# Essays on the Industrial Organization of Mortgage Markets

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Boston College Electronic Thesis or Dissertation, 2018

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A dissertation
submitted to the Faculty of
the department of Economics
in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy

Boston College
Morrissey College of Arts and Sciences
Graduate School

May 2018

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## Abstract

This dissertation consists of two chapters on the industrial organization of mortgage markets in the United States. Both chapters share a theme of studying costly consumer search and imperfect information in mortgage markets, and how these mechanisms affect market structure and welfare.

In the first chapter, titled "Consumer Search Costs in U.S. Mortgage Markets", I focus on estimating the distribution of consumer search costs in the market for government-backed mortgages in the US during the period from September 2013 to March 2015. Costly search explains two observations about U.S. mortgage markets: borrowers in the US shop from very few lenders, and price dispersion exists even for homogeneous and insured mortgages. To estimate the effects of costly search, I adapt the Hortasu and Syverson (2004) search model to mortgage markets. I estimate the distribution of consumer search costs in each U.S. state using recent data on government-insured mortgages. I find that estimated search costs are large; a median borrower would face a search cost equivalent to about \$40 in monthly repayment. At the state-level, search cost magnitude is related positively to household income and age and negatively to years of education.

I solve counterfactual scenarios in order to study the relationship between search costs and welfare. Compared to the full information scenario, the presence of costly consumer search decreases social welfare by about \$600 in monthly repayment per borrower. This decrease

in welfare occurs because under costly search borrowers are matched with lower quality lenders and spend resources on searching. At the national level, this decrease corresponds to approximately $35 million per-month. Reductions in search costs would raise social welfare monotonically. A 10% reduction in search cost may raise social welfare by as much as $130 per borrower per month. These findings support recent policies that aim to reduce search costs of mortgage borrowers.

In the second chapter, titled "Price Discrimination in U.S. Mortgage Markets", I examine the existence of price discrimination generated by costly consumer search in the market for mortgages. Positive search costs affect borrowers' demand-elasticity by changing their willingness to engage in mortgage shopping, the consideration set of lenders, as well as their outside option when negotiating with a particular lender. Consequently, price discrimination may arise as lenders have an incentive to vary the markup based on directly or indirectly observed search costs.

I develop a stylized model of consumer search in mortgage markets where firms charge optimal prices that depend on borrowers' search cost level. The model produces testable restrictions on the conditional quantile function of observed transacted rates. Specifically, under price discrimination a quantile regression of transacted rates on any loan observable should produce coefficients that either vary monotonically or are equal to a constant across quantiles, depending on whether the observable is affiliated with marginal cost, search cost, or both.

Using the data on insured Federal Housing Agency loans where price variation is not driven by default risk, I run a quantile regression of transacted interest rates on a set of loan observables, including borrower's credit score, original principal balance, and loan-to-value ratio, among others. I find that predictions of the theoretical model are satisfied for all loan observables under consideration, and price discrimination created by costly consumer search is likely to exist in U.S. mortgage markets. For policy makers aiming to increase competition and welfare in the mortgage market, these results suggest that not only the number of lenders but also the magnitude of consumer search costs is relevant.

The two chapters are independent but complement each other. Each examines a separate hypothesis that the other assumes away. In Chapter 1, lenders are viewed as differing in quality, and their pricing decision depends on loan observables only through the marginal cost channel: any changes in observables affect only the marginal cost of lending and are then passed on to price in a one-to-one manner. In contrast, chapter 2 models lenders as homogeneous firms but allows loan observables to be informative of consumer-specific search costs. As a result, optimal markups vary with loan observables through the effects of observables both on marginal costs and on search costs. The combination of the two chapters provide a more complete picture of how pricing relates to costly search in the market for government-backed mortgages.

# Acknowledgements

This work would not have been possible without the continued support of many individuals. I thank my advisors, Professors Michael Grubb and Julie Holland Mortimer, for their invaluable support and advice during my time at Boston College. Michael Grubb spared so much of his time to meet with me and discuss my research throughout the years; he has always been an important source of inspiration and encouragement. Julie Mortimer taught me in my first Industrial Organization class I've ever taken. I found her class so intellectually stimulating that I later decided to specialize in this field. My thanks and gratitude also go to Richard Sweeney for his helpful advice and comments. I thank my friends and colleagues in the Department of Economics at Boston College for the support throughout my doctoral studies.

I dedicate this dissertation to my late grand-father, Luu Duc Hong, who passed away in June 2017 and therefore will not be reading these lines. He has been my life-long role model, and I still miss him very much. I am also immensely grateful to my grand-mother, Nguyen Thi Tuan, my Dad, Luu Duc Hai, and my Mom, Le Minh Hien, for nurturing me and encouraging me to pursue an Economics PhD. Without their kind encouragement and belief in me, I have no doubt that my PhD journey would have been a lot more challenging. Last but not least, I could not have finished this dissertation without the constant love and support of my wife, Phuong Nguyen. There is nothing I can say or give that equals her support. I hope that this dissertation will be a small source of joy for my grand-mother, parents, and wife.

