Inaction, Search Costs, and Market Power in the US Mortgage Market

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Abstract

Many US mortgage borrowers do not refinance, despite seemingly having financial incentives to do so. We explore the role of search costs in explaining this inaction, focusing on the 2009-2015 period when mortgage rates declined significantly. We estimate a (dynamic) discrete choice model of refinancing and search decisions using a proprietary panel data set, which includes information on the sequence of refinancing decisions and search intensity (the number of mortgage inquiries). We find that search costs significantly inhibit refinancing through two channels. First, higher search costs directly increase the cost of refinancing. Second, they also indirectly increase loan originators' market power and thus raise the offered refinance rates. We find that the indirect market power effect dominates. We use our model to study an alternative market design, in which a centralized refinance market replaces the current decentralized one. We find, under specific assumptions, a centralized refinance market can significantly increase refinancing activities by eliminating market power, even if we keep the refinancing costs unchanged.

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1 Introduction

The average refinance mortgage rates in the US declined from 6.0% in 2008 to a historical low of 3.5% in 2013. However, many mortgage borrowers failed to refinance, despite apparently having incentives to do so.[1] This inaction is puzzling, since borrowers who do not refinance could lose out on substantial savings. Keys et al. (2016) argue that a household with a 30-year mortgage of $200,000 could save more than $60,000 in interest payments over the life of the loan by refinancing a 6.0% fixed-rate mortgage (FRM) at 4.5%, even after accounting for the refinance transaction costs. One explanation for this inaction could be that borrowers find it costly to search for a new mortgage. There is evidence to suggest that search friction exists in the US mortgage market. Specifically, more than half of the mortgage borrowers contact only one lender to refinance, despite the wide dispersion of interest rates and fees for a homogeneous mortgage contract.

In this paper, we bridge the evidence on search friction and refinancing inactivity to explore the role of search costs in explaining refinancing inaction. Specifically, we ask two questions. First, what is the effect of search costs on refinancing activities? We explore two channels through which search costs inhibit refinancing. Higher search costs directly increase the cost of refinancing, and they also (indirectly) increase the loan originators' market power and thus raise the mortgage rates offered. The second question we ask is: What is the contribution of direct versus indirect market power effect on refinancing activities? The answer to the second question is important because it would enable policy makers to evaluate which policies, mortgage designs, or market designs might be more effective in reducing search friction and, consequently, inactivity in refinancing.

To address these questions, we first use a data set, which includes information on search intensity and refinancing decisions. Next, we present evidence from the data that is indicative of refinancing inaction, search friction, and also how search intensity and refinancing decisions are related. Motivated by the evidence, we develop and estimate a dynamic equilibrium model of refinancing and search decisions. Finally, we use the estimated model to conduct counterfactual experiments.

The proprietary panel data set that we use contain detailed information on mortgage contracts and borrower characteristics. To control for the role of the borrowers' creditworthiness in refinancing decisions, we follow the FICO® credit scores and the marked-to-market loan-to-value (LTV) ratios of the borrowers over time. These data enable us to follow the sequence of borrowers' refinancing decisions, which means that we have access to the characteristics of both old and newly refinanced mortgages. The data includes the number of mortgage inquiries per borrower. We use the inquiries as a measure of search intensity.

From our data, we first present evidence of refinancing inactivity. We argue that at least 25% of the

[1] Agarwal et al. (2015), Johnson et al. (2015) and Keys et al. (2016) document inaction in refinancing in the US.

borrowers could have reduced their interest rates by at least 1.125 percentage points if they chose to refinance between 2009 to 2013. This is equivalent to a monthly payment reduction of at least \$120. Second, we provide evidence that is indicative of search friction. We document the wide dispersion of transacted refinance interest rates for homogeneous mortgage contracts. We find that the difference between the 1^{th} and the 99^{th} percentiles of this distribution is almost 1.625 percentage points. We also present a negative correlation between interest rates and the number of mortgage inquiries in the refinance market, suggesting that it pays to search more. Despite this, almost 60% of the mortgage borrowers in our dataset made only one inquiry when they refinanced their mortgages. Third, we explore the relationship between search intensity and refinancing probabilities. We document a positive correlation between these two variables. Specifically, borrowers who search more at the time of a mortgage origination are more likely to refinance their mortgages later.

To explain these facts and explore their implications, we develop an equilibrium model by incorporating search into a dynamic discrete choice model of refinancing decisions. On the demand side, borrowers first decide whether or not to refinance in each period. If they choose to refinance, they search sequentially in order to find the lowest rates. Specifically, borrowers decide whether to accept the offered rate and apply for the mortgage, or whether to reject the offer and continue searching. If they apply and the application is approved, they refinance with the offered rate. If their application is rejected, they continue searching. On the supply side, loan originators take into account that gathering many quotes is costly for borrowers. They respond accordingly by offering a distribution of rates that are higher than the marginal cost of the loan origination. This model enables us to explore how search costs, directly and indirectly through market power, inhibit refinancing.

A refinancing decision requires a cost-benefit analysis for the mortgage borrowers. Refinancing costs include search costs and switching costs. The search costs of borrowers are equal to the cost of each inquiry (marginal search costs) times the total number of inquiries that they gather. The latter depends on how many times the borrowers refuse offers and the number of times their applications are declined by the loan originators. The higher the search costs, the lower the probability to refinance. This channel is what we call the direct effect of search costs on refinancing.

The benefit of refinancing comes from the flow of utilities throughout the life of a new mortgage contract. Borrowers know the distribution of the offered rates. If those who want to refinance in order to lower the interest rate of their mortgages, do not expect that they are able to reduce it significantly, they may choose not to refinance. Loan originators take into account the search friction of the borrowers and thus raise the offered refinance rates. This equilibrium effect weakens the benefit of refinancing. This channel is what we call the indirect market power effect of search costs on refinancing.

We use the model to back out the search cost distribution from the observed interest rate distribution. To do this, we need to address two complexities. First, loan originators may reject an application based on creditworthiness. Borrowers with low creditworthiness know that their chances of being approved are small; thus, they may be willing to accept a mortgage with a high interest rate in order to avoid additional search. This implies that these borrowers will behave as if their search costs are high. If we use only the interest rate distribution to estimate the search costs, we will back out search cost distribution conditional on creditworthiness, but not the unconditional one. We therefore need to separately identify the probabilities of whether loans are rejected by the loan originators or by the borrowers. We use the relationship between the number of mortgage inquiries and the interest rates to address this complexity. We document that the negative correlation between the interest rates and search intensity becomes weaker as we explore riskier borrowers, because they are more likely to accept any offer in order to avoid additional search to get approved. Finally, the relationship between the interest rate and the number of mortgage inquiries becomes flat among the riskiest borrowers.

The second complexity comes from selection. If high search cost mortgage borrowers are less likely to refinance, then the participants in the refinance market are biased in favor of low search cost borrowers. In order to take into account this selection, we use the dynamic refinancing behavior of the borrowers. Specifically, the mentioned positive correlation between search intensity and refinancing odds helps us to infer the search costs of the borrowers based on their refinancing frequencies. The higher the search costs, the lower the refinancing probability.

We estimate the model using data from 2008 to 2015, during a period of mortgage rates' transition of high to low. Solving a dynamic model during a transition period is computationally challenging, because we have to keep track of the distribution of offered rates and many state variables. That is why we incorporate a search model into a dynamic discrete choice framework in order to estimate the model using conditional choice probability (CCP) techniques. We build on Arcidiacono and Miller (2011) since it allows us to incorporate unobserved search costs. Specifically, we use their two-stage approach in order to estimate the model.

We find that search costs significantly inhibit refinancing. Specifically, if we completely remove search friction by assuming a zero marginal search cost for all the borrowers, the mortgage rates on outstanding mortgages decrease by 1.4 percentage points from 2009 to 2015. Eliminating the search costs directly decreases the refinancing costs. Note that we assume that switching costs are still in place. Our estimates show that, on average, the search costs are at least 30.8% of the total refinancing costs. We also find that the indirect market power effect dominates the direct effect of search costs on inhibiting refinancing. We find that almost 75% of the decrease in outstanding mortgage rates (1.4 percentage points) is attributed to the indirect market power effect.

Finally, we use our model to study an alternative market design, that under specific assumptions can significantly increase refinancing activity by eliminating market power, even if we keep the refinancing costs unchanged. We specifically assume a centralized refinance market replaces the current decentralized one. In this market, we assume Bertrand competition among the loan originators. They compete by posting interest rates to the centralized market. Borrowers observe only one interest rate at each point in time, and they can lock in the posted rate by choosing to refinance. We assume refinancing is still costly for the borrowers. They pay for the switching costs in full, and they also pay a search cost equal to one inquiry.

Literature Review

We contribute to various branches of the literature. First, we contribute to the literature that studies the sources of inaction in consumer decision-making. Inaction in switching to financially more beneficial contracts is well documented in many markets (Ausubel, 1991; Handel, 2013; Honka, 2014; Heiss et al., 2016; Nelson, 2017; Fleitas, 2017). Moreover, search friction is also a well-documented feature of many markets (Brown and Goolsbee, 2002; Hortaçsu and Syverson, 2004; Roussanov et al., 2018; Galenianos and Gavazza, 2019; Allen et al., 2019). Our contribution is to bridge these two evidence in order to explore the role of search costs in explaining inaction.

Second, we contribute to the studies exploring decision-making in the mortgage market. Since this market is important from both the micro and the macro perspectives, exploring the poor decision-making of borrowers in this market has received particular attention (Green and LaCour-Little, 1999; Bucks and Pence, 2008; Chang and Yavas, 2009; Woodward and Hall, 2012; Agarwal et al., 2015; Keys et al., 2016; Agarwal et al., 2017). We are the first that explore the role of search costs in making poor refinancing decisions. There are examples in the US that have explored the role of the creditworthiness of the borrowers as a barrier to refinancing (Agarwal et al., 2015 and Lambie-Hanson and Reid, 2018). We highlight the importance of search costs in explaining inaction while we take into account the effect of creditworthiness. In this regard, our paper is similar to Andersen et al. (2018), who study inactivity in refinancing in Denmark, where the borrowers' creditworthiness is not a barrier to refinancing. Their paper highlights the role of inattention and the psychological costs. Similarly, Johnson et al. (2015) highlight the role of other factors than creditworthiness. They argue that suspicion about the motives of the financial institutions and time preference contribute to failures to refinance in the US.

Third, this paper explores and highlights the importance of selection in markets with search friction. In a search model, price elasticity of demand depends on the search cost distribution. Ignoring the selection results in the mis-measurement of this elasticity and, consequently, of the market power. Using price dispersion in a static search model is the standard method for estimating search costs (Hortaçsu and Syverson, 2004; Hong and Shum, 2006; Gavazza, 2016; Salz, 2017; Allen et al., 2019). Some studies use detailed information on shopping behavior to estimate search costs (De los Santos et al., 2012; Honka, 2014; Honka et al., 2017), but these studies also ignore the selection. The selection problem is unlikely to be an issue in retail shopping. However, in markets, in which consumers choose long-term contracts and may be inactive in adjusting their terms to more favorable ones over time, selection can lead to considerably mis-measured search costs. We address this selection by estimating a dynamic search model.

Fourth, we contribute to an estimation method for search models. We incorporate search into a dynamic discrete model in order to use CCP techniques. Moreover, we use Arcidiacono and Miller (2011) tools to estimate a search model.

Since our paper is linked to Agarwal et al. (2017) and our other study Ambokar and Samaee (2019) in many dimensions, we review them separately in the following.

Our paper is related to Agarwal et al. (2017) in many aspects. We follow them to use the number of inquiries as a measure of search intensity. They have access to total number of inquiries (mortgage and nonmortgage), while we fortunately have access to the number of mortgage inquiries. We follow them to use search intensity to separately identify the probabilities of whether loans are rejected by the loan originators or by the borrowers. Since screening in the refinance market is mostly based on the hard information of the borrowers captured by credit scores and LTV ratios, unlike them, we do not introduce an adverse selection. We instead write a model in which the borrowers' creditworthiness is fully observable. They explore search friction in a static model in which approval process by lenders affect the search behavior. We extend their static model into a dynamic one to explore the role of search friction in refinancing inaction. This dynamic model allows us to highlight the importance of selection in the refinance market.

A lack of refinancing can weaken the transmission of monetary policy. Scharfstein and Sunderam (2016), Di Maggio et al. (2017), Beraja et al. (2018) and Auclert (2019) explored the mortgage refinancing channel of monetary policy. In our related study, Ambokar and Samaee (2019), we incorporate a mortgage market with search friction into a standard New-Keynesian general equilibrium model to explore the role of search friction in the transmission of monetary policy. In that study, we also allow for statistical discrimination by lenders based on the characteristics of the current mortgage. In both studies, we find that the loan originators' market power induced by search friction has an important role to understand how search friction affects refinancing decisions.

2 Data

Our analysis relies on Equifax Credit Risks Insight Servicing and Black Knight McDash (referred to CRISM), a panel data set that merges Equifax's credit bureau data on consumer debt liabilities with mortgage servicing data from McDash. CRISM covers about 60% of the US mortgage market during our sample period and is well suited to studying refinancing (Lambie-Hanson and Reid, 2018).

In this data set, we have access to detailed information of the mortgage contracts (LTV raio, Debt-to-Income ratio, location of the property, mortgage size, quarter of the origination, property type, etc.). CRISM is merged with Home Mortgage Disclosure Act (HMDA) data set. We therefore have access to many characteristics of the borrowers at the time of mortgage origination (sex, ethnicity, race, income, etc.).

The Equifax data contains a borrower's updated FICO® Score for each month. In order to measure the borrowers' updated LTVs, we use borrowers' remaining principal balance in the numerator, while for the denominator (home value) we follow standard practice and assume that the value of the property (whose appraisal we observe at the time of the loan origination) evolves according to a local home price in the Zillow Home Value Index (ZHVI). We specifically follow Lambie-Hanson and Reid (2018) and Abel and Fuster (2018) approach to build marked-to-market LTV ratios for each mortgage borrower.

The formal process to refinance a mortgage is as follows. First, mortgage borrowers apply to refinance by filing an application. Depending on the loan originator, this step may be completed over the phone, online, or in person. In this application, borrowers provide information on themselves and the property. This information includes employment, income details, asset information, and details about the location and features of the property. By submitting this application, borrowers provide a consent to proceed, permitting their loan originators to move forward with the application. Second, a loan originator is required by law to provide a Loan Estimate document within three days of receiving a loan application. This document estimates the fees and closing costs for the new mortgage, such as appraisal and origination fee and title work. It also summarizes the loan terms and monthly payment. At this point, the borrower's credit report is "pulled" by the lender in order to determine both the borrower's eligibility for specific loans and the interest rate to be charged to the borrower. This "pull" is recorded as "an inquiry" by the credit bureau. At this stage, borrowers have already locked in the interest rates for a specific period, typically up to 45 days. By this stage, borrowers can decide whether to continue with the current loan originator or contact other originators. Third, Before approving the refinance loan, loan originators will order a home appraisal to get the property's estimated market value. Fourth, mortgage loan officers forward the application and home appraisal to a loan processor, who will prepare and review the loan. An underwriter will then review the completed application to make a final decision based on the loan originators' criteria. At this step, borrowers inform of the final decision on the loan application. The last step is the closing process. Once borrowers have received the final approval, they review and sign the closing documents, and also pay the costs of processing the loan application. The borrower makes monthly payments once the mortgage is settled, which depending on the loan, are either paid directly to the loan originator or to a separate loan servicer.

