>
</tr>
<tr>
<td>gamma</td>
<td>-0.417***</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>pa</td>
<td>-2.166***</td>
<td>(0.263)</td>
<td></td>
</tr>
<tr>
<td>log_kappa</td>
<td>0.054***</td>
<td>(0.0046)</td>
<td></td>
</tr>
<tr>
<td>pm</td>
<td>-2.823</td>
<td>(2.340)</td>
<td></td>
</tr>
<tr>
<td>savings_cat</td>
<td>0.129***</td>
<td>(0.0048)</td>
<td></td>
</tr>
<tr>
<td>_cons</td>
<td>-7.492***</td>
<td>(2.151)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>15360</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses.

* p < 0.05, ** p < 0.01, *** p < 0.001
• All sensible: more patient people pay more in upfront closing costs, more risk-averse people pay less, borrowers who are more likely to pay attention pay less, borrowers with higher refinancing hassle costs pay more, borrowers who are more likely to move pay less, borrowers with more savings pay more.

A.5 ADL

A.5.1 Implications of market pricing of low upfront closing cost mortgages

Next, I show that the pricing of lower upfront closing cost mortgages is especially favorable to the benchmark optimally refinancing borrowers of Agarwal, Driscoll, and Laibson (2013) but unfavorable to non-refinancing borrowers. Figure A.4 compares the expected NPV of an optimally refinancing borrower from the model of Agarwal, Driscoll, and Laibson (2013) under a variety of choices of upfront closing costs with that of a non-refinancing borrower. Both borrowers have a moving hazard of 10% per year, and interest rate movements are assumed to be Brownian motion with a calibrated annualized standard deviation from the post-crisis period. The borrowers are assumed to always pick the same upfront closing costs, which is justifiable as a benchmark by the stationarity of the problem.

Figure A.4a shows that the expected NPV of the optimally refinancing borrower increases significantly with lower upfront closing costs at a market price of +0.17% in higher interest rate per percentage of the loan amount reduction in upfront closing costs. In particular, the expected NPV for the optimally refinancing borrower goes from 1.3% of the loan amount if the borrower were to always choose a mortgage with an upfront closing cost of 5% to 5.3% if the borrower were to always choose a “no closing cost” mortgage, a fourfold increase. The reason for this increase is that the interest rate increase for lower upfront closing cost mort-

\[ \sigma = 0.4597\% \]

For the period of January 2010 to January 2021, I find the annualized standard deviation of monthly average mortgage interest rates from the Freddie Mac Mortgage Survey to be \( \sigma = 0.4597\% \).
gages is too low for the optimally refinancing borrower: it is significantly cross-subsidized, and the optimally refinancing borrower is able to derive significant value by choosing a lower upfront closing cost and then refinancing. Indeed, the pattern is opposite, though less drastic, for the non-refinancing borrower: their expected NPV is 0.3% with a 5% upfront closing cost and -0.3% with no upfront closing costs. The fact that non-refinancing borrowers (indeed, almost all borrowers) choose lower upfront closing cost mortgages implies that they cross-subsidize the optimally refinancing borrowers’ mortgages. Comparing across the two types of borrowers, Figure A.4b shows that the prevalence of low to zero upfront closing cost mortgages increases the NPV advantage to optimally refinancing by a factor of five.

Figure A.4: Expected NPV by Upfront Closing Costs

![Chart](image)

(a) NPV by upfront closing costs

(b) NPV advantage to actively refinancing

Figure A.5 shows the implications of lower upfront closing cost mortgages for the optimally refinancing borrower’s “refi cutoff” and expected number of refinances per mortgage. The “refi cutoff” is computed directly from the formula of Agarwal, Driscoll, and Laibson (2013), and as shown in Figure A.5a it is significantly declining in the level of upfront closing cost chosen, from 1.4% for mortgage with all closing costs paid upfront to 0% for a no upfront closing cost mortgage. Correspondingly, the expected number of refinances per mortgage, which I compute by simulating Brownian motion paths for interest rates and counting the number of refinances, is significantly increasing in upfront closing cost choice as shown in Figure A.5b. It goes from 0.25 per mortgage with 5% in closing costs, to 1.25 refinances per
mortgage for a 1% in closing costs, to a degenerate number with zero closing cost mortgage.\footnote{Because I simulate the Brownian motion of Agarwal, Driscoll, and Laibson (2013) in monthly intervals, I get 9.3 expected refinances per new mortgage origination with zero closing cost mortgages.}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure.png}
\caption{Optimal refinancing strategy with upfront closing cost choice}
\end{figure}

\subsection*{A.5.2 Counterfactual pricing of low upfront closing cost mortgages}

Next, I investigate the cross-subsidization of low upfront closing cost mortgages from the perspective of lender rate-setting under my model of the competitive supply side. Instead of using my model, I use the model of Agarwal, Driscoll, and Laibson (2013) for my model of actively refinancing borrower behavior.

Results are shown in Figure A.6. In particular, I find that the revenue neutral rate and upfront closing cost trade-off matches the empirically observed rate and upfront closing cost well. Furthermore, Figure A.6 suggests that actively refinancing borrowers (in the sense of Agarwal, Driscoll, and Laibson (2013)) receive a substantially lower rate than what they would have received under perfect information: if all borrowers were optimally refinancing, lenders would charge substantially higher interest rates particularly for low upfront closing cost mortgages, on the order of 1.49\% more with a 1\% upfront closing cost mortgage.
compared to only 0.13% with a 5% upfront closing cost mortgage.\textsuperscript{16} In other words, the interest rates on lower upfront closing cost mortgages appear to be substantially discounted for optimally refinancing borrowers due to the presence of non-refinancing borrowers in the market.

Figure A.6: Pricing of mortgages by upfront closing cost choice and borrower type

\textsuperscript{16}With zero upfront closing costs and optimally refinancing borrowers, I find that lenders would have to charge a rate of 57\% to remain revenue-neutral.