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# Chapter 1

# Consumer Search Costs in U.S. Mortgage Markets

## 1.1 Introduction

Mortgage borrowers in the United States shop from very few lenders. Recent survey data show that nearly 80% of borrowers consider only two lenders or fewer prior to applying, and 50% consider only one lender (Consumer Financial Protection Bureau, 2015). The small number of lenders that are considered is not due to a scarcity of lenders. In 2014, for instance, there were a total of 7,062 registered mortgage lenders in the Home Mortgage Disclosure Act database. One important explanation for the lack of shopping activity is that borrowers face considerable search costs.

Despite the prevalence of online search engines, exact price quotes for mortgages are only provided in a form called the Good-Faith Estimate (GFE), which the borrower typically obtains after having filed and submitted an application. However, submitting an application and acquiring the GFE incurs a certain cost on the borrower. The cost includes not only a non-refundable application fee but also the value of time spent filling an application. There are also implicit costs, such as the reduction in credit rating every time the borrower's credit report is assessed.

Market frictions created by costly consumer search, as described above, certainly hinder the competitiveness of U.S. mortgage markets. Unfortunately, there are few estimates on the magnitude of search frictions in this industry and the resulting effects on market welfare. The welfare effects can be especially pronounced considering the enormous size of the market for mortgage products in the US. In 2014, total mortgage debt outstanding exceeded 13 trillion dollars, which corresponds approximately to 70% of U.S. annual GDP. Estimates of the search cost distribution quantify an important feature of this industry that is useful for policy evaluations.

This paper estimates the distribution of consumer search costs in an important segment of U.S. mortgage markets and measures the impact of costly search on market welfare. In many settings, price dispersion can be very informative about the search cost distribution. For instance, in a market where firms and consumers are homogeneous apart from the variation in consumer search costs, the distribution of search costs can be recovered using only observations of prices (Hong and Shum, 2006). This is possible partly because the expected price saving from one more search, given the observed transacted price, provides a lower bound for consumers' search cost level.

In reality, some price dispersion in mortgage markets is driven by factors unrelated to consumer search. Variation in the quality of service provided by lenders, such as the responsiveness of representatives, the speed of processing applications and brand reputations, can drive price dispersion. Hence, the relevant quantity for the consumer's search problem is not the expected price saving but the expected utility gain, which accounts for both price saving and quality gain that result from the marginal search. Perhaps more importantly, the marginal cost of lending, which is predominantly related to borrowers' default risks, may also vary and create price dispersion.

I account for variation in lender quality by allowing vertical differentiation among profit-maximizing lenders. Although the search cost distribution can be estimated without imposing structure on the firms (Honka, 2014), specifying a profit-maximizing supply side is necessary to quantify effects of costly search on market welfare. Hence, I follow Hortaçsu and Syverson (2004) and specify that lenders choose prices to maximize profit given the quality distribution and the search cost distribution. By assuming that observed prices are profit-maximizing, I can account for price dispersion that is due to quality differences and later conduct counterfactual experiments where the price equilibrium is endogenously changed.

In order to alleviate variation in prices due to default risks, I focus on a subset of mortgages that are government-backed. Unlike conventional mortgages, government-backed mortgages provide lenders with insurance in the case of borrower default. The insurance is administered through four separate government agencies that correspond to four types of government-backed loans: the Federal Housing Administration (FHA), the Department of Veteran Affairs (VA), the Department of Agriculture (Rural Development (RD) loans), and the Department of Housing and Urban Development (Permanent Indian Housing loans). While only FHA loans feature full insurance, all the other types require at least a partial insurance on the loan amount. Government-backed mortgages comprise about a third of all mortgages in the US in terms of origination volume (Simkovic, 2013). As in Allen, Clark and Houde (2014c) who study the Canadian mortgage market, the use of insured mortgages in this chapter ensures observed price dispersion is less likely to be driven by heterogeneous default risks.

I estimate the model using data on government-backed mortgages from October 2013 to March 2015 obtained from Ginnie Mae. The sample represents the full population of government-backed mortgages that were originated in the US during this period. Consistent with the presence of costly search, the sample displays a significant degree of price dispersion even though all sampled mortgages are insured. For example, for a 30-year mortgage with a median loan amount of $120,000, a borrower at the 10$^{\text{th}}$ percentile of the interest rate distribution is paying $71 less per month compared to a borrower at the 90$^{\text{th}}$ percentile. The pattern of price dispersion holds regardless of whether monthly payments or interest rates are used as the measure for price, and persists even after controlling for loan and lender characteristics.

I estimate the search cost distribution separately in each U.S. state. By treating each state as a separate market, I can examine how state-level demographic factors relate to the search cost distribution. Establishing the role of demographics in estimating search costs is useful for understanding the exact nature of search costs in this market. Furthermore, since the relationship between search cost magnitudes and market prices is not well established, both theoretically and in the context of this particular market, I perform counterfactual simulations to characterize how search cost reductions would affect price level and price dispersion.