A unique feature of the CRISM dataset is that we have access to the number of mortgage inquiries as a proxy for search intensity. Unlike Agarwal et al. (2017), who use the total number of inquiries as a proxy for search intensity, including both mortgage and non-mortgage inquires, we have directly access to the number of mortgage inquiries.

We use the credit bureau data on mortgage inquiries around the "final" mortgage application (and approval) to capture the intensity of borrower search. As discussed in Agarwal et al. (2017), it is possible that borrowers may search for mortgages informally without a credit pull, such as searching for lenders and interest rates offered on the Internet. However, the final terms offered to the borrower depend on the creditworthiness of the borrowers. Lenders can therefore only offer full contract terms after verifying the borrower's credit score ("an inquiry") and knowing the house characteristics. Therefore, not being able to measure such informal searches should not impact the manner in which we intend to consider borrower search.

3 Descriptive Evidence

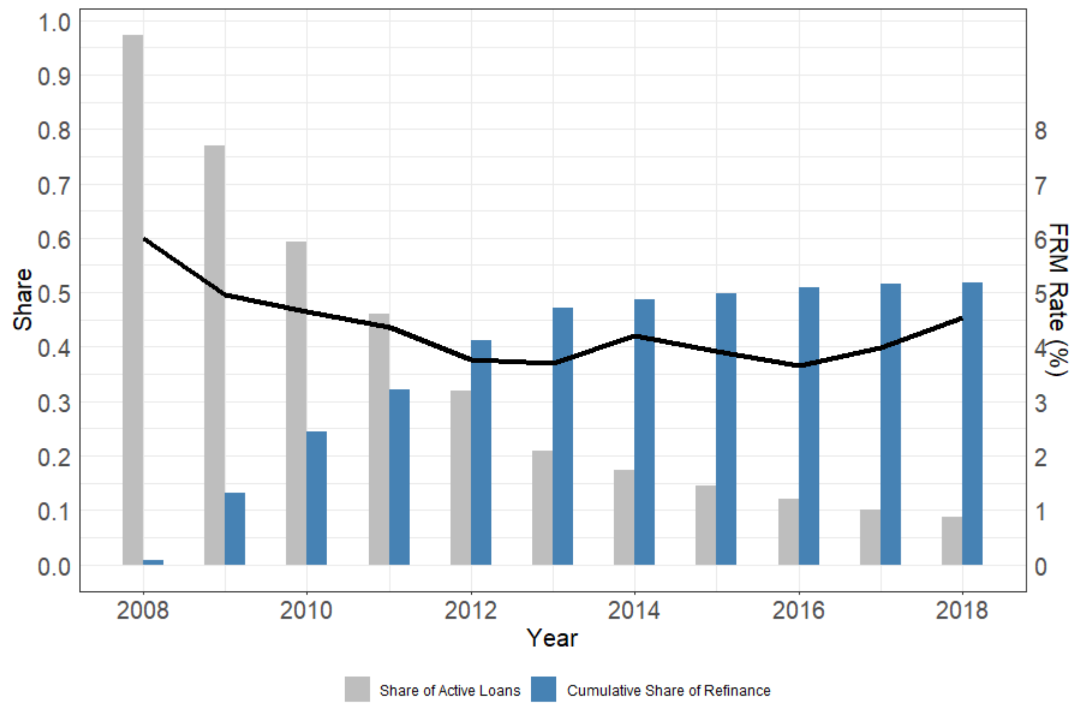
In this section, we document three descriptive patterns. First, we present patterns that suggest inaction in refinancing. Second, we present evidence that is indicative of search friction. Third, we document evidence indicates that search and inaction are correlated: the higher the search intensity, the higher the refinancing odds.

The evidence provided motives a model of search and refinancing decisions. We need to take into account two complexities in developing and estimating the model. First, loan originators may reject an application. We therefore need to be able to separately identify inquiries that are rejected by the borrower or by the loan originators. Second, there is a selection in the refinance market because high search cost borrowers are less likely to refinance. In this section, we provide evidence of how we use the data on the number of mortgage inquiries to address the first complexity and the dynamic data on refinancing decisions to address the second complexity.

3.1 Inaction and Incentive to Refinance

Mortgage rates declined significantly in the US in the wake of the Great Recession. Figure 1 presents the dynamic of the average FRM rate in the refinance market from 2008 to 2018. The interest rate declined from 6.0% in 2008 to the historically low rate of 3.5% in the first quarter of 2013. Moreover, the interest rate was significantly lower than that of 2008 during all periods after 2013. There were potential financial incentives for many mortgage borrowers to refinance mortgages during the periods after 2008. Figure 1 follows all the loans that were originated in 2008 until they were refinanced for the first time. From 2008 to 2010, the interest rates declined by almost 1.5 percentage points, however, almost 60% of the mortgages were still not refinanced by the end of 2010. The graph indicates that more than 20% of the mortgages remained active at the end of 2013, despite the historical low rate at the begging of 2013.

Figure 1: Dynamic of Refinancing Decisions



Note: This graph follows a representative sample of fixed-rate mortgages originated in 2008 until 2018. The right axis represents the unit of the black line. The black line presents the average of the refinance rate from the transacted data. The left axis represents the columns. The gray columns present the share of active loans from the cohort of 2008 at each point in time. The blue columns demonstrate the cumulative refinance fraction of the cohort of mortgages originated 2008. The sum of blue and gray columns at each point in time is less than one. This is because loans originated in 2008 may be terminated over time for reasons other than refinance (like early pay off, default, etc.).

Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

To get a more accurate measure of the incentives for refinancing, we explore how much outstanding mortgage borrowers could save in interest rates through refinancing. More specifically, we follow each borrower with a mortgage over time by building an interest rate saving measure for them. This is the interest rate reduction that mortgage borrowers could have got by refinancing their mortgages to a new refinance rate $\hat{r}_{izt}$. The average of the refinance interest rate $\hat{r}_{izt}$ is predicted by:

$$r_{izt} = \beta X_{it} + \mu_t + \mu_z + \epsilon_{izt} \tag{3.1}$$

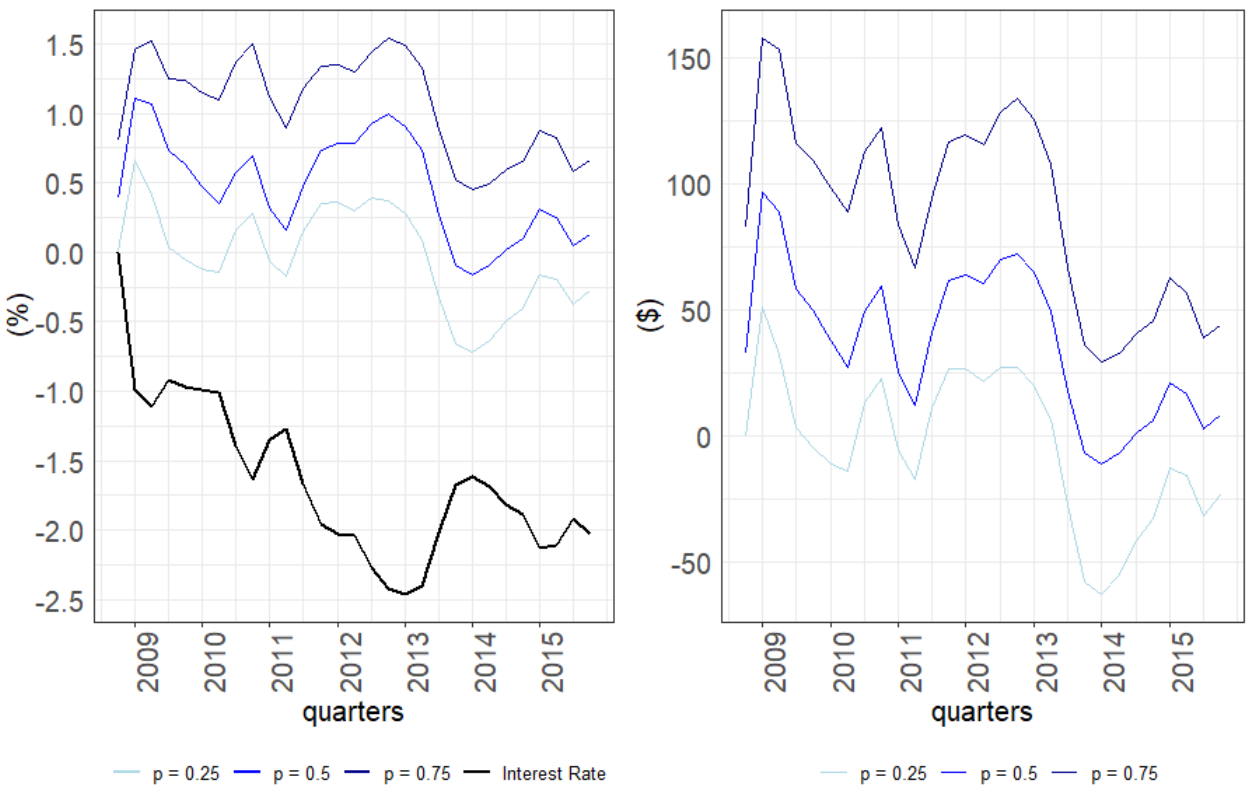
in which r_{izt} is the transacted interest rate in the refinance market of borrower i at time t in location z. X_{it} includes the FICO® Score groups, the loan-to-value (LTV) ratio groups, their interactions, and the remaining term of the mortgage contract. μ_t and μ_z are quarter and five-digit zip code location dummies. The following equation enables us to find the measure of interest rate saving for borrowers indexed by i

if they refinance at time t in location z.

$$\Delta r_{izt} = r_{iz} - \hat{r}_{izt} \tag{3.2}$$

in which r_{iz} is the interest rate on the current mortgage for borrower i with a property located in location z. Note that r_{iz}, the interest rate on the current mortgage, is constant over time for borrower i. The interest rate that the borrower can refinance their mortgage to, $\hat{r}_{izt}$, may change over time. This occurs because the average mortgage interest rate in the market changes over time, or because the creditworthiness of the borrower, such as their FICO® Score or LTV changes over time, or because the remaining term of the mortgage varies.

Figure 2: Incentive to Refinance



Panel (a): Interest Rate Savings

Panel (b): Monthly Payment Savings

Note: We use representative sample of all outstanding fixed-rate mortgages in every quarter to generate thees two graphs. Panel (a) presents the percentiles of the interest rate saving if borrowers would have chosen to refinance. The black line is the dynamic of average refinance rates, which is normalized to zero at the fourth quarter of 2008. Panel (b) replicates Panel (a) in terms of monthly payment savings.
Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

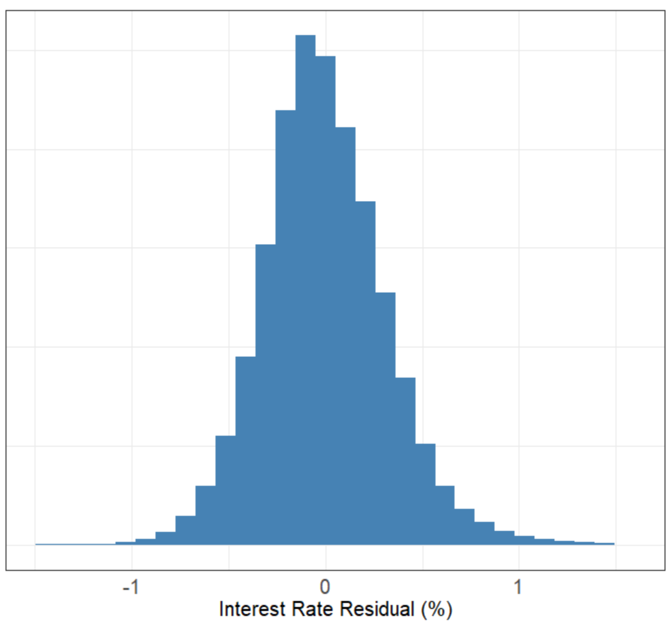
Figure 2 presents the distribution of this measure for all the outstanding mortgages in each quarter. To clarify, Figure 2 includes all the outstanding mortgages, not only those that were originated in 2008.

The panel (a) in Figure 2 shows the 25%, 50% and 75% percentiles for the interest rate saving measure (Δr_{izt}) distribution from the fourth quarter of 2008 to 2015. We observe that the 25% percentile of the interest rate saving measure from 2009 to 2013 was typically positive. This means that at least 75% of the mortgages were potentially in the money to refinance. More interestingly, the 75% percentile shows that at least 25% of the borrowers from 2009 to 2015 could have saved more than 1.125 percentage points through refinancing. The panel (b) in Figure 2 shows the equivalent graph in terms of monthly payment savings. This graph indicates that at least 25% of the borrowers from 2009 to 2015 could have saved almost $120 in monthly payments through refinancing.

We interpret the persistently wide positive gap between the interest rates of the outstanding mortgages and the average refinance rates as suggestive evidence of inactivity in refinancing. Inactivity in refinancing for the periods after the Great Recession has been well documented in other studies with different data sets (Agarwal et al., 2015 and Keys et al., 2016).

3.2 Interest Rate Dispersion and Search Intensity in the Refinance Market

Figure 3: Interest Rate Residual



Note: This graph shows the residual of transacted interest rates. We control for a long list of variables such as the FICO® Score, the loan-to-value (LTV) ratio, Debt-to-Income (DTI), income, term, demographics, five-digit zip code location dummies and quarter dummies. The difference between the 1^{th} and the 99^{th} distribution of the transacted interest rates is 162.5 basis points. The graph shows a wide dispersion in refinance interest rates for homogeneous mortgage contracts.

Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

Our data present a wide dispersion in interest rates for a homogeneous mortgage contract in the refinance market. We specifically focus on the refinance market, since this is the market that borrowers only enter for mortgage shopping. We suspect that, at the time of purchase, most borrowers put more effort into searching for the best property than into finding the lowest mortgage rate. As a result, the dispersion in interest rates in the purchasing market may be a misleading indication of the mortgage shopping of borrowers. The following regression uses our data to document that a long list of variables cannot explain the wide dispersion in interest rates.

$$r_{izt} = \beta X_{it} + \mu_t + \mu_z + \epsilon_{izt} \tag{3.3}$$

in which r_{izt} is the transacted interest rate in the refinance market of borrower i at time t in location z. X_{it} includes variables such as the FICO® Score, the loan-to-value (LTV) ratio, Debt-to-Income (DTI), income, term, and demographics. μ_t and μ_z are quarter and five-digit zip code location dummies. Figure 3 shows the interest rate residuals. The difference between the 5$^{\text{th}}$ and the 95$^{\text{th}}$ distribution of the transacted interest rates is 108.0 basis points. Moreover, the difference between the 1$^{\text{th}}$ and the 99$^{\text{th}}$ distribution of the transacted interest rates is 162.5 basis points. We also find similar dispersion in Ambokar and Samaee (2019) from a different data set in the US mortgage market. In our data, we do not have access to points and fees information. Some borrowers may pay higher upfront fees in order to lower the interest rates. These borrowers are not necessarily the low search cost ones, who could find lower rates. Ignoring the points and fees could potentially invalidate our interpretation that dispersion in interest rates is suggestive of search friction. However, Agarwal et al. (2017) and Alexandrov and Koulayev (2018) still find that borrowers pay substantially different mortgage rates, even after adjusting for points and fees.