Estimates of search cost magnitudes are measured on a per-month basis. As in Allen, Clark and Houde (2014a), this per-month measurement unit follows directly from the specification of marginal cost and utility in per-month dollars. Two borrowers who have the same per-month search cost need not have the same total search cost, because they may plan to hold the mortgage for a different time length. Holding total search cost constant, a borrower who plans to refinance soon would have a higher per-month search cost and would search less. Intuitively, she has less time to benefit from finding a low monthly price and thus have less incentive to search hard. In contrast, a borrower who plans to hold the mortgage for a longer period of time would have a lower per-month search cost, would benefit more from finding a low monthly price, and would search harder.

In the context of mortgage markets, a per-month unit is more empirically relevant than a total unit, because prices in this industry are quoted not in absolute terms but in monthly and annual terms. For example, knowing that the total search cost of a borrower is \$3000 does not reveal much about her search behavior, because how long she plans to hold the mortgage is usually her private information. On the other hand, knowing that her per-month search cost is \$30, one can reasonably predict what her cut-off level of utility is, which lenders would be acceptable to her, and how many times she would be expected to search.

Estimation results confirm that search costs are sizable in this industry. Because interest rates are quoted on an annual or monthly basis, search costs are also estimated with the same units. Across all 51 markets (including Washington, DC), the median search cost level is about \$40 per month of mortgage repayment. A median borrower therefore stops searching when the expected utility gain of the marginal search, which results from either finding a lower price or a higher quality lender, becomes less than \$40. In order to quantify the welfare effects of costly search, I solve for welfare changes in a range of counterfactual scenarios where search costs are reduced discretely from 5% to 100%. I find that social welfare increases monotonically with the degree of search cost reduction. In the context of the model, there are two separate sources of welfare changes when search costs are reduced: first, borrowers are matched with better quality lenders, and second, borrowers spend less resources on searching before finding a match. The counterfactual results show that in the full information case, social welfare is increased by approximately \$600 per borrower per month because of these effects. At the national level, this welfare reduction corresponds to about \$35 million per month.

Demographic factors are found to be related to the magnitude of search costs at the state-level. In particular, search costs are increasing in household income and age, and are decreasing in years of education. These results are consistent with Goldman and Johansson (1978)'s hypothesis that consumer search costs reflect both opportunity costs and the cognitive and information-processing ability of individuals. Policies that aim to educate consumers (i.e., improve the information-processing ability) is likely to be beneficial in reducing search costs and improving consumer welfare, although one should be aware of the substantial difficulty in using financial education to improve consumers' financial outcomes (Hastings, Madrian and Skimmyhorn, 2013).

Counterfactual simulations predict an increase in average absolute markup charged by lenders in most state-level markets. The incentive to charge a low price and capture a larger share of consumers with low search costs becomes less and less relevant as more consumers become "shoppers" with low search costs. Search cost reductions also have a monotonic impact on the dispersion of posted prices. As search costs are reduced, in most markets dispersion of posted prices will increase, with the largest dispersion occurring in the case of complete elimination of search costs.

Results presented in this chapter treat search costs as a broadly-defined term. If borrowers search using an optimal stopping rule, I find that their search costs have to be very large in order to rationalize the pattern of prices and market shares observed in each geographical market. However, if borrowers are confused about the mortgage market, as Woodward and Hall (2012) suggest, they may stop shopping at an earlier than optimal point. Furthermore, consumers may not be informed about the distribution of posted prices, a requirement for optimal shopping. As discussed in Grubb (2015), there is a growing literature in behavioral industrial organization that explain why consumers fail to shop for the best price. In the context of this chapter, estimated search costs should therefore be interpreted as encompassing both the cost of shopping as well as other behavioral limitations that prevent consumers from implementing an optimal shopping program.

The contribution of this chapter is threefold. First, along with Woodward and Hall (2012), this chapter is the one of the first to provide estimates of consumer search costs in the market for mortgages in the United States. Because of the prevalence of search frictions in this industry, systematic estimation of their magnitudes is useful for policy analysis. Second, in addition to Nishida and Remer (2015), this chapter is one of the few studies that make the connection between the distribution of search cost and demographic characteristics. The estimated relationship between demographics and search costs is informative for understanding the nature of search costs. Third, through the use of a structural model, the paper performs counterfactual simulations to estimate the effects of costly consumer search on welfare. The counterfactual results establish the relevance of costly search in mortgage markets, and help predict changes in welfare, price dispersion, and price level following policies of search cost reductions.

## 1.2 Related Literature

In terms of methodology, this research is most closely related to the work by Carlson and McAfee (1983), Hong and Shum (2006), and Hortaçsu and Syverson (2004). Carlson and McAfee (1983) provide the theoretical foundation with a model of equilibrium price dispersion due to consumer search.[1] Hong and Shum (2006) develop a method to recover the search cost distribution for a homogeneous product using only data on prices. Hortaçsu and Syverson (2004) build on these two papers to recover the search cost distribution of a vertically differentiated product using prices and market shares. They apply their method to investigate how search frictions create sizable price dispersion in the U.S. mutual funds industry. In the mortgage search model presented in Section 1.4, transacted prices can be separated into two components: the marginal cost of lending and lender's absolute markup. This assumption permits a relatively straightforward adaptation of the methodology employed by Hortaçsu and Syverson (2004).