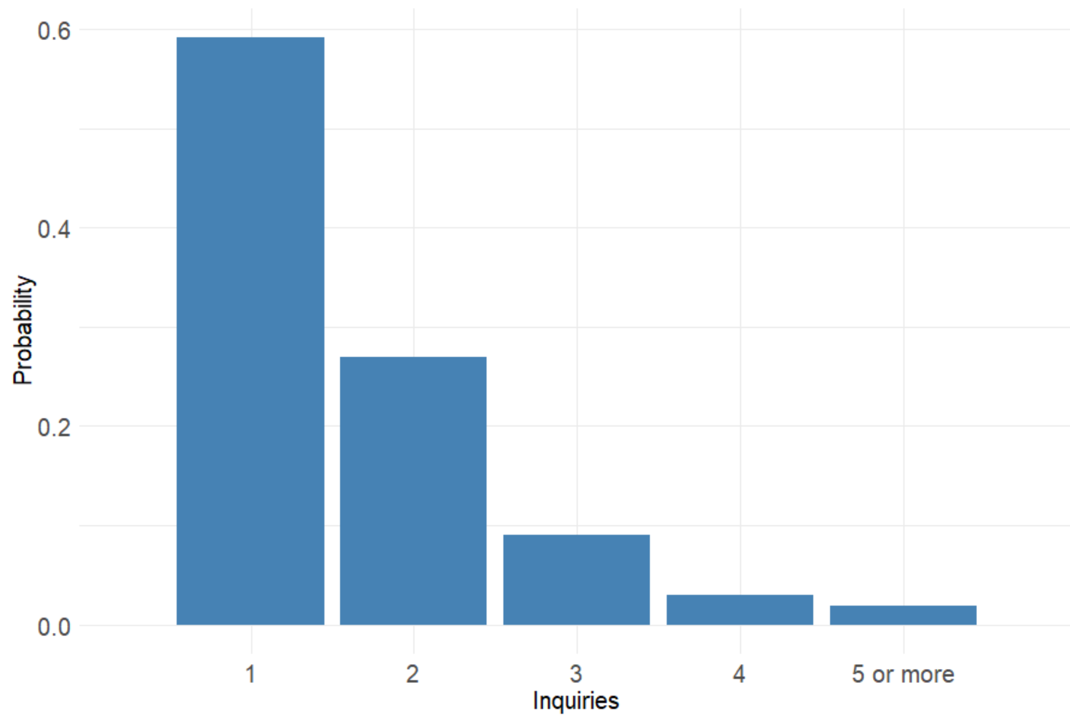
We use the number of mortgage inquiries as a measure of search intensity. Analyzing this variable provides more suggestive evidence of search friction in the US mortgage market. The distribution of the number of mortgage inquiries suggests a lack of mortgage shopping. Figure 4 indicates that almost 59.1% of the mortgage borrowers in our data only get one inquiry regarding refinancing a mortgage, despite the wide dispersion in the refinance interest rates. The evidence of a lack of mortgage shopping is also documented by Alexandrov and Koulayev (2018) and Ambokar and Samaee (2019), using the National Survey Mortgage Origination (NSMO) data set.

We finally explore how search intensity and refinance interest rates are correlated. The following regression provides the correlation between interest rate and number of mortgage inquiries.

$$r_{izt} = \sum_{n=1}^{5} \beta_n 1(n_{izt} = n) + \beta X_{it} + \mu_t + \mu_z + \epsilon_{izt} \tag{3.4}$$

in which r_{izt} is the transacted interest rate in the refinance market of borrower i at time t in location z. X_{it} includes variables such as Debt-to-Income (DTI), income, and demographics. μ_t and μ_z are quarter

Figure 4: Number of Mortgage Inquiries Distribution



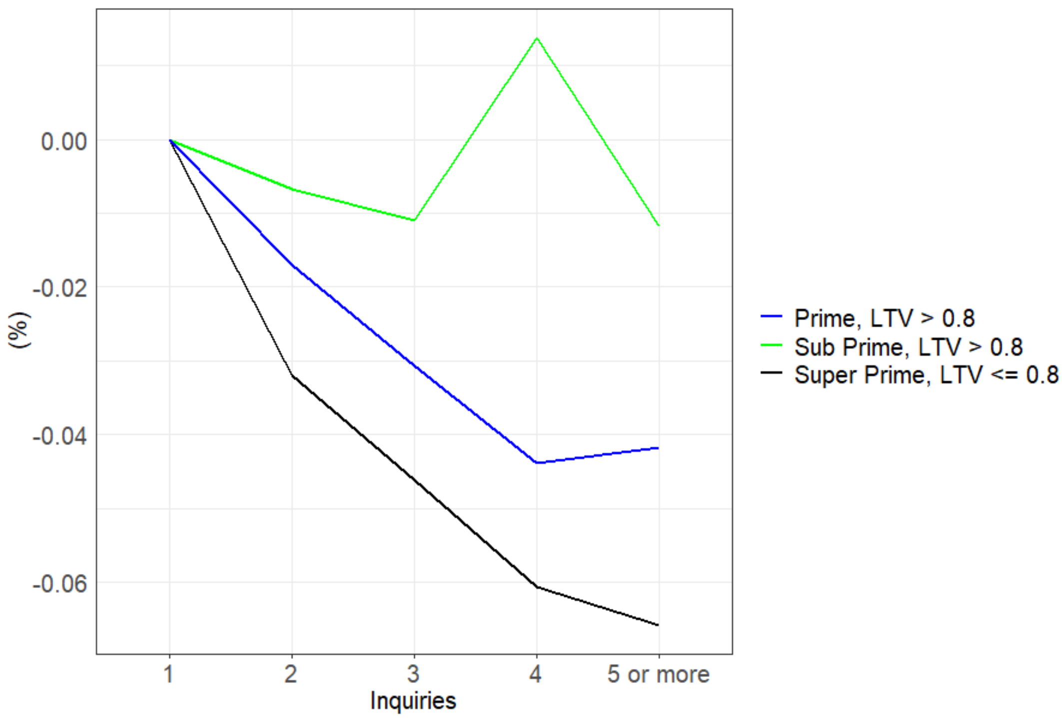
Note: This graph shows the distribution of the number of mortgage inquiries in the refinance market between 2009-2015. The last column includes 5 and more number of inquiries. It is unlikely to observe more than 5 inquiries in our data.
Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

and five-digit zip code location dummies. From the regression, we can find the conditional correlation between interest rates and number of mortgage inquiries $\{\hat{\beta}_n\}$. We analyze this correlation for different groups of the FICO® Score and loan-to-value (LTV) ratio by running separate regressions among each group.

Figure 5 presents $\{\hat{\beta}_n\}_{n=1}^{5}$ across the borrowers' creditworthiness. We document that the correlation between interest rate and number of mortgage inquiries is either negative or flat across the borrowers' creditworthiness. Figure 5 shows a negative correlation among superprime borrowers (with FICO® Scores above 740) with an LTV below 80%. This negative correlation suggests that it pays to search more.

One complexity that we need to take into account in developing and estimating the model is that loan originators may reject an application. We therefore need to be able to separately identify inquiries that are rejected by the borrower or by the loan originators. We do not have access to the application data for identifying these two channels. Borrowers with poor creditworthiness may accept any offer in order to avoid future searches. If we ignore such behavior, we may incorrectly classify borrowers

Figure 5: Search Intensity and Interest Rate Across Borrowers' Creditworthiness



Note: This graph shows the correlation between interest rates and number of mortgage inquiries among borrowers with different creditworthiness. As we explore riskier borrowers, the correlation becomes weak.
Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

with a low credit quality as borrowers with high search costs (Agarwal et al., 2017). We argue that the correlation between the number of mortgage inquiries and the interest rates differ across the borrowers' creditworthiness, and this evidence helps us to identify these two probabilities. In Figure 5, we observe that the correlation between interest rates and search intensity becomes weaker as we explore riskier borrowers. We can see this weaker correlation among prime borrowers (with FICO® Scores between 620 and 740) with an LTV above 80%. Finally, we do not observe a significant correlation between interest rate and number of mortgage inquiries among subprime borrowers (with FICO® Scores below 620) and LTV ratios above 80%.

We interpret the wide dispersion in interest rates and the lack of mortgage shopping, while it pays to search more, as suggestive evidence of search friction in the refinance market.

3.3 Search Intensity and Refinance

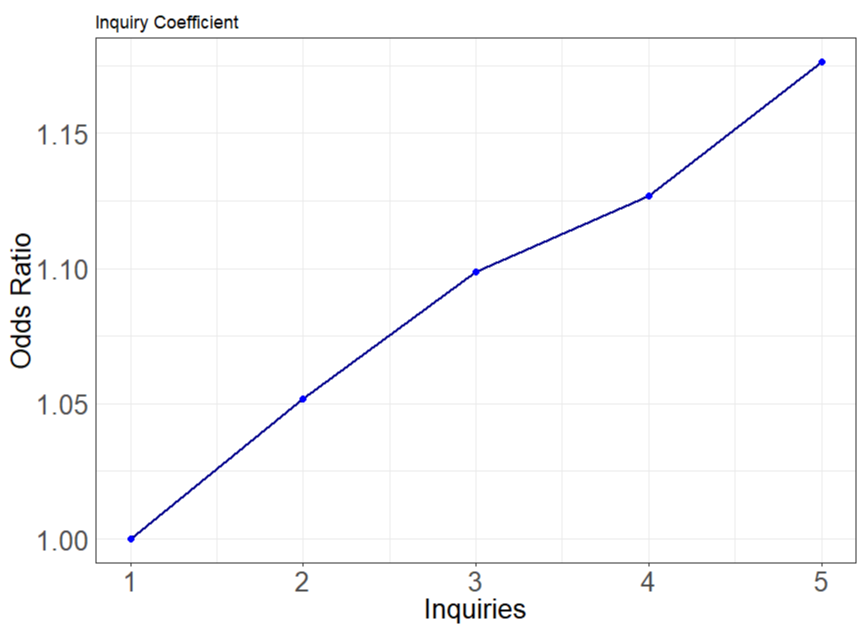
Having documented evidence suggestive of search friction and inaction in refinancing, we want to explore how these two are correlated. Specifically, this section explores the correlation between search intensity and refinancing probability.

In order to find this correlation, we specify a logit regression in equation 3.5. The dependent variable is the binary refinancing decision with $\text{Refi}_{izt} \in \{0, 1\}$. Specifically, this binary variable is equal to 1 if the borrower i refinance their mortgage at time t in location z. Otherwise, it is equal to 0. On the right-hand side of equation 3.5, we include the number of mortgage inquiries at the time of mortgage origination. Note that the number of mortgage inquiries are the fixed effects in this regression. We also control for the incentive to refinance measure that we built in section 3.1. The logit regression is as follows:

$$\text{Refi}_{izt} = \sum_{n=1}^{5} \beta_n 1(n_{iz} = n) + \beta_r \Delta r_{izt} + \beta X_{it} + \mu_z + \mu_t + \epsilon_{izt} \tag{3.5}$$

in which X_{it} include variables such as the FICO® Score, the loan-to-value (LTV) ratio, Debt-to-Income (DTI), income, term, and demographics. μ_t and μ_z are quarter and five-digit zip code location dummies.

Figure 6: Search Intensity and Refinance Probability



Note: This graphs shows the conditional correlation between refinance probabilities and the number of mortgage inquiries (search intensity) at the time of origination. More specifically, we use the number of mortgage inquiries at the time of mortgage origination as a fixed effect of a Logit regression in which the binary refinancing choice is the dependent variable. The refinancing odds for the first inquiry is normalized to one. We control for a long list of variables to find the conditional correlation such as time of origination, incentive to refinance measure, creditworthiness, etc.
Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

Figure 6 presents the odds ratio for the number of inquiries. It shows that borrowers who search five times to originate a mortgage are 17% more likely to refinance a mortgages in every quarter, although this is conditional on them having the same incentives to refinance and the same creditworthiness. This evidence indicates that those who search more at the time of mortgage origination (shoppers) are more likely to refinance their mortgages, conditional on having the same incentives to refinance and creditworthiness. This evidence documents the heterogeneity in refinancing among borrowers, with the same incentives for refinancing and the same creditworthiness, but a different search intensity.

We need to take into account a complexity coming from selection in the refinance market in developing and estimating the model. The evidence of this section suggests that there is selection because borrowers with low search intensity, potentially high search cost borrowers, are less likely to refinance. We use the dynamic data on refinancing to address this complexity. Specifically, the documented positive correlation between search intensity and refinancing odds helps us to infer their search behavior based on their refinancing frequencies.

4 An Equilibrium Model of Mortgage Refinancing and Search Decisions

Motivated by the evidence from the data, we develop a model of mortgage refinancing and search decisions. We extend the static sequential random search model in Agarwal et al. (2017) into a dynamic discrete choice framework. In a random search model, there is a distribution of offered rates for a homogeneous mortgage contract. Therefore, borrowers only know the range of interest rates they may find. This range depends on both the offered rate distribution and the borrower choice for the reservation interest rate. Given the offered rate distribution and reservation interest rate, we can find the transition probability of interest rates. Therefore, we develop a search model within a dynamic discrete choice framework by adding the transition probability of interest rates into the transition probability of a dynamic discrete choice model.

The model is an equilibrium model. On the demand side, there are borrowers who are heterogeneous in search costs and creditworthiness. They make refinancing and search decisions. On the supply side, there are homogeneous loan originators who offer rates while they take borrowers' search friction into account. We discuss the demand in section 4.1 and the supply in section 4.2.

4.1 Demand

We propose a model for a borrower with a mortgage who decides whether or not to refinance. We only take into account fixed-rate mortgage (FRM) contracts, which are the dominant type of contracts in the US. The borrowers are indexed according to their type and the characteristics of their current mortgage during each period. The borrower type includes two variables: search costs (c) and FICO® Score (θ_t). The search costs are not observable to the loan originators, while the credit scores are. Search costs are persistent, meaning that borrowers' search costs do not change over time. Credit scores (θ_t) change over time based on a Markov Process. We represent the current mortgage of a borrower by its interest rate (r) and other characteristics (x_t), which include current loan-to-value ratio (LTV$_t$) and the remaining term of the mortgage (term$_t$). x_t evolve according to a Markov Process. In Equation 4.1, we summarize the state variable of a borrower:

$$z_t = (\underbrace{c, \theta_t}_{\text{Type}}, \underbrace{r, x_t}_{\text{Mortgage}}) \tag{4.1}$$

All the variables in the model are discrete. We define five groups of search costs ($c \in \{1, 2, .., 5\}$) and eleven groups of credit scores ($\theta_t \in$ {below 620, 620-639 , 640-659 , ... , above 800}). We define seven groups for LTV ratios (LTV$_t$ $\in$ {(0, 0.6] , (0.6-0.7] ,(0.7-0.75] ,(0.75-0.8] ,(0.8-0.9] ,(0.9-1] , (1,+∞)}). We consider three groups for the remaining term of the mortgage in months (term$_t$ $\in$ {below 209, 210-329, above 330}). The interest rates are also discrete because we almost always observe the interest rates in increments of 12.5 basis points in the data.