A few papers also examine consumer search in mortgage markets. Woodward and Hall (2012) study the use of brokers among borrowers using a sample of mortgages insured by

[1] For related theoretical models of consumer search, see the extensive review by Baye, Morgan and Scholten (2006).

the Federal Housing Administration (FHA). The authors find that from the perspective of a model of optimal shopping, the cost of contacting an additional broker is unreasonably high. They conclude that borrowers are not shopping optimally and may be confused about their broker's incentives. A working paper by Allen et al. (2014a) studies consumer search in the Canadian mortgage market. They implement an analysis at the lender-borrower level, and find that search reduces consumer welfare by $20 per month of repayment per consumer. Related papers by the same authors document price discrimination and the effects of mergers on price dispersion among mortgage lenders in Canada. Allen et al. (2014c) run quantile regressions of transacted rates on loan observables and find evidence consistent with price discrimination caused by bargaining and negotiating. Allen, Clark and Houde (2014b) examine the relationship between concentration and price dispersion, and find that mergers reduce the dispersion of prices. The authors argue that the evidence supports the presence of costly search in the Canadian mortgage market.

This paper shares similarities with a few empirical studies that quantify search costs in markets other than that of mortgage products. Honka (2014) studies search in the auto insurance industry, a market in which transacted prices vary according to consumer characteristics. This feature is also shared by mortgage markets and does not readily permit an adoption of the Hong and Shum (2006) method to recover search costs. Honka (2014) circumvents this problem by regressing prices on characteristics and predicts a distribution of price that each consumer faces. She finds that consumer search costs for automobile insurance plans range from $35 to $170 per search, with an average of about $40. Wildenbeest (2011) looks at how vertical differentiation and consumer search could explain price dispersion among supermarkets in the United Kingdom. He finds that in this market most of the dispersion in price can be attributed to product differentiation rather than consumer search. The examination presented in Section 1.6.2 on the relationship between search cost magnitudes and state-level demographic factors is closely related to that of Nishida and Remer (2015). Nishida and Remer (2015), studying the retail gasoline market, find that median household income is positively correlated with search costs.

## 1.3 Industry Background and Data Sources

### 1.3.1 Overview of the Market for Government-backed Mortgages

I study a sample of mortgages that are insured by the U.S. government. Lenders are protected from credit risk: in case of default they get a reimbursement from the government for the portion of unpaid principal balance under insurance. Currently four different government agencies are responsible for insuring mortgages: the Federal Housing Administration, the Department of Veteran Affairs, the Department of Agriculture, and the Department of Housing and Urban Development. Loans originated under these programs are respectively abbreviated as FHA, VA, RD, and PIH. Each of these programs targets a specific borrower demographic and requires certain qualifications from the borrower. Only FHA loans currently require full insurance, while VA, RD, and PIH loans require a partial insurance on the loan amount.

After origination, government-backed loans are securitized exclusively by Ginnie Mae. The securitization process consists of pooling individual mortgage loans together to form a mortgage-backed security, which can then be sold in the secondary mortgage market. In terms of volume, government mortgages occupy a sizable part of new mortgage originations in the United States. In 2010, for example, new issuances of securities backed by government mortgages comprised a third of total mortgage-backed security issuances (Simkovic, 2013).

Because of Ginnie Mae's participation in the secondary market, two different layers of protection exists in government-backed mortgages: government insurance that protects lenders in case of borrower default, and the Ginnie Mae's guaranty that protects investors in case of lender default. Over the course of a mortgage loan, lenders are typically responsible for remitting monthly payments of principal and interest from borrowers to investors. There is a risk of a lender defaulting on its remitting duty that investors must face. Ginnie Mae provides a guaranty to investors and negates that risk.

### 1.3.2 Ginnie Mae Loan-Level and Lender-State-Level Data

I treat each state as a separate market and perform the analysis at the lender-state level. I therefore collapse the primary dataset, the Ginnie Mae loan-level data, from the loan-level to the lender-state level. Below is a brief description of both original and collapsed datasets.

The Ginnie Mae loan-level data consists of the population of government-backed mortgages securitized by Ginnie Mae from October 2013 to March 2015 (Ginnie Mae, 2013). This dataset includes several loan and borrower characteristics, as well as the state where the property is located and the lender who underwrites the loan. In table 1.1, I provide a description of key variables included in this dataset. A key advantage of this dataset is the inclusion of data on the mortgage-backed security for which each loan is serving as the collateral. This inclusion permits merging the Ginnie Mae data with the Bloomberg data, described below, in order to estimate the marginal cost of lending.

I make several restrictions on the sample. First, I focus on new home purchases only and drop loans that are refinances (about 30% of the sample), since borrowers who refinance are likely to belong to a different market segment and therefore have different search costs compared to new homebuyers. I drop adjustable-rate mortgages (2% of the sample) in order to achieve a more tractable analysis. I also focus on loans with a common 30 year amortization period and drop those with a shorter term (5% of the sample). For each state, I also drop small lenders who represent less than 1% market share, presuming that these lenders are local and do not compete at the statewide scale. Lastly, I drop loans where

Table 1.1: Description of Key Variables in the Ginnie Mae Loan-Level Dataset

| Variables | Description |
|---|---|
| Bank/Lender Characteristics | |
| Lender ID | Unique identifier and the name of the lender |
| Agency | Agency that provides the insurance (FHA, VA, RD, PIH) |
| Mortgage Contract Characteristics | |
| Loan Purpose | Identifier whether the loan is a purchase or a refinance |
| Origination Date | Month in which the loan is originated |
| Loan Term | Length of the loan, in months |
| Interest Rate | Transacted interest rate (in basis points) |
| Original Principal Balance | Dollar amount of the loan |
| Loan-to-Value | Loan amount divided by property sell value |
| Credit Score | Minimum borrower credit score |
| Total Debt Expense Ratio | Ratio of all debts to the borrower's income |
| Buy Down Status | Identifier whether the borrower purchases discount points |
| Mortgage Insurance Rate | Mortgage insurance premium rate (FHA loans only) |
| Borrower Characteristics | |
| Number of Borrowers | Number of borrowers in the contract |
| First Time Homebuyer | Identifier for first-time homebuyer |
| Property Characteristics | |
| State | State where the property is located |
| Number of Units | Number of units in the property |
| MBS Characteristics | |
| Coupon Rate - Pool | Coupon (interest) rate on the MBS into which the loan is pooled |

Source: Ginnie Mae Loan-Level Data, September 2013 - March 2015.

the borrower decides to purchase discount points (0.8% of the sample), since the transacted interest rate in those cases is not simply the outcome from a search equilibrium. After these adjustments, the sample consists of 1,091,897 loan-level observations.

In collapsing the loan data, I compute the mean interest rate, monthly payment, and loan amount at the lender-state level.In total there are 51 markets, one for each of the 50 states and Washington, D.C. On average, about 20 lenders are present in each market, with Alaska having the least number of lenders (13), and Connecticut having the most (27). In terms of market size, Texas is the largest, with nearly 11% of all observed loans originated in this state. North Dakota is the smallest; only 0.2% of loans are originated here.

In Table 1.2, I present an example of this lender-state-level data for five lenders with the largest market share in Texas. Interest rate, monthly payment, and loan amount are calculated as the mean for all loans that a particular lender originates in the state of Texas. There is a considerable dispersion in the transacted interest rates across lenders, suggesting the presence of consumer search costs. As will be shown later, dispersion also exists when we use absolute markups, instead of transacted rates, as the measurement for prices.

Table 1.2: Summary Statistics for the Top 5 Lenders in Texas

| Lender's Name | Interest Rate (bps) | Monthly Payment ($) | Loan Amount ($1000) | Loan Count | Market Share (%) |
|---:|:---:|:---:|:---:|:---:|:---:|
| Wells Fargo | 429.30 | 830.04 | 168.36 | 31,760 | 29.71 |
| | (32.84) | (350.76) | (72.38) | | |
| PennyMac | 422.73 | 871.81 | 178.20 | 10,394 | 9.72 |
| | (28.31) | (324.06) | (67.40) | | |
| US Bank | 454.68 | 716.14 | 141.35 | 7,610 | 7.12 |
| | (42.52) | (251.02) | (53.12) | | |
| USAA Federal Bank | 395.66 | 1,003.37 | 211.25 | 5,007 | 4.68 |
| | (27.03) | (413.56) | (86.74) | | |
| JPMorgan Chase | 439.54 | 833.20 | 167.13 | 4,982 | 4.66 |
| | (30.87) | (381.76) | (78.45) | | |

Standard deviations are reported in parentheses for Interest Rate, Monthly Payment and Loan Amount.

### 1.3.3 Bloomberg Data on MBS Yield

To control for the marginal cost of lending, I collect yield rates of mortgage-backed securities from Bloomberg. These yield rates are obtained on a monthly basis from October 2013 to March 2015. In this section, I describe the origination process of a mortgage and argue that the MBS yield rates provide a good approximation for the marginal cost of lending.

In mortgage markets, the funds used to finance loans usually come not from lenders but from investors in the secondary market. This channeling of funds from investors to homebuyers is carried out in several steps. First, a mortgage lender sells a mortgage-backed security to investors in a forward-market called the TBA market. This sale essentially amounts to a promise that the lender would deliver the MBS to investors at a given future date. At the time of this forward market transaction, the face value, the coupon rate, and the price of the mortgage-backed security are determined. Second, the lender proceeds to originate loans and repackage them with Ginnie Mae to form a mortgage-backed security. This step typically takes two to three months. Finally, after all the underlying loans are originated and the MBS is created, the lender delivers the MBS to investors at the previously agreed delivery date. A more extensive discussion on the institutional details of the TBA market can be found in Vickery and Wright (2013).

The lender is typically responsible for the servicing of loans. For our purpose servicing can be viewed as consisting of two duties: collecting monthly payments from homebuyers, and remitting part of those payments to investors who hold the MBS. The size of the monthly payments is determined by the loan amount and the interest rate of the mortgage contract; similarly, the size of remittances is determined by the face value and the coupon rate of the MBS. The mortgage lender, who acts as a middle-man between the homebuyer and the investor, can keep the difference between the monthly payments and the remittances.