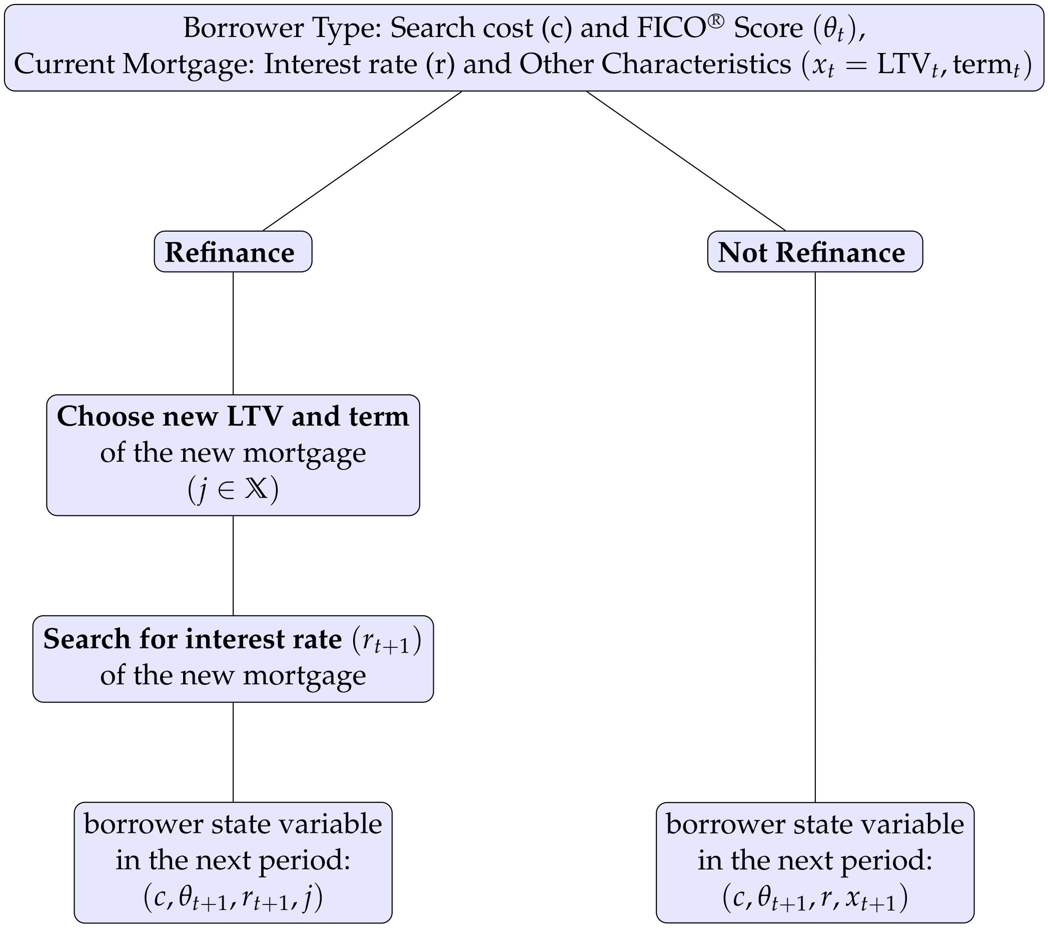
Borrowers may refinance due to different incentives. Since the interest rate on a FRM contract is fixed, borrowers may want to refinance in order to get a lower rate if they can find one (a rate refinance). However, the borrowers may also refinance for other reasons, such as: cashing out a home equity (cash-out refinance), paying off a fraction of the remaining principal (pay-off refinance), or changing the term of the current mortgage (term-refinance).

If a borrower chooses to refinance, the old mortgage is terminated and they are expected to choose a new mortgage with new features (LTV, term, and interest rate). We assume a specific sequence for the borrower's decision-making. The borrowers first choose the new LTV and term, and they then choose the interest rate of the new mortgage. We assume that all loan originators provide all the possible combinations of mortgages with different LTV and terms. They may offer different interest rates for a homogeneous (identical LTV and term) mortgage contract, and the borrowers know that there is price dispersion.[2] However, borrowers will not know what rate the originators are offering to them until they request a quote. Borrowers can gather quotes from various loan originators. Gathering quotes are costly for the borrowers because of search costs. These search costs may come from various sources. For some borrowers, search costs exist because their opportunity cost of time is high. For some, it exists, for instance, because they find it costly to interact with the financial institutions.

In Figure 7, we demonstrate the decision sequence of a borrower with a mortgage. Borrowers first decide whether to refinance or not. Second, those who choose to refinance, decide $j \in \mathbb{X}$, which is the LTV and term of the new mortgage contract. $\mathbb{X}$ includes 21 contracts that comes from all the combinations of LTV ratios and terms. We use $j \in \{0\}$ to denote borrowers who choose not to refinance. Third, those who choose to refinance a new mortgage with specific LTV and term, search sequentially to find the best rates. The borrowers know the distribution of the rates offered. Each loan originator offers a rate

[2] Alexandrov and Koulayev (2018) explore a model in which the borrowers are unaware of price dispersion.

Figure 7: A Borrower Refinancing and Search Decision Tree



Note: This graph presents the decision making on the demand side of the model. This is a Nested Logit model. Borrowers with a mortgage first decides whether to refinance or not. If they refinance, they then decide which LTV ratio and term choose for the new contract. Finally, they search for the best rates. Those who do not refinance keep the mortgage with the same rates. We also show how the state variables of those who refinance versus those who do not evolve over time.

based on the credit score, LTV, and term at each point in time. We denote the offered rate distribution by $h_{j\theta t}(r)$ and its CDF by $H_{j\theta t}(r)$. More specifically, for contract j, credit score θ in period t, there is a distribution of interest rates. Borrowers draw *i.i.d.* with replacement from the offered distribution.

In the search stage, borrowers decide whether to accept the offered rate and apply for the mortgage, or whether to reject the offer and continue searching. If they apply and the application is approved, they refinance with the offered rate. However, if their application is rejected, they will search again. Note that, when borrowers choose to refinance and subsequently they start to search, they cannot go back to the original mortgage anymore. They must search until finally they refinance with a new interest rate.

A refinancing decision requires a cost-benefit analysis for the mortgage borrowers. The refinancing costs include search costs and switching costs. The presence of refinancing costs makes the borrower's problem dynamic because borrowers may hold on to a mortgage for quite a while. Therefore, the benefit of refinancing comes from the flow of utilities throughout the life of the new mortgage contract plus the realization of an extreme value i.i.d. taste shock.

Equation 4.2 is the indirect utility of the borrower with a state variable of $z_t = (c, \theta_t, r, x_t)$ who chooses j at time t before receiving the taste shock.

$$u_{jt}(z_t) = \begin{cases} u_{\theta x} - r & \text{if} \quad j \in \{0\} \\ u_{\theta x} - r - \mathcal{R}_{jc\theta xt}, & \text{if} \quad j \in \mathbb{X} \end{cases} \tag{4.2}$$

We use $\mathcal{R}$ to denote the total refinancing costs, which is the sum of the switching costs and the search costs. The flow utility of the borrower comes from the current mortgage during every period, irrespective of whether or not they choose to refinance. If borrowers choose to refinance in period t, they pay for the refinancing costs. The benefit of refinancing comes from the future life of the new mortgage, which starts from period $t+1$. The utility of a borrower comes from borrower's type and the characteristics of the mortgage. We normalize the coefficient of the interest rate to one, with the higher the interest rate of a mortgage contract, the lower the utility. Borrowers have utility over LTV ratio and term of their mortgage. These characteristics are also interacted with credit scores. $u_{\theta x}$ captures the incentives for refinancing other than lowering the interest rate.

Since the problem of a borrower is dynamic, they compare the total expected payoff for a given choice when they want to make a refinancing decision. We use $v_{jt}(z_t)$ to denote the total expected payoff (before receiving the taste shock) for choice j at time t when the borrower is at the state of z_t. After receiving the taste shock ϵ_{jt}, the borrower chooses whether not to refinance $(j \in \{0\})$ or refinance, and chooses a new mortgage ($j \in \mathbb{X}$):

$$\max_{j \in \{0, X\}} \quad v_{jt}(z_t) + \epsilon_{jt} \tag{4.3}$$

in which ϵ_{jt} is the nested logit shock that comes from a generalized extreme value distribution. Specifically, there is no correlation between nests, and ($\text{Cov}(\epsilon_{0t}, \epsilon_{jt}) = 0$, $\forall j \in \mathbb{X}$). $1 - \sigma$ is the correlation within the nest ($\sigma \in [0, 1]$).

$v_{jt}(z_t)$ is the sum of the flow utility from Equation 4.2 and also a discounted expectation of continuation values:

$$v_{jt}(z_t) = u_{jt}(z_t) + \beta \sum_{z_{t+1}} V_{t+1}(z_{t+1}) f_{jt}(z_{t+1}|z_t) \tag{4.4}$$

in which $V_{t+1}(.)$ is the unconditional value function and $f_{jt}(.)$ is the transition probability.

The transition probability depends on whether or not the borrower chooses to refinance. If the borrower chooses not to refinance, they will keep the same mortgage. Since the contract is a fixed-rate mortgage, the interest rate remains unchanged. We need to follow how the credit score, the LTV ratio, and the reaming term of the contract may change over time. The LTV ratio evolves for two reasons. First, the remaining mortgage principal declines over time and, second, the value of the property may change over time. The borrower who does not choose to refinance starts the following period with a state variable of $(c, \theta_{t+1}, r, x_{t+1})$, as we demonstrated in the decision tree of a borrower in Figure 7. If the borrower chooses to refinance, they first choose the new LTV and the term of the new mortgage. They then search to find a rate. The set of interest rates that a borrower may find depends on the distribution of offered rates and on the reservation interest rate of the borrower. Specifically, the borrower with reservation interest rate of $r^*_{jc\theta t}$ who chooses to refinance to contract j, will get interest rate r_{t+1} with probability of $h_{j\theta t}(r_{t+1}|r^*_{jc\theta t})$. In other words, $h_{j\theta t}(r_{t+1}|r^*_{jc\theta t})$ is the transition probability of the interest rate for the borrower who chooses to refinance to contract j. This borrower will start the following period with a state variable of $(c, \theta_{t+1}, r_{t+1}, j)$, as we demonstrated in the decision tree of a borrower in Figure 7. In fact, by incorporating the distribution of offered rates into the transition probability, we develop a search model within a standard dynamic discrete choice framework. The Equation 4.5 presents the transition probability:

$$f_{jt}(z_{t+1}|z_t) = \begin{cases} (1-\delta_\theta) f_{0t}(\theta_{t+1}, x_{t+1}|\theta_t, x_t) & \text{if} \quad j \in \{0\} \\ (1-\delta_\theta) h_{j\theta t}(r_{t+1}|r^*_{jc\theta t}) f_{1t}(\theta_{t+1}|\theta_t), & \text{if} \quad j \in \mathbb{X} \end{cases} \tag{4.5}$$

The transition function $f_{0t}(.)$ captures the dynamic of (θ, x) when the borrower chooses not to refinance. $f_{1t}(.)$ captures the dynamic of the credit scores when the borrower chooses to refinance and, $h_{j\theta t}(r_{t+1}|r^*_{jc\theta t})$ captures the transition to the new mortgage rate. As a standard dynamic discrete choice model, both $f_{0t}(.)$ and $f_{1t}(.)$ evolve according to a Markov Process.

A mortgage contract may also be terminated for reasons other than refinancing, such as default shock, moving shock, etc. We need to take this into account because it may affect the refinancing decision. For example, if the borrowers know that they want to sell the property to move to another city, they may not have the incentive to refinance the mortgage to a lower rate. δ_θ in Equation 4.5 captures the termination shock for reasons other than refinancing. We allow that the termination shock to be a function of the creditworthiness of the borrowers. For example, we expect that the higher the creditworthiness of the borrowers, the lower the default probability of the mortgage.

The transition probability of the interest rate when borrowers choose to refinance to contract j, namely $h_{j\theta t}(r_{t+1}|r^*_{jc\theta t})$, is both a function of offered rate distribution and the choice of borrowers for reservation interest rate. We therefore need to present the borrower's search decision in the search stage, as demonstrated in the decision tree of the borrower in Figure 7. A borrower contacts a loan originator in the search stage in order to get quotes. A borrower with an offered interest rate of $\tilde{r}$ decides whether to accept the offer or whether to reject it and search for a lower rate. The marginal cost of a borrower of search type c for getting another quote is κ_c. We assume that the marginal cost of the search is constant, and that it does not depend on the number of inquiries. We denote the benefit of an additional search function with $B_{jc\theta t}(.)$ in Equation 4.6:

$$B_{jc\theta t}(\tilde{r}) \equiv \beta(1-\delta_\theta)\lambda_{j\theta t} \sum_{\theta_{t+1}} \sum_{r_{t+1} \leq \tilde{r}} \left(V_{t+1}(c, \theta_{t+1}, r_{t+1}, j) - V_{t+1}(c, \theta_{t+1}, \tilde{r}, j)\right) h_{j\theta t}(r_{t+1}) f_{1t}(\theta_{t+1}|\theta_t) \tag{4.6}$$

The marginal benefit of search captures the additional benefit of refinancing a mortgage with a lower interest rate. Several forces affect this marginal benefit. One is the termination shock δ_θ. If borrowers expect that they are likely to hold on to a mortgage for quite a while, they will have low termination shock, and will have more incentive to search for better rates. The approval probability $\lambda_{j\theta t}$ also affects the marginal benefits of a search. If the borrowers know that that their application is unlikely to be rejected, they will search more to find lower rates. Moreover, the marginal benefit of a search depends on the expected value of getting a lower rate. If it is possible that the borrowers will find significantly lower rates by increased searching, then they will have more incentive to search. The difference between the unconditional value function for lower rates and current rates is presented in Equation 4.7:

$$V_{t+1}(c, \theta_{t+1}, r_{t+1}, j) - V_{t+1}(c, \theta_{t+1}, \tilde{r}, j) = \tilde{r} - r_{t+1} + \ln\left(\frac{P_{1,t+1}(c, \theta_{t+1}, \tilde{r}, j)}{P_{1,t+1}(c, \theta_{t+1}, r_{t+1}, j)}\right) \tag{4.7}$$

The first part is the interest rate saving $\tilde{r} - r_{t+1}$, which also appears in a static model. The second part depends on the probability of refinancing in the following period. This part appears due to the dynamic nature of the problem. Specifically, we use $P_{1,t+1}(.)$ to denote the probability of refinancing in period $t+1$, regardless of the choice of the contract. In the appendix A.1, we show the closed form solution for this probability.Finally, we can find the reservation interest rates through marginal benefit and cost of searching. The Equation 4.8 indicates how we find the reservation interest rate:

$$B_{j\theta ct}(r^*) \leq \kappa_c \implies r^*_{j\theta ct} \tag{4.8}$$

in which $r^*_{j\theta ct}$ is the maximum interest rate that satisfies the above inequality. As mentioned earlier, a refinancing decision requires a cost-benefit analysis. We described the benefit of refinancing by presenting $v_{jt}(.)$ and its components. In the following, we discuss the refinancing costs, which include search costs and switching costs. We first describe the search costs. In the search stage, borrowers search sequentially in order to find the best rates. For every draw, the borrower of type (c) pays the marginal search cost κ_c and draws a rate r_{t+1} from the offered rate distribution $h_{j\theta t}$. The draws are *i.i.d.* with replacement. The borrower decides whether to accept the offered rate r_{t+1} and apply for the mortgage, or whether to reject the offer and continue searching. If they apply, the application is approved with the probability $\lambda_{j\theta t} \in [0, 1]$, and they refinance with interest rate r_{t+1}. However, if their application is rejected, or they choose not to apply for the loan, they will search again.

The total search costs of a borrower with search cost type c who ends up getting n inquiries to refinance is $\kappa_c n$. Borrowers form an expectation of the expected search costs before refinancing, and this depends on their type (c, θ_t), and on the contract they want to choose (j). We use $\mathbb{E}_{jc\theta t}[n]$ to denote the expected number of inquiries. The expected search costs conditional on refinancing for a borrower of type (c, θ_t) who chooses mortgage j at time t is $\kappa_c \mathbb{E}_{jc\theta t}[n]$. The expected number of inquiries depends on two probabilities, namely the probability that a borrower may reject an offer and the probability that a mortgage originator declines an application. The borrowers may choose a reservation interest rate (r^*) and reject any offer above that. Specifically, Equation 4.9 presents the expected number of mortgage inquiries:

$$\mathbb{E}_{jc\theta t}[n] = \frac{1}{\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})} \tag{4.9}$$

in which $(r^*_{jc\theta t})$ is the reservation interest rate that the borrowers choose.

Search costs are not the only refinancing costs that may inhibit refinancing. We also assume that there are switching costs. Such costs may include the financial costs associated with refinancing a mortgage. They may also include an unwillingness to terminate a contract and originate a new contract. We use $s_{jc\theta x}$ to denote switching costs. We assume that switching costs depend on the type of the borrowers, the current and new mortgage contracts, the LTV ratios and the terms. The Equation 4.10 presents the refinancing cost, which is the sum of the switching cost and the search costs:

$$\mathcal{R}_{jc\theta xt} = \underbrace{s_{jc\theta x}}_{\text{switching cost}} + \underbrace{\frac{\kappa_c}{\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})}}_{\text{search cost}} \tag{4.10}$$

One source of inactivity in refinancing may come from the high cost of refinancing. However, since refinancing costs do not all come from the financial costs of refinancing, we use our model to estimate the total refinancing costs from refinancing frequency of the borrowers. We do that and also the model helps us to separately identify the search costs from the switching costs.

Refinancing costs have a direct effect on refinancing incentives. The direct effect of search costs on refinancing incentives go through the expected search costs $\kappa_c \mathbb{E}_{jc\theta t}[n]$. This is the most obvious channel that search costs may inhibit refinancing. In fact, borrowers may find it costly to search for a new mortgage. The second channel is that search costs indirectly increase the loan originators' market power and thus raise the offered refinance rate. The first channel directly affects the costs of refinancing, while the second channel affects the benefit of refinancing through the equilibrium interest rates.

The Equation 4.5 provides the intuition of how the indirect effect of search costs may affect the benefit of refinancing. $h_{j\theta t}(r_{t+1}|r^*_{jc\theta t})$ governs the incentive to refinance in order to lower the interest rate of the current mortgage. If the loan originators offer high interest rates, borrowers do not have incentives to refinance.

The following section discusses the supply side of the model.

4.2 Supply

On the supply side, we follow Agarwal et al. (2017) in specifying the loan originator model. Since most of the residential mortgages are originated through an originate-to-sell mechanism, we assume a static model for the supply side.

A Loan originator offers interest rate r in order to maximize its expected profit. Moreover, loan originators accept an application with exogenous probability $\lambda_{j\theta t}$. Like Agarwal et al. (2017), we do not endogenize the approval probabilities. The marginal costs of the loan originator include two parts. The first is the marginal cost of origination in the refinance market (χ). The second is the marginal cost that depends on the type of borrower, contract and time (j, θ, t). This part is given to the loan originator and potentially comes from how the loan buyers price the loan using different characteristics. We find $\hat{r}_{j\theta t}$ by running a regression of interest rates in the refinance market on (j, θ, t) and their interactions. Note that the changes in the funding costs, such as those due to changes in the federal funds rate, will be reflected in $\hat{r}_{j\theta t}$.

Loan originators choose what interest rate to offer on the basis of the marginal costs and demand function. The loan originators take the borrowers' search friction into account and respond accordingly. More specifically, a loan originator has a rational expectation over the distribution of the search cost of the borrowers, who choose to refinance to mortgage j, with credit score θ at time t. In this model, the price elasticity of demand depends on the search behavior of the borrowers. Therefore, the demand function is endogenous and Equation 4.11 presents it :

$$q_{j\theta t}(r) = \sum_{\tilde{r} \geq r} \frac{\sum_{(c,x,r')} \mu_{\theta t}(c, x, r') P_{j\theta t}(c, x, r') 1\{r^*_{j\theta ct} = \tilde{r}\}}{H_{j\theta t}(\tilde{r})} \tag{4.11}$$

in which μ is the mass of borrowers with a mortgage in period t with the current characteristics of the borrowers and the mortgages. In appendix A.2, we discuss in details how we find the demand function. The expected profits of charging an interest rate r are therefore:

$$\Pi_{j\theta t}(r) = (r - \hat{r}_{j\theta t} - \chi) q_{j\theta t}(r) \tag{4.12}$$

The loan originators choose the interest rate in order to maximize their profits. Following Agarwal et al. (2017), we assume a logit shock $\epsilon_{j\theta tk}$ with Type I EV distribution. We find the offer rate distribution as follows:

$$\max_{r_k} \quad \Pi_{j\theta t}(r_k) + \epsilon_{j\theta tk} \implies h_{j\theta t}(r_k) = \frac{\exp(\frac{\Pi_{j\theta t}(r_k)}{\sigma_\pi})}{\sum_{\tilde{k}} \exp(\frac{\Pi_{j\theta t}(r_{\tilde{k}})}{\sigma_\pi})} \tag{4.13}$$

Since the loan originators take the search friction into account, their demand function is inelastic. This means that borrowers can charge higher interest rates than the marginal costs of originating a mortgage.

We can find the average of the markups as follow:

$$\sum_{\tilde{r}} \tilde{r} h_{j\theta t}(\tilde{r}) - \hat{r}_{j\theta t} - \chi \tag{4.14}$$

The higher the search costs, the higher the markups for the loan originators. As a result, the loan originators offer higher rates than the marginal cost, which is the indirect channel by which search costs inhibit refinancing.

5 Estimation

In this section, we discuss how we estimate the parameters of the model. The goal is to estimate search cost distribution along with other parameters of the model. The standard approach, in industrial organization, is to back out search cost distribution from the observed price distribution (Hong and Shum, 2006). Many used this approach to estimate the search cost distribution in the mortgage market (Agarwal et al., 2017, Alexandrov and Koulayev, 2018 and Allen et al., 2019). In section 3.3, we documented that: the higher the number of inquiry, the higher the probability of refinancing. If high search cost mortgage borrowers are less likely to refinance, then the participants in the refinance market are biased in favor of low search cost borrowers. By writing a dynamic model, we took into account this selection.

We estimate the model using data from 2008 to 2015, during a period of mortgage rates' transition of high to low. Solving a dynamic model during a transition period is computationally challenging, because we have to keep track of the distribution of offered rates and many state variables. That is why we incorporate a search model into a dynamic discrete choice framework in order to estimate the model using conditional choice probability (CCP) techniques. We build on Arcidiacono and Miller (2011) since it allows us to incorporate unobserved heterogeneity. Search costs are the only unobserved heterogeneity in our model. We specifically use the two-stage Arcidiacono and Miller (2011) tools to estimate the model.

5.1 First Stage

We follow Arcidiacono and Miller (2011) to estimate the empirical CCPs and transition probabilities in the first stage. We incorporate a sequential search model into a dynamic discrete choice framework. As a result, the distribution of the offered rates are included in the transition function when the borrowers choose to refinance. In this stage, we should estimate this offered rate distribution. However, estimating an equilibrium search model is computationally challenging, because we need to estimate the equilibrium offered rates through solving a functional fixed point problem. We therefore complete this stage in two steps. First, we estimate the empirical refinancing probabilities. Second, given the empirical refinancing probabilities, we estiamte the offered rate distribution, marginal search costs and approval probabilities.

Note that empirical refinancing probabilities cannot be directly calculated from data since search costs are unobservable. Following Arcidiacono and Miller (2011), we use EM algorithm to estimate the empirical refinancing probabilities. We assume that there are five groups of search costs $c \in \{1,2,3,4,5\}$, higher the index number, potentially higher the (marginal) search costs. The goal of the algorithm is to classify these five groups of search costs. Mortgage borrowers within each group of search costs are similar in refinancing probability, given having the same incentive to refinance (Δr), credit scores, LTV ratios and terms of the mortgage contract (θ, x). The difference across these five groups is that, conditional on other variables, they may refinance with significantly different odds. Note that, in this stage we do not use any information of search behavior of the individuals to identify the groups. Hence, the intuition for identification comes from the evidence in section 3.3 that, the higher the search intensity, the higher the refinancing odds.

We use $p_{jt}(z_{it})$ to denote the empirical refinancing probabilities. This is the probability that an individual chooses to refinance to contract j at time t, given the observed state of z_{it}. Denote $\mathcal{L}_t$ in equation 5.1, the likelihood of observing $(d_{it}, z_{i,t+1})$, conditional on state z_{it}. $d_{it} \equiv (d_{i1t}, ..., d_{iJt})$ is the vector of dummy variables. If individual i chooses to refinance to contract j, $d_{ijt} = 1$, otherwise, it is zero.

$$\mathcal{L}_t(d_{it}, z_{i,t+1}|z_{it}) = \prod_j [\mathbb{1}\{j=0\} p_{0t}(z_{it}) f_{0t}(z_{i,t+1}|z_{it}) + \mathbb{1}\{j \in X\} p_{jt}(z_{it})]^{d_{ijt}} \tag{5.1}$$

where the transition probablity conditional on not refinancing is as follow:

$$f_{0t}(z_{i,t+1}|z_{it}) = (1-\delta_\theta) f_{0t}(\theta_{i,t+1}, x_{i,t+1}|\theta_{i,t}, x_{i,t}) \tag{5.2}$$

in which $z_{it} = (c_i, \theta_{it}, r_{it}, x_{it})$. We specify the refinancing probability of individual i at time t in equation 5.3.

$$p_{jt}(z_{it}) = \begin{cases} \frac{1}{1+\exp(\beta_{c\theta x} + \beta_1 \Delta r_{it})} & \text{if} \quad j = 0 \\ \\ \frac{\exp(\beta_{c\theta x} + \beta_1 \Delta r_{it})}{1+\exp(\beta_{c\theta x} + \beta_1 \Delta r_{it})} \tilde{p}_{j|1}(c, \theta_{it}, x_{it}), & \text{if} \quad j \in X \end{cases} \tag{5.3}$$

where $\Delta r_{it} = r_{it} - \hat{r}_{it}$ is the amount of interest rate saving by rate refinancing the current mortgage to a lower rate (Equation 3.2). $\beta_{c\theta x}$ captures interaction between search costs, creditworthiness and mortgage characteristics. $\tilde{p}_{j|1}$ denotes contract choice conditional on refinancing, $\Sigma_{j \in X} \tilde{p}_{j|1}(c, \theta_t, x_t) = 1$. We nonparametrically estimate $\tilde{p}_{j|1}$ and f_{0t}. We estimate $(\beta_{c\theta x}, \beta_1)$, and $g_0(c)$ through the EM algorithm. In appendix A.4, we discuss the details of the EM algorithm. By completing this step, we find the search costs probabilities but not the marginal search costs.

In the second step of the first stage, we estimate the offered rate distributions $h_{j\theta t}(.)$, marginal search costs κ_c and approval probabilities $\lambda_{j\theta t}$. At the end of this step, we can fully characterize the search cost distribution. To estimate these parameters, we build a likelihood function that is quite similar to Agarwal et al. (2017). Given the offer rate distribution $h_{j\theta t}(r)$ and approval probability $\lambda_{j\theta t}$, for both of which we assume a parametric form, we denote the likelihood of observing (r_{it}, n_{it}) conditional on reservation interest rate r^* in equation 5.4:

$$l(r_{it}, n_{it}|r^*_{jc\theta t}) = \lambda_{j\theta t} h_{j\theta t}(r_{it}) \left(1 - \lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})\right)^{n_{it}-1} \tag{5.4}$$

where n_{it} is the number of inquiries when a borrower refinances a mortgage. $H_{j\theta t}(.)$ is the CDF of the offered rate distribution. When we observe (r_{it}, n_{it}) for borrower i, it means that the borrower refinanced the mortgage to interest rate r_{it} in the n_{it}th search attempt. For $n_{it} - 1$ inquiries, either the application was rejected by the loan originators with probability $1 - \lambda_{j\theta t}$ or the offered refinance rate was rejected by the borrower because the offer was above the reservation interest rate. Thus, the rejection probability of an offer is $\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})$ for a borrower who chooses to refinance to a mortgage with characteristics j at time t with FICO® Score θ. Given the offered rate distribution, we find the reservation interest rates from the Equation 4.8. In this step, we also take into account that the offered rate distribution is an equilibrium object. We therefore find the offered rate distribution from the Equation 4.13. From this step, we estimate the parameters from the supply side which are marginal cost of origination (χ) and the standard error of the logit shock to profit (σ_π). Finding the offered rate distribution is a functional fixed point problem. We follow the algorithm in Agarwal et al. (2017) to estimate the offered rate by fitting a normal distribution.

We use β^λ to denote the vector of parameters that characterizes the functional form of the approval probabilities. Similarly, we use β^h to denote the vector of parameters that characterizes the normal distribution for offered rate distribution $h^N_{j\theta t}$. Finally, we maximize the objective function in equation 5.5 to find the estimate of the parameters.

$$(\beta^\lambda, \beta^h, \sigma_\pi, \chi, \kappa_c) \in \operatorname{argmax} \quad \sum_j \sum_\theta \sum_t \frac{1}{N} \sum_{i=1}^{N} \sum_c \mu_{j\theta t}(c) \ln l(r_{it}, n_{it}|r^*_{j\theta ct}) - \sum_j \sum_\theta \sum_t \sum_r \left(h^N_{j\theta t}(r) - h_{j\theta t}(r)\right)^2 \tag{5.5}$$

in which the first term is the likelihood function that we want to maximize. The second term is the distance between equilibrium offered rate $h_{j\theta t}$ derived in the Equation 4.13 and the approximated normal distribution for offered rates $h^N_{j\theta t}$ that we want to minimize. The reservation interest rates for any guess for offered rate distribution comes from the Equation 4.8.

5.2 Second Stage

Given the estimation results from section 5.1, we estimate the switching costs and utility parameters of the model following the second stage of Arcidiacono and Miller (2011). Intuitively, we minimize the distance between the empirical refinancing probabilities $p_{jt}(z_t)$ estimated in 5.3 from the structural refinancing probabilities $P_{jt}(z_t)$ derived in A.2 to estimate the utility and switching costs. Following 5.1, we estimate the parameters as follow:

$$\{u_{\theta x}, s_{jc\theta x}\} \in \text{argmin } ||v_{jt}(z_t) - v_{0t}(z_t) + \psi_j[p_t(z_t)] - \psi_0[p_t(z_t)]|| \tag{5.6}$$

where $\psi_j[.]$ is the correction term for a nested logit model.

$$\psi_k[p_t(z_t)] = \begin{cases} -\ln(p_{0t}) & \text{if} \quad k = 0 \\ -\ln(p_{1t}) - \sigma \ln(p_{kt|1}), & \text{if} \quad k \in X \end{cases} \tag{5.7}$$

The difference $v_{jt}(z_t) - v_{0t}(z_t)$ is a function of the future empirical refinancing probabilities. Calculating this can be potentially difficult if we want to simulate for many periods ahead. However, our model provides one-period finite dependence property, which makes the estimation of the parameters in the second stage fairly easy. In fact, we can characterize the $v_{jt}(z_t) - v_{0t}(z_t)$ as a function of the one-period ahead empirical refinancing probabilities. The intuition behind the one period ahead finite dependence is as follows. Suppose that two borrowers with the same search costs refinance to different arbitrary contracts. If they both refinance to a same arbitrary contract in the next period, they will have the same continuation value.