The origination process, as described above, implies that in order to originate a mortgage, a lender borrows funds from the secondary market. For each dollar of borrowed funds, the yield rate of the mortgage-backed security provides a measure for the cost of borrowing. I therefore use yield rates to calculate the marginal cost of lending in Section 1.5.2. Yield rates of mortgage-backed securities have been used to measure the marginal cost of lending in other studies as well, for example Scharfstein and Sunderam (2014).

### 1.3.4 State-Level Demographics from the American Community Survey

In order to estimate the relationship between the search cost distribution and state-level demographics, I utilize data from the American Community Survey (ACS) on household income, age, and education in 2014. With the exception of Nishida and Remer (2015), most previous studies on consumer search do not draw the connection between search costs and demographics in order to explain search cost heterogeneities across markets. The ACS is an annual statistical survey conducted by the US Census Bureau, with the primary aim of determining how federal and state funds should be distributed. Nishida and Remer (2015), in a study of the retail gasoline market, also employ the ACS and find that the mean and variance of household income is closely related to the mean and variance of the search cost distribution.

In Table 1.3, I present summary statistics of state-level demographics in 2014. There are 51 observations for each variable, corresponding to the total number of markets. The ACS does not report standard deviations directly but provides the number of observations that fall into a certain brackets of income, age and education. Following the standard exercise of finding standard deviations for grouped data, I compute the standard deviations for household income, age, and education, assuming the mid-point in each bracket is the mean for the sub-population belonging in that bracket. I report the mean for household income and years of education; as for age, since a mean is not readily provided by the ACS, I report the median.

Table 1.3: Summary Statistics of State-level Demographics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Household Income - Mean | 51 | 72,778 | 12,136 | 54,881 | 104,615 |
| Household Income - Std. Dev. | 51 | 57,308 | 6,630 | 48,171 | 77,513 |
| Age - Median | 51 | 37.73 | 2.38 | 29.90 | 43.50 |
| Age - Std. Dev. | 51 | 22.95 | 0.50 | 21.08 | 23.69 |
| Years of Education - Mean | 51 | 12.96 | 0.25 | 12.45 | 13.72 |
| Years of Education - Std. Dev. | 51 | 2.12 | 0.09 | 1.86 | 2.41 |

Source: The American Community Survey, 2014.

### 1.3.5 Price Dispersion, Cost Differentials and Firm Heterogeneity

Although loan-level observations are not required for the estimation of search cost distributions, their presence allows us to investigate how interest rate dispersion is driven by cost differentials and firm heterogeneity. Following Lin and Wildenbeest (2013) and Sorensen (2000), I compare the $R^2$ values obtained from OLS regression of interest rates under three specifications. The regression results are presented in Table 1.4.

In column (1), interest rates are regressed only on state and month fixed effects. If a mortgage is a homogeneous product, and there is no firm heterogeneity, the source of marginal cost difference would come from time and location varying conditions in the secondary market. Hence, controlling for state and monthly dummies should explain most, if not all, the variations in interest rates. With the $R^2$ at 20%, however, this case is not likely.

In column (2), I allow marginal cost to also be varying across borrowers. Even though loans are insured and default risks are mitigated, prepayment risks may still differ across borrowers. I account for borrower-specific cost differences by incorporating loan observables into the regression. All loan observables are statistically significant, and the $R^2$ is raised to

Table 1.4: Price Dispersion, Cost Differentials and Firm Heterogeneity

| Interest Rates (bps) | (1) | (2) | (3) |
|---|---|---|---|
| Original Principal Balance | | -.0389*** | -.0377*** |
| | | (.0003) | (.0003) |
| Loan-to-Value Ratio | | .1372*** | .1307*** |
| | | (.0051) | (.0048) |
| Credit Score | | -.1718*** | -.1448*** |
| | | (.0006) | (.0005) |
| Other Loan Observables | No | Yes | Yes |
| Lender Dummies | No | No | Yes |
| State Dummies | Yes | Yes | Yes |
| Monthly Dummies | Yes | Yes | Yes |
| Observations | 1,091,897 | 1,007,707 | 1,007,707 |
| Adjusted $R^2$ | 0.20 | 0.29 | 0.38 |

Source: Ginnie Mae Loan-Level Data, September 2013 - March 2015.

29%, suggesting that borrower-specific costs are relevant. In Section 1.4, I assume that these loan observables affect only the marginal cost of lending and are captured by a borrower idiosyncratic cost term denoted by $e_i$.

In column (3), I add lender fixed effects to the regression. These fixed effects capture the variations in transacted interest rates across lenders. Both consumer search and firm-level quality differentiation may lead to dispersion at the lender-level, although the reduced-form regressions do not allow discerning the two hypotheses separately. However, since all lender fixed effects are statistically significant, search and lender differentiation is relevant in determining the transacted interest rate distribution. The explanatory power of the model also increases to nearly 40% once lender fixed effects are included.