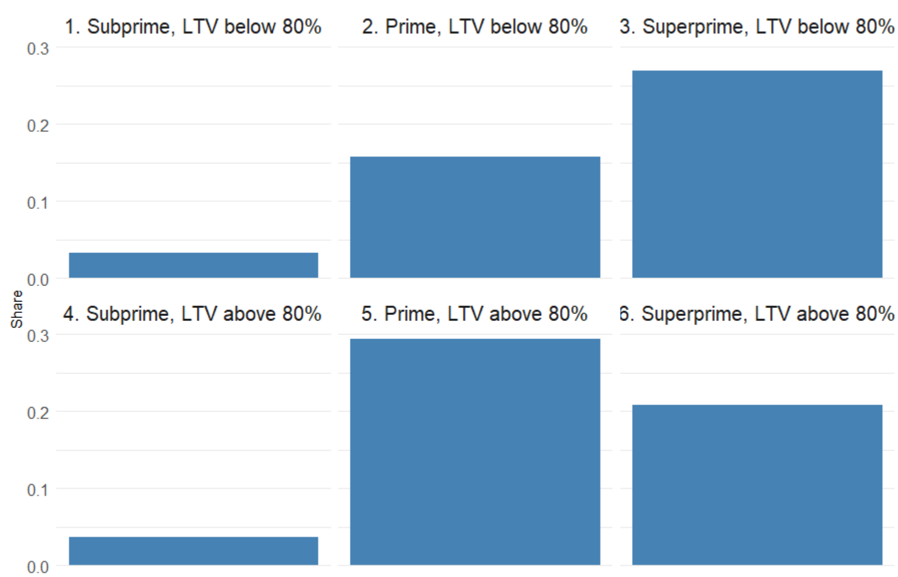
6 Estimation Results

In this section, we discuss the estimation results. As discussed earlier, we estimate a search cost model while considering two complexities. The first complexity is that loan originators may reject an application based on creditworthiness. To address this complexity, we separately identify the probabilities of the loans being rejected by the loan originators or by the borrowers. In the Section 6.1, we present the estimates of the approval probabilities. The second complexity is derived from the selection. If high search cost mortgage borrowers are less likely to refinance, then the participants in the refinance market are biased in favor of low search cost borrowers. In Section 6.2, we argue how search cost distribution is different from the distribution of those who choose to refinance. In Section 6.3, we then present the estimates for search costs and their shares in total refinancing costs. In the last two Sections, we discuss the answers to the two research questions that we raised. In Section 6.4, we discuss the effects of search costs on refinancing activities. In Section 6.5, we explore the contribution of the direct and the indirect market power effect on refinancing.

6.1 Borrowers' Creditworthiness and Approval Probability

Loan originators may reject an application based on the borrowers' creditworthiness, which affects the borrowers' search behavior. Those with low creditworthiness know that their chances of being approved are small; thus, they may be willing to accept a mortgage with a high interest rate to avoid the additional search. This implies that these borrowers will behave as if their search costs are high. If we use only the interest rate distribution to estimate the search costs, we will back out the search cost distribution conditional on creditworthiness, but not the unconditional one. In this Section, we detail the distribution of the borrowers' creditworthiness and approval probabilities.

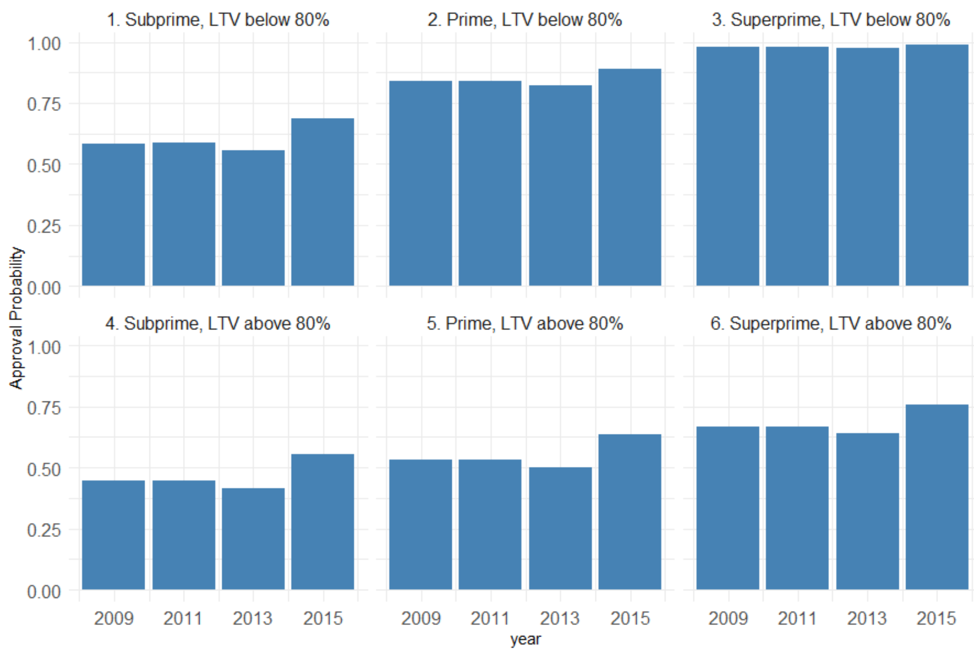
Figure 8: Distribution of Borrowers' Creditworthiness



Note: This graph presents the distribution of the borrowers' creditworthiness in 2008. The columns from left to right present subprime (FICO® Scores below 619), prime (FICO® Scores between 620 to 739) and superprime (FICO® Scores above 740) borrowers, respectively. The first row presents the low LTV borrowers (LTV ratio below 80%). The second row presents the high LTV borrowers (LTV ratio above 80%).
Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

In Figure 8, we present the distribution of borrowers with different levels of creditworthiness in 2008. For improved data presentation, we aggregate LTV ratios into two groups: LTV ratios above 80% and those below 80%. We also aggregate the FICO® Scores into three groups: subprime (FICO® Scores below 619), prime (FICO® Scores between 620 and 739) and superprime (FICO® Scores above 740) borrowers. Tis distribution is directly derived from the raw data. The graph illustrates that most of the borrowers, 93%, are prime or subprime borrowers. However, almost 54% of the borrowers have LTV ratios above

Figure 9: Estimates of Approval Probabilities



Note: In this graph, we present the estimates of approval probabilities ($\lambda_{j\theta t}$). The columns from left to right represent subprime (FICO® Scores below 619), prime (FICO® Scores between 620 and 739) and superprime (FICO® Scores above 740) borrowers, respectively. The first row represents the low LTV borrowers (LTV ratio below 80%). The second row represents the high LTV borrowers (LTV ratio above 80%).

Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

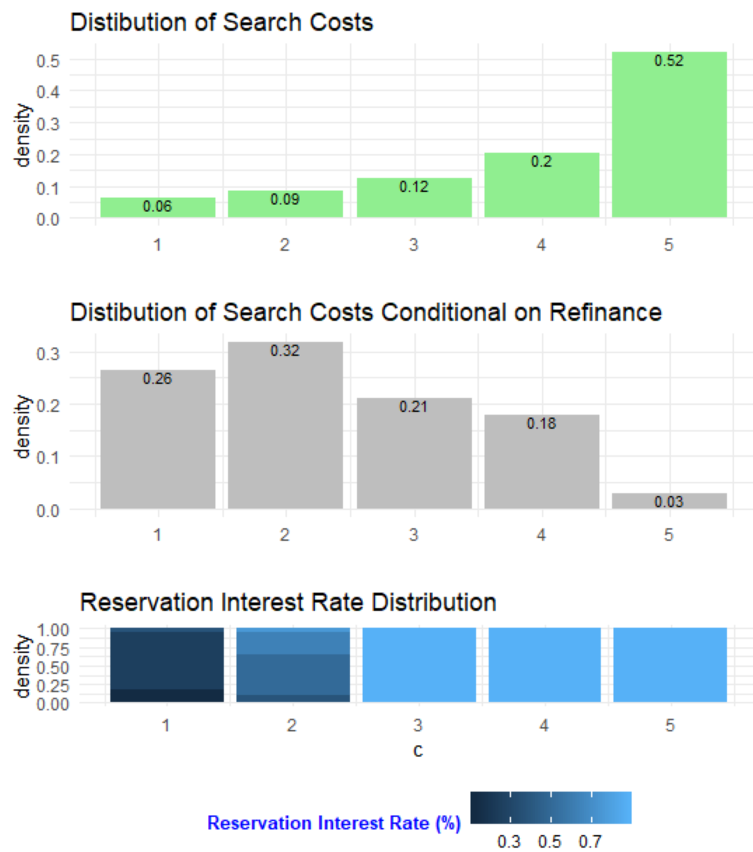
80%. This result is consistent with a significant house price shock in the wake of the Great Recession. Furthermore, Figure 8 confirms that there is heterogeneity in the borrowers' creditworthiness. If the borrowers' approval probabilities are different, we should consider this difference in the search cost estimation.

Figure 9 displays the estimates of the approval probabilities across borrowers' creditworthiness and time. The approval probabilities can range from 0.42 to 0.99. There is also a significant difference between the approval probabilities among borrowers with LTV ratios below 80% and those with LTV ratios above 80%.

6.2 Search Cost Distribution and Selection

Figure 10 illustrates the distribution of the search costs. Since we estimate a dynamic model, we can verify from the estimates whether the selection exists in the refinance market. The top row presents the distribution of the search costs, and the second row presents a distribution of the search costs in a typical

Figure 10: Search Cost Distribution



Note: This graphs depicts the distribution of the search costs. Five groups of search costs are indexed by $c \in \{1, 2, ..., 5\}$. The higher the index, the higher the (marginal) search costs. The first row presents the distribution of search costs. The second row presents a typical search cost distribution in the refinance market. Comparing these two graphs indicates that the selection exists in the refinance market. The third row displays the reservation interest rate distribution for each search cost type. The reservation interest rates fill in the range from -0.75 to 0.875 basis points around the mean of the offered rates. For example, borrowers with search costs $c \in \{3, 4, 5\}$ choose the highest reservation interest rates whenever they refinance. Borrowers with search costs $c \in \{1, 2\}$ choose interior reservation interest rates.

Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

refinance market.[3] This distribution is similar to the log-normal search cost distribution estimated in static search cost models in the US mortgage market (Agarwal et al., 2017 and Alexandrov and Koulayev, 2018). The high search cost borrowers ($c = 5$) includes more than half of the borrowers in the mortgage market who also have a low share in the refinance market. These borrowers have low probabilities of refinancing.

The third row in Figure 10 presents the reservation interest rate distribution for each group of search costs. Interest rates and reservation interest rates in any refinance market can fill in the range of {-

[3]Refinance markets are characterized by LTV ratios, terms, FICO® Scores and quarters (j, θ, t). To find the *typical* refinance market we find the weighted average of all refinance markets.

0.75 , -0.625 , ... , 0.875} percentage points around the mean of the offered rates. For example, if the average offered rates in a refinance market is 4 percentage points, the offered rates can range between 3.25 and 4.875 percentage points. The third row in Figure 10 displays the distribution of the reservation interest rates of each group of search costs in different refinance markets (LTV ratios, terms, FICO® Scores and quarters (j, θ, t)). This graph illustrates that borrowers with search costs $c \in \{3, 4, 5\}$ have the highest reservation interest rate (0.875 percentage points above the average offered rates) in any refinance market. Borrowers with search costs $c \in \{1, 2\}$ are shoppers in the model. They never choose an interior value for the reservation interest rates, meanings that there are offered rates that these borrowers do not accept.

Borrowers with different search costs, in equilibrium, have different refinancing and search behavior. The search cost group $(c = 5)$ is not likely to refinance. If these borrowers refinance, they accept any offer. Borrowers with search costs $c \in \{3, 4\}$ are more likely to refinance compared to the highest search cost group. However, like the highest search cost group, these borrowers do not search for lower rates and accept any offer. Borrowers with search costs $c \in \{1, 2\}$ are more likely to refinance than other groups; they are the shoppers and search for lower rates.

6.3 Search Costs and Switching Costs

In this section, we discuss the estimation results for refinancing costs. As discussed in detail in section 4.1, refinancing costs include search costs and switching costs. Search costs $(\frac{\kappa_c}{\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})})$ depend on the marginal search costs (κ_c), approval probabilities by loan originators $(\lambda_{j\theta t})$ and approval probabilities by borrowers $(H_{j\theta t}(r^*_{jc\theta t}))$. Search costs can differ across search costs groups, LTV ratios, terms, FICO® Scores and quarters (c, j, θ, t).

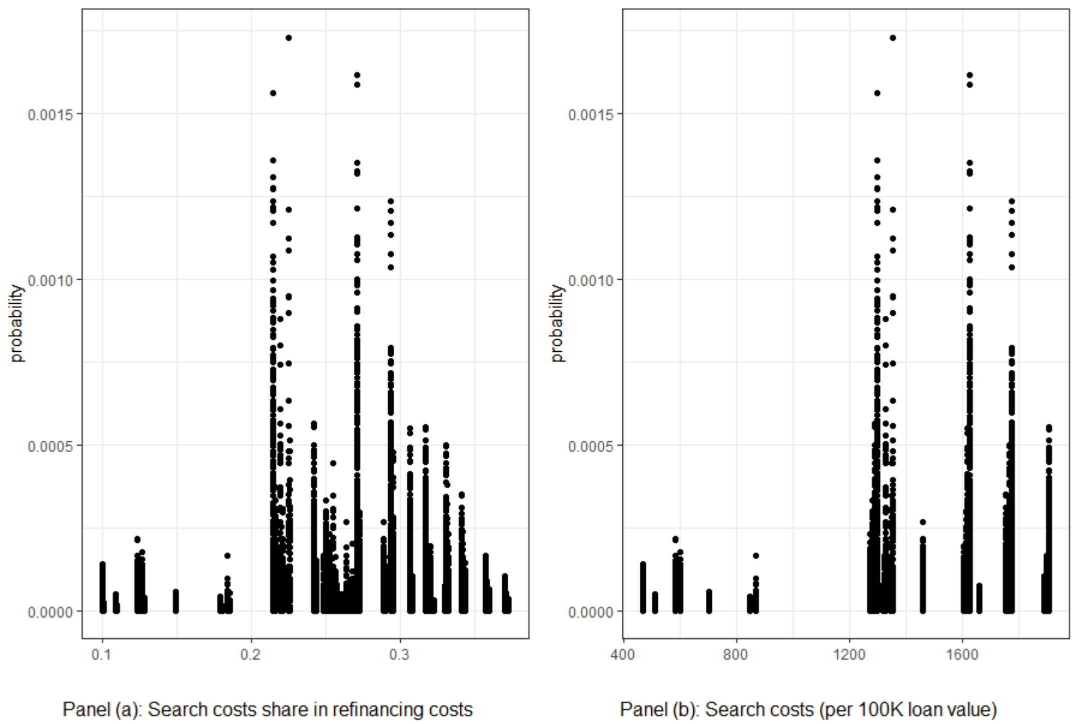
Based on the notation defined in the model in Section 4.1, we find the share of the search costs $(\frac{\kappa_c}{\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})})$ of the refinancing costs $(\mathcal{R}_{jc\theta xt})$. The panel (a) in Figure 11 depicts the share of the search costs of the refinancing costs across different refinance markets. The share of the search costs ranges from almost 0.1 to 0.4 of the refinancing costs. The search costs include almost 30.8% of the refinancing costs on average.

The panel(b) in Figure 11 presents the search costs in monetary values. We estimate that the search costs for a mortgage of $100,000 are in the range of $400 to $2000, and are $1586.6 on average.

6.4 The Effect of the Search Costs on Refinancing

In this section, we address the first question of the paper: what is the effect of the search costs on refinancing activities? Since the period of 2008-2015 is a period of mortgage rates' transition from high to low, borrowers mainly refinanced to lower their mortgage rates. Therefore, we can implicitly analyze

Figure 11: Estimates of Search Costs in Refinancing Costs



Note: This graph reports the estimates of the search costs. The panel (a) presents the share of the search costs ($\frac{\kappa_c}{\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})}$) in total refinancing costs ($\mathcal{R}_{jc\theta xt}$). Each dot represents this share for a specific search cost, LTV ratio, term, FICO® and and quarter (c, j, θ, t, x). The panel (b) displays the search costs for a loan of $100,000.
Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

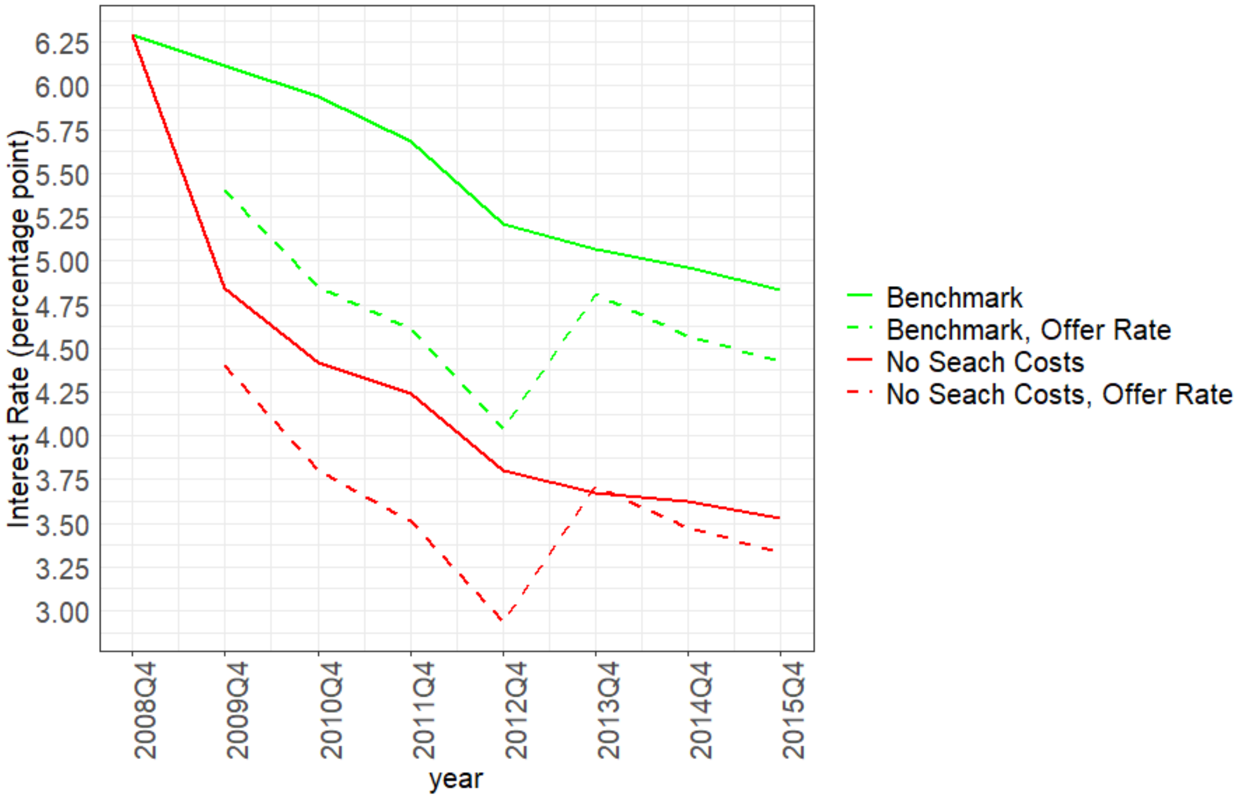
the refinancing activities by following the dynamic of the mortgage rates on outstanding loans and its gap from the offered rates in the refinance market.

In Figure 12, we compare the benchmark economy to an alternative economy in which there is no search costs. The solid green line represents the average mortgage rates on outstanding loans in the benchmark economy. The green dashed line represents the average of the offered rate distribution. There is a gap between the mortgage rates and the offered rates, which results from inactivity in refinancing. Borrowers with search costs and switching costs choose not to refinance their mortgages to lower rates.

In the alternative economy, we assume that the marginal search costs for all borrowers equal zero ($\kappa_c = 0 \ \ \forall c \in \{1, 2, ..., 5\}$). We then use our structural model to solve for the new model. The solid red line in Figure 12 is the average of the mortgage rates in the economy without search costs. The interest rates on outstanding mortgages decline by about 1.4 percentage points on average, so the answer to the first question of the paper is that the search costs significantly inhibit refinancing.

The dotted red line in Figure 12 is the average offered rate in the alternative economy. We observe

Figure 12: Search Costs and Refinancing



Note: The solid lines represent the average mortgage rates on outstanding loans. The dashed lines represent the average offered rates. The green lines are the estimate of the model for the benchmark economy. The red line is the alternative economy in which there are no search costs. We assume that the marginal search costs for all borrowers equal zero ($\kappa_c = 0 \quad \forall c \in \{1, 2, ..., 5\}$). Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

that there is a significant reduction in the offered rates. The average decline in the offered rates during this period is 1.08 percentage points. Like the benchmark model, there is a gap between the interest rates on outstanding mortgages and the offered rates in the counterfactual model because switching costs exist in the counterfactual economy. Switching costs inhibit refinancing activities in the alternative economy. The gap between the average mortgage rates and the offered rates is smaller in the model without search costs.

Search costs inhibit refinancing through two channels. The first channel is the direct effect, and the second is the indirect market power effect. The average reduction of the offered rates by 1.08 percentage points result from the elimination of the market power of the loan originators induced by search friction. This reduction in the interest rates encourages the mortgage borrowers to refinance their mortgages. In Section 6.5, we explain how we find the the contributions of the direct effect versus the indirect effect on refinancing activities.

6.5 The Direct Effect versus the Indirect Effect of Search Costs on Refinancing

In this section, we address the second question of the paper: what are the contributions of the direct versus the indirect market power effect on refinancing activities?

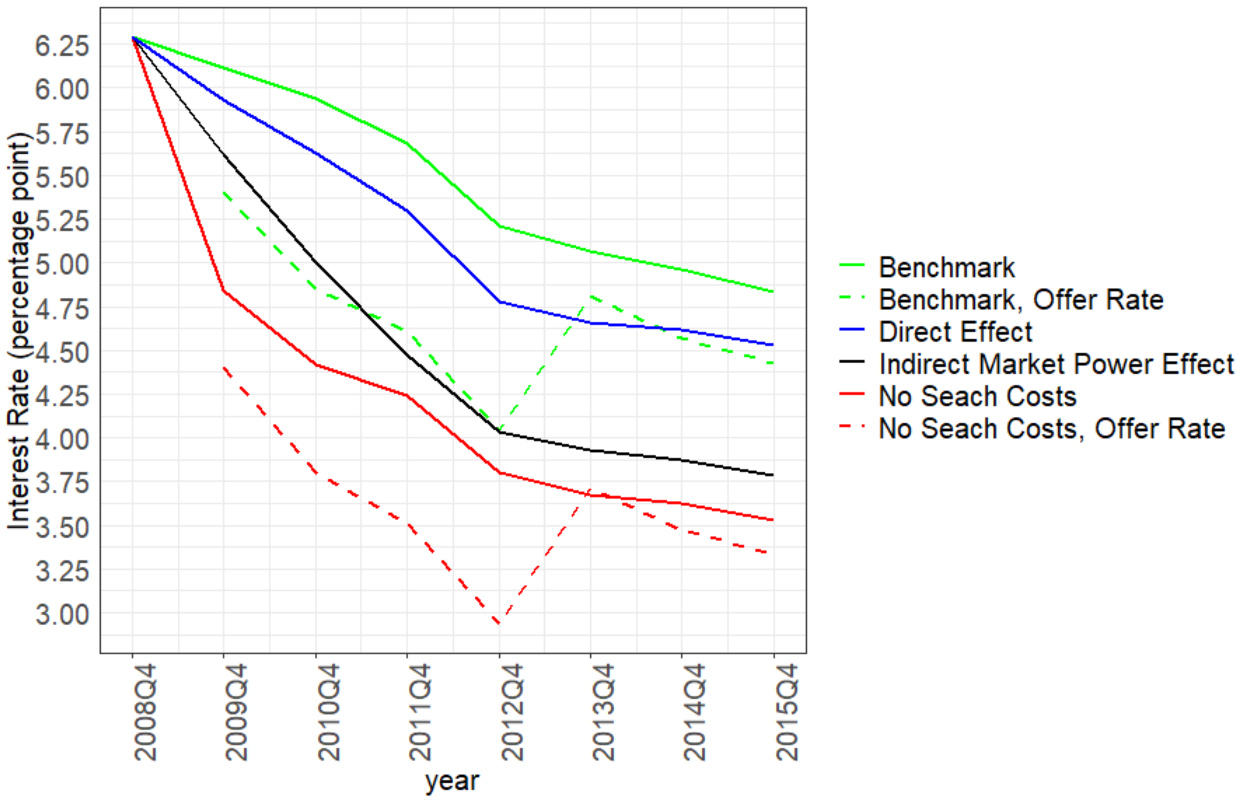
First, we explain how we determine the direct effect. We assume that borrowers do not pay for the search costs while they still have their marginal search costs. We set $\frac{\kappa_c}{\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})}$ equal to zero for borrowers. If borrowers choose to refinance, they do not pay for this search costs. However, the marginal search costs κ_c are still in place. We also assume that offered rate distributions are equal to the one in the benchmark. We assume this to keep the market power effect unchanged. Under this scenario, the borrowers will not change their search behavior when they refinance.

Second, we explore the indirect effect of the search costs on refinancing. To find the indirect effect, we assume that what borrowers pay for the search costs equals what they pay in the benchmark model. We set $\frac{\kappa_c}{\lambda_{j\theta t} H_{j\theta t}(r^*_{jc\theta t})}$ equal to the benchmark economy. However, the marginal search costs for all borrowers equal zero ($\kappa_c = 0 \ \ \forall c \in \{1, 2, ..., 5\}$). This is as if borrowers must pay upfront search costs if they choose to refinance; however, getting an inquiry becomes free during the search process. Next, we solve for the equilibrium and find the new offered rate. This assumption eliminates the loan originators' market power induced by search costs. All borrowers search for the lowest rates offered. In equilibrium, there is a single price equal to the minimum of the offered rate distribution in the benchmark economy.

Figure 13 compares the direct and the indirect effect. In this graph, we display the average of the mortgages rates and offered rates in the benchmark economy (solid and dashed green lines, respectively). We also present the results from Section 6.4, which are the average of the mortgages rates and offered rates in the counterfactual economy without search costs (solid and dashed red lines, respectively). The blue line represents the average mortgage rates on outstanding loans when we remove the search costs. Since refinancing costs decline for borrowers, it is more likely that they will choose to refinance. As a result, the average mortgage rates on outstanding loans decline. The black line represents the average mortgage rates when we remove the indirect market power effect. In this alternative economy the offered rates that borrowers choose interest rate from is exactly equal the one in the economy without search costs (dashed red line). As we can see in Figure 13, interest rates on outstanding mortgage rates are significantly lower in the economy without the indirect effect compared to the one without the direct effect. Thus, the answer to the second question of the paper is that the indirect market power effect dominates the direct effect of search costs.

To understand the direct effect, we provide an example here. We estimate that the marginal search cost for the highest search cost borrowers is at least \$1712 per inquiry. In addition, applications are

Figure 13: Direct versus Indirect Effect of Search Costs on Refinancing



Note: The graph details the direct versus indirect effect of search costs on refinancing. The solid lines are the average of the interest rates on outstanding mortgages. The dashed lines are the average of the offered rates. The green lines represent the benchmark model, and the red lines represent the alternative economy without search costs. We assume that the marginal search costs for all borrowers equal zero ($\kappa_c = 0 \ \ \forall c \in \{1, 2, ..., 5\}$). The blue line represents the mortgage rates on outstanding loans when we remove the direct effect, and the black line represents the economy when we remove the indirect market power effect.

Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

assumed to always be accepted. Based on our estimation results, these borrowers always receive one inquiry whenever they refinance a mortgage. One can imagine a mechanism that can evaluate the expected search costs for all borrowers and subsidize them the exact amount if they choose to refinance. However, the search is still costly for borrowers. For high search cost borrowers, this means that the first inquiry is free, but they must still pay $1712 per inquiry if they want to search further. The mechanism directly encourages borrowers to refinance. We assume that the offered rate distribution remains unchanged compared to the economy without such a subsidy. This means that borrowers are not going to change their search behavior. For example, the high search cost borrowers are not going to obtain the second inquiry. To understand the indirect effect, the same environment can be assumed with a different mechanism. Borrowers must pay for their expected search costs before refinancing; however, the search cost per inquiry becomes free when they enter the refinance market. This policy removes search friction, and loan originators lose their power to offer rates higher than the lowest possible rate. This policy encourages indirectly refinancing while the direct effect remains a barrier. Our paper finds that the second mechanism is significantly more effective in increasing refinancing. Knowing this is important because it would enable policy makers to evaluate which policies, mortgage designs or market designs might be most effective in reducing search friction and, consequently, inactivity in refinancing. In the next Section, we propose a market design that under specific assumption can eliminate the indirect effect of search costs while the direct effect remains in place.

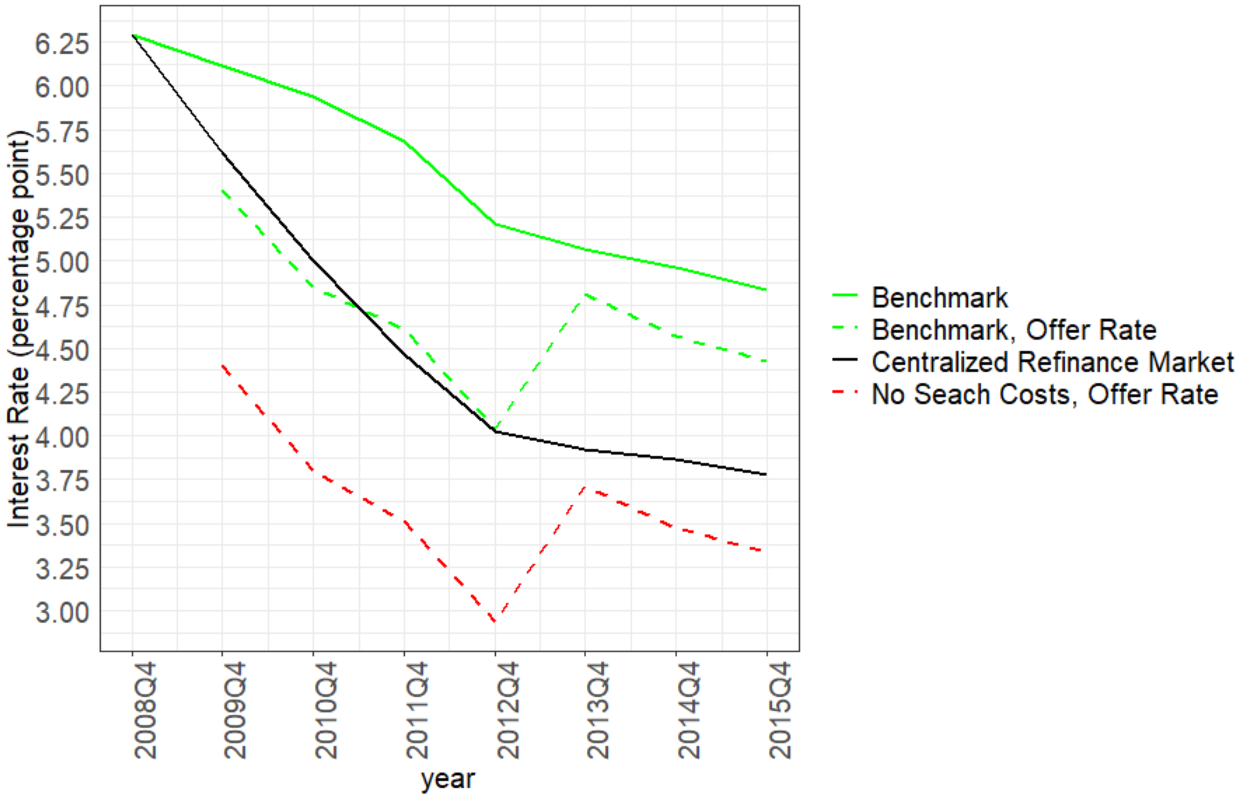
7 A Centralized Refinance Market

In this section, we use our model to study a counterfactual in which borrowers can refinance their mortgages through a centralized origination market. Loan origination currently occurs in a decentralized market where borrowers contact loan originators to refinance. We impose specific assumptions to study this counterfactual. We assume that loan origination can only be done through this centralized market. In this centralized platform, markets are defined based on LTV ratios, terms and FICO® Scores (j, θ). Loan originators post interest rates to markets (j, θ, t) every quarter, and we assume that a Bertrand competition exists among the loan originators when they post interest rates to the centralized market. Borrowers (with type θ) observe only one interest rate for (j, θ, t), and they can lock in the posted rate by choosing to refinance to contract j. We assume that refinancing is still costly for borrowers. They pay for the switching costs in full, and they also pay a search cost equal to number of inquiries until they get approved. We assume that the search cost is $\frac{\kappa_c}{\lambda_{j\theta t}}$. In this alternative economy, the offered rates will be equal to the minimum range of the offered rates due to Bertrand competition.

Figure 14 presents the results for this centralized market. The red dashed line represents the offered rates for the economy without search costs. In the centralized market, the offered rates are equal to the offered rates in the economy without search costs. The black line represents the average of the mortgage rates on outstanding loans in the centralized market. There is a significant reduction in the rates in this alternative economy. However, there is still a gap between the outstanding mortgage rates (solid black line) and the offered rate (dashed red line). This gap forms because the switching costs and search costs inhibit refinancing activities.

This counterfactual experiment highlights the importance of the result of the paper, which is that search friction inhibits refinancing activities mostly through the market power of the loan originators, not directly through refinancing costs. In this counterfactual economy, the market power of the loan originators is eliminated; however, we still assume that the refinancing costs are mostly in place.

Figure 14: A Centralized Refinance Market



Note: The solid lines are the average of the interest rates on outstanding mortgages. The dashed lines are the average of the offered rates. The green lines represent the benchmark model, and the red lines represent the alternative economy without search costs. We assume that marginal search costs for all borrowers are equal to zero ($\kappa_c = 0 \quad \forall c \in \{1, 2, ..., 5\}$) in the economy with no search costs. The black line represents an alternative economy in which refinance occurs in a centralized market.

Data Source: Equifax Credit Risk Insight Servicing and Black Knight McDash.

8 Conclusion

In this paper, we highlight the evidence on search friction and inactivity in refinancing in the US mortgage market. We bridge these two pieces of evidence to explore the role of search costs in explaining refinancing inaction. We empirically demonstrate that search costs significantly inhibit refinancing. We explore two channels through which search costs affect refinancing: the direct effect and the indirect market power effect. We find that the indirect market power effect dominates the direct effect. This result indicates that the main reason that search costs inhibit refinancing is NOT that getting only one quote to refinance is a very costly action for the borrowers. The main issue is that if borrowers get only one quote, the loan originators take into account that borrowers do not get multiple quotes to find the lowest rates, thus, they respond accordingly by offering high interest rates. This indirect effect weakens the benefit of refinancing for borrowers and this is the main channel that we find search costs inhibit refinancing. This is the main result of this paper.

To understand the main result, we explored an alternative economy in which the current decentralized system is replaced by a centralized market for refinancing. In this centralized market, borrowers observe only one price at each point in time. Loan originators post interest rates in the centralized market and we assume that there is Bertrand competition among them. We find that a centralized market for refinancing can significantly increase refinancing activity by eliminating market power, even if the refinancing costs remain unchanged.

The results of this paper raise thie question of which policies, mortgage designs or market designs might be most effective in reducing the indirect market power effect of search friction and, consequently, decreasing inactivity in refinancing.

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A Mathematical Appendix

A.1 Structural Refinance Probabilities

Given the nested logit model of a refinancing decision described in section 4.1, we can find the structural refinancing probabilities. The equation A.1 presents the probability of refinancing of a borrower with state variable z_t:

$$P_{1t}(z_t) = \sum_k P_{kt}(z_t) = \frac{\left(\sum_k \exp(\frac{v_{kt}(z_t)-v_{0t}(z_t)}{\sigma})\right)^{\sigma}}{1+\left(\sum_k \exp(\frac{v_{kt}(z_t)-v_{0t}(z_t)}{\sigma})\right)^{\sigma}} \tag{A.1}$$

In the language of a nested logit model, this is the probability of choosing the nest. The Equation A.2 presents the choice probabilities within the nest of refinancing. Specifically, Equation A.2 shows the structural probability of refinancing to contract j conditional on choosing to refinance in period t:

$$P_{jt}(z_t) = \frac{\exp(\frac{v_{jt}(z_t)-v_{0t}(z_t)}{\sigma})\left(\sum_k \exp(\frac{v_{kt}(z_t)-v_{0t}(z_t)}{\sigma})\right)^{\sigma-1}}{1+\left(\sum_k \exp(\frac{v_{kt}(z_t)-v_{0t}(z_t)}{\sigma})\right)^{\sigma}} \tag{A.2}$$

A.2 Calculating Demand

In this section we discuss how we find the demand function, $q_{j\theta t}(r)$, presented in the Equation 4.11. The probability that a borrower with reservation interest rate r^* in market (j,θ,t) refinance with an interest rate r is as follows:

$$Pr\{\tilde{r} = r | r < r^*, j, \theta, t\} = \frac{h_{j\theta t}(r)}{H_{j\theta t}(r^*)} \tag{A.3}$$

Let $\Phi_{j\theta t}(r^*)$ and $\phi_{j\theta t}(r^*)$ be the distribution and density of the reservation interest rates, respectively, of type θ borrowers in market j at time t. Summing over the borrower's reservation rate yields the share of market for loan originators charging a rate less than r,

$$Pr\{\tilde{r} = r | j, \theta, t\} = \sum_{r^* \geq r} \frac{h_{j\theta t}(r)}{H_{j\theta t}(r^*)} \phi_{j\theta t}(r^*) \tag{A.4}$$

Finally, since a mass $h(r)$ of loan originators charge interest rate r, and the borrower samples each of these lenders with equal probability, the residual demand curve for a loan originator charging rate r is the above quantity divided by $h(r)$:

$$q_{j\theta t}(r) = \sum_{r^* \geq r} \frac{\phi_{j\theta t}(r^*)}{H_{j\theta t}(r^*)} \tag{A.5}$$

This calculation is quite similar to Agarwal et al. (2017). The difference is that the reservation distribution depends on the search costs distribution of the borrowers with type θ who choose to refinance to contract

j at time t.

$$\sum_{(c,x,r')} \mu_{\theta t}(c,x,r') P_{j\theta t}(c,x,r') \tag{A.6}$$

in which μ is the mass of borrowers. Therefore we can find the distribution of the reservation interest rate:

$$\phi_{j\theta t}(r^*) = \sum_{(c,x,r')} \mu_{\theta t}(c,x,r') P_{j\theta t}(c,x,r') 1\{r^*_{j\theta ct} = \tilde{r}\} \tag{A.7}$$

A.3 Dynamic of Borrowers Mass

We define $\mu_t(z_t)$ as the mass of borrowers with a mortgage at time t in state z_t. Precisely, it captures the mass of borrowers at time t with type (c,θ) and mortgage contract (r,x). To find μ_{t+1} in every state we need to know the transition probabilities of states and refinancing choice of borrowers. Additionally, we need to know the mass of new mortgage originators.

$$\begin{aligned} \mu_{t+1}(c,\theta_{t+1},r_{t+1},x_{t+1}) &= \sum_{\theta_t} \mu^0_t(c,\theta_t)\delta^0_t(c,\theta_t) f_{1t}(\theta_{t+1}|\theta_t) \\ &+ \sum_{\theta_t}\sum_{r_t}\sum_{x_t} \mu_t(c,\theta_t,r_t,x_t)(1-\delta_t(x_t))P_{0t}(c,\theta_t,r_t,x_t) f_{0t}(x_{t+1},\theta_{t+1}|x_t,\theta_t) \\ &+ \sum_{\theta_t}\sum_{r_t}\sum_{x_t} \mu_t(c,\theta_t,r_t,x_t)(1-\delta_t(x_t))P_{x_{t+1}t}(c,\theta_t,r_t,x_t) f_{1t}(\theta_{t+1}|\theta_t) h_{x_{t+1}\theta_t t}(r_{t+1}|r^*_t(c,\theta_t,x_{t+1})) \end{aligned} \tag{A.8}$$

The dynamic of potential borrowers are as follow,

$$\begin{aligned} \mu^0_{t+1}(c,\theta_{t+1}) &= \sum_{\theta_t}\sum_{r_t}\sum_{x_t} \mu_t(c,\theta_t,r_t,x_t)\delta_t(x_t) f_{0t}(\theta_{t+1}|\theta_t) \\ &+ \sum_{\theta_t} \mu^0_t(c,\theta_t)(1-\delta^0_t(c,\theta_t)) f_{0t}(\theta_{t+1}|\theta_t) \end{aligned} \tag{A.9}$$

We assume that there is no growth in the potential borrowers in the mortgage market:

$$\sum_{\theta_t} \mu^0_t(c,\theta_t) + \sum_{\theta_t}\sum_{r_t}\sum_{x_t} \mu_t(c,\theta_t,r_t,x_t) = g_c \qquad \forall t \tag{A.10}$$

g_c is the mass of borrowers with search cost c.

Moreover, we assume the probability of becoming a homeowner is independent of search cost:

$$\delta^0_t(c,\theta_t) = \delta^0_t(\theta_t) \qquad \forall c \tag{A.11}$$

A.4 EM Algorithm

To estimate empirical CCPs, we follow the first stage EM algorithm in Arcidiacono and Miller (2011). In this appendix section, we explain the expectation and maximization steps.

Expectation Step:

The first step of mth iteration is to calculate the conditional probability of being in each unobserved state given the values of the structural parameters and conditional choice probabilities from the mth iteration, $\{\Theta^{(m)}, g^{(m)}\}$. The likelihood of the data on i given the parameters at mth iteration is found by evaluating equation A.12.

$$L(d_i, z_i|\hat{z}_{i1}; \Theta^{(m)}, g^{(m)}) \equiv \sum_{c_i} g^{(m)}(c_i|\hat{z}_1) \left(\prod_{t=1}^{T} \mathcal{L}_t(d_{it}, z_{i,t+1}|z_{it}; \Theta^{(m)}, g^{(m)}) \right) \tag{A.12}$$

where $\Theta \equiv (\beta_{c\theta x}, \beta_1, \tilde{p}_{j|1}(c, \theta, x))$ and $\hat{z}_1 = (\theta_1, r_1, x_1)$. To simplify, we define the following:

$$L_i^{(m)} \equiv L(d_i, z_i|\hat{z}_{i1}; \Theta^{(m)}, g^{(m)}) \tag{A.13}$$

Similarly, we denote by $L_i^{(m)}(c_i = c)$ the joint likelihood of the data and unobserved state c, given the parameter evaluation at iteration m.

$$L_i^{(m)}(c_i = c) \equiv L(d_i, z_i, c_i = c|\hat{z}_{i1}; \Theta^{(m)}, g^{(m)}) \tag{A.14}$$

where,

$$L(d_i, z_i, c_i = c|\hat{z}_1; \Theta^{(m)}, g^{(m)}) = g^{(m)}(c|\theta_{i1}, r_{i1}, x_{i1}) \left(\prod_{t=1}^{T} \mathcal{L}_t(d_{it}, z_{i,t+1}|z_{it}; \Theta^{(m)}, g^{(m)}) \right) \tag{A.15}$$

At iteration $m+1$, the probability of i being in unobserved state c, $q_{ic}^{(m+1)}$, then follows from Bayes rule:

$$q_{ic}^{(m+1)} = \frac{L_i^{(m)}(c_i = c)}{L_i^{(m)}} \tag{A.16}$$

We update the probabilities of unobserved states in equation A.17.

$$g^{(m+1)}(c|\hat{z}_1) = \frac{\sum_{i=1}^{N} q_{ic}^{(m+1)} 1(\theta_{i1} = \theta_1, r_{i1} = r_1, x_{i1} = x_1)}{\sum_{i=1}^{N} 1(\theta_{i1} = \theta_1, r_{i1} = r_1, x_{i1} = x_1)} \tag{A.17}$$

Maximization Step

$$\Theta^{(m+1)} \equiv \text{argmax} \quad \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{c} \sum_{j=1}^{J} q_{ic}^{(m+1)} \ln \mathcal{L}_t(d_{it}, z_{i,t+1}, c_i = c|z_{it}; \Theta^{(m)}, g^{(m+1)}) \tag{A.18}$$

To estimate the empirical CCPs, we use random sample of loans originated between 2008 to 2009 that are followed until 2015.

A.5 Parametric Assumptions for the First Stage

In this section, we discuss the parametric assumptions for approval probability and the offered rate distribution. In the Equation A.19 we specify the approval probability:

$$\lambda_{j\theta t} = \frac{\exp(\beta_j^\lambda + \beta_\theta^\lambda + \beta_t^\lambda)}{\sum_{\tilde{\theta}} \sum_{\tilde{j}} \exp(\beta_{\tilde{j}}^\lambda + \beta_{\tilde{\theta}}^\lambda + \beta_t^\lambda)} \tag{A.19}$$

where $\{\beta_\theta^\lambda, \beta_j^\lambda, \beta^\lambda\}$ for all j and θ are the parameters to be estimated. β_θ^λ are the dummies for FICO® Score groups, β_j^λ are the dummies for LTV groups, and β_t^λ are the year dummies.

Based on 4.3, offer rate distribution from the supply side of the model is as follows:

$$h_{j\theta t}(r) = \frac{\exp(\frac{(r - \hat{r}_{j\theta t} - \chi) q_{j\theta t}(r)}{\sigma_\pi})}{\sum_{\tilde{k}} \exp(\frac{(r - \hat{r}_{j\theta t} - \chi) q_{j\theta t}(r)}{\sigma_\pi})} \tag{A.20}$$

where $\{\chi, \sigma_\pi\}$ are parameters to be estimated given the marginal demand function $q_{j\theta t}(r)$.

In order to find the offer rate distribution from equation A.20, we need to have the marginal demand function $q_{j\theta t}$, which itself is a function of $h_{j\theta t}$. This is a fixed point problem, that is time-consuming to estimate. To simplify, we guess a functional form for the offered rate distribution, $h^N_{j\theta t}$ and then we make sure that the guess is a good approximation of structural offered rate distribution $h_{j\theta t}$ presented in the Equation A.20. We assume a normal distribution $h^N_{j\theta t} \sim N(\hat{r}_{j\theta t} + \beta^h_j + \beta^h_\theta + \beta^h_t, \sigma_h)$ in which $\{\beta^h_j, \beta^h_\theta, \beta^h_t\}$ are the dummies for contract, creditworthiness and year.