## 1.4 A Mortgage Search Model

### 1.4.1 Main Assumptions

The mortgage search model hinges on several key assumptions. First, borrowers search only along the price dimension of their mortgage contract. All non-price dimensions of the contract, such as the loan amount and the loan-to-value ratio, are determined outside the model and are kept constant during the shopping occasion. This assumption is not unrealistic since most borrowers do decide how much they want to borrow before shopping for the lowest price. The decision to fix all non-price terms is also employed by Honka (2014) in her study of consumer search in the U.S. auto insurance industry. I interpret price as the monthly payment of the mortgage contract. The model is estimable regardless of whether one chooses interest rate or monthly payment as the measure for price. However, using monthly payment would yield more intuitive results, because estimated search costs would be measured in dollars instead of basis points.

Second, borrowers visit lenders and gather price quotations sequentially. The sequential search assumption is adopted because an accurate price quote can only be obtained from the Good-Faith Estimate. At each sampled lender, the borrower files an application, obtains a GFE, and decides whether to continue to search or not. For tractability, I assume the sampling probability to be equal across lenders. It is possible to relax this assumption and incorporate varying sampling probabilities into the model. Following Carlson and McAfee (1983), I also assume that sampling occurs with replacement.

Third, lenders in each geographical market are vertically differentiated. Mortgage lenders usually provide service of differing qualities. Higher quality lenders have better branding, faster billing services, more responsive customer service, and swifter processing times. Because the Ginnie-Mae data only identify geographical locations up to the state level, I treat each state as a separate geographical market. Admittedly, finer location details would be useful. However, because I drop small lenders with less than 1% of market shares from the analysis (the data do not distinctly identify them), the remaining lenders presumably are large and compete at the statewide level.

Following Hortaçsu and Syverson (2004), I do not allow for horizontal differentiation. The presence of horizontal differentiation along with heterogeneous search costs creates an identification problem; when a borrower rejects a lender in favor of further search, the rejection can be attributed to both a low search cost or a low preference for that particular lender. Horizontal differentiation may be particularly relevant if a borrower prefers a certain lender over others because of the home-bank effect or geographical proximity.

I assume that lenders are profit-maximizing entities, with one exception. In each market, the markup charged by the lender with the highest quality measure is taken as given. This exception is reflected in the system of first-order equations in Section 1.5.1, where the number of equations is one less than the number of lenders. This problem, also shared by Hortaçsu and Syverson (2004), does not affect recovering the search cost distribution, but it implies that the optimal markup vector solved in the counterfactual would be an approximation.

Finally, I assume that loan observables only affect the marginal cost of lending and not the search cost of borrowers. As a consequence of this, lenders set price based on observables only to the extent that they affect marginal cost. I also assume that marginal cost's pass-through to price is one-to-one. Lenders take the distribution of search costs as given, observe the marginal cost that may be a function of loan observables, and charge a markup accordingly. The assumption that observables do not affect search costs is relaxed in Chapter 2 where I examine price discrimination. In Chapter 2, I show that even when loan observables are informative about consumer search costs, the search model implies that changes in cost are passed on to prices in a one-to-one fashion.

### 1.4.2 Model Development

#### Borrowers and Lenders

Following standard frameworks of consumer search, I posit that borrowers know the distribution of indirect utility in their respective geographical market, but do not know exactly which lender provides which level of utility. I specify the indirect utility that borrower $i$ gets from lender $j$ as:

$$u_{ij} = \delta_j - p_{ij} \tag{1.1}$$

where $p_{ij}$ is the monthly mortgage payment and $\delta_j$ is a lender fixed-effect that captures quality differences. Since a borrower can only get one loan, the subscript $i$ indexes both the borrower and the loan.

I normalize the coefficient on monthly payment to -1. This formulation deviates from standard models of vertical differentiation, in which an idiosyncratic willingness-to-pay term $\alpha_i$ precedes price. The varying willingness-to-pay is typically needed in standard models in order to explain observed market shares; otherwise the firm providing the highest indirect utility would have a 100% market share. Here, observed market shares are explained through the presence of heterogeneous search costs. Because of uncertainties when sampling, not all borrowers would sample the lender that provides the highest utility. The best lender would not have a 100% market share, and even the worst lender is still chosen by some customers with a high enough search cost (which prevents them from sampling again).

I separate monthly payments into two components according to the following equation:

$$p_{ij} = mc_i + m_j \tag{1.2}$$

Here $mc_i$ is the marginal cost of originating loan $i$. As shown in Section 1.3.5, the marginal cost of lending is loan-specific. I calculate the marginal cost of lending in Section 1.5.2. The term $m_j$ represents a lender-specific markup added on top of the marginal cost to compensate lenders for their service of mortgage underwriting. In this specification, markup refers to an absolute markup instead of the usual ratio of profit margin over cost. I assume that marginal cost can be further separated into a constant term and a borrower-specific error:

$$mc_i = \overline{mc_i} + e_i \tag{1.3}$$

The term $e_i$ reflects idiosyncratic effects of borrowers on transacted price. I interpret $e_i$ as unobserved cost shocks that are realized only when the borrower comes into contact with the lender, and are then passed on to the transacted price. Lenders observe $mc_i$ for each of their borrowers, while the econometrician observes only the average $\overline{mc_i}$. I further assume that, given the yield rate $y_i$ of the mortgage-backed security for which loan $i$ serves as a collateral and the vector of loan observables $X_i$, $e_i$ has a zero mean. Also, $e_i$ is independent of search costs, so in equilibrium there is no selection on $e_i$ across lenders. Thus, we have:

$$E[e_i \mid y_i, X_i, j] = 0 \tag{1.4}$$

Because $e_i$ is unrelated to the yield, an alternative interpretation of $e_i$ would be servicing costs. I calculate servicing costs and marginal costs in more details in Section 1.5.2. An equivalent way to state the zero-mean assumption of $e_i$ is to write:

$$\overline{mc_i} = E[mc_i \mid y_i, X_i, j] \tag{1.5}$$

A lender $j$ chooses an absolute markup $m_j$ in order to maximize expected profit. Lender

$j$'s monthly profit on a loan $i$ can be written as:

$$v_{ij}(m_j) = p_{ij} - mc_i = m_j \tag{1.6}$$

Expected profit for lender $j$ is obtained by summing $v_{ij}$ over the total number of loans that lender $j$ underwrites. Let $ms_j$ denote the market share of lender $j$ and $M$ the market size, expected profit is:

$$\Pi_j(m_j) = E\left[\sum_{i=1}^{M \times ms_j} v_{ij}(m_j)\right] = M \times ms_j \times m_j \tag{1.7}$$

Assuming the lender chooses $m_j$ to maximize profit yields the standard first-order condition:

$$\frac{\partial ms_j}{\partial m_j} \times m_j + ms_j = 0 \tag{1.8}$$

**Search Cost Cut-offs**

In the model all borrowers will eventually decide to transact with a lender; there is no outside option of not getting a mortgage. The equilibrium search strategy for a borrower takes the form of an optimal stopping rule (Weitzman, 1979). I describe this optimal stopping rule and its implications on cut-off points in the search cost distribution below.

Since lenders are vertically differentiated, it is possible to rank them in the order of increasing indirect utility. Let $j = \{1, \ldots, N\}$ be the index in this ranking, where $N$ is the number of lenders in the market. In the estimation, all lenders have non-zero market share, and this order corresponds to that of increasing market shares. Let $\rho$ denote the constant sampling probability. A borrower will optimally stop searching as soon as her search cost $s_i$

exceeds the expected marginal benefit of searching:

$$s_i \geq \sum_{k=j}^{N} \rho(u_{ik} - u_{ij}) \tag{1.9}$$

where $\rho = 1/N$ is the sampling probability that is constant across lenders, and $u_{ij}$ is the highest indirect utility sampled up to that point. The additive assumption on $e_i$ and $mc_i$ in equation (1.2) implies that they both drop out of the expected marginal benefit of searching (the right-hand side of equation (1.9)). Since both of the borrower-specific terms are canceled out, the expected marginal benefit of searching does not vary across borrowers. Any two borrowers, having the same level of $u_{ij}$ as their highest utility sampled, would face the same expected marginal benefit of search. This result is convenient and allows us to define search cost cut-offs $c_j$ by rewriting equation (1.9) and removing borrower effects:

$$c_j \equiv \sum_{k=j}^{N} \rho(u_k - u_j) \tag{1.10}$$

where $u_k - u_j$ is the difference in indirect utility between lender $k$ and $j$, and this difference is constant across all borrowers.

Search cost cut-offs $c_j$ are lender-specific and represent the lowest search cost for which a transaction with lender $j$ is viable. These cut-offs allows us to conveniently summarize a borrower $i$'s optimal strategy. Upon sampling lender $j$, if borrower $i$'s search cost $s_i$ satisfies that $s_i < c_j$, it is optimal for her to bypass $j$ and resume searching for a better deal. Otherwise, if $s_i > c_j$, it is optimal to transact with lender $j$.

Because lenders are indexed in ascending order of utilities, the associated search cost cut-off vector $\{c_1, c_2, \ldots, c_N\}$ is a decreasing sequence; the highest utility lender would have the lowest cut-off. Equation (1.10) implies that the cut-off for the highest utility lender is zero ($c_N = 0$), an implication of having no outside option. It is possible to introduce an outside option, but its market share would have to be specified.

## 1.5 Estimation

### 1.5.1 Estimation of the Search Cost Distribution

Estimation of the search cost distribution follows closely the steps outlined by Hortaçsu and Syverson (2004). The exposition here is brief; detailed derivations of equations in this section can be found in Hortaçsu and Syverson (2004) and Carlson and McAfee (1983).

Denote the CDF of the search cost distribution by $G(\cdot)$ and the PDF by $g(\cdot)$. The objective is to identify the two sequences of $\{G(c_1), G(c_2), \ldots, G(c_N)\}$ and $\{c_1, c_2, \ldots, c_N\}$, and then extrapolate to approximate the entire search cost distribution. The procedure consists of three steps: first, calculate $\{G(c_j); j = 1, \ldots, N\}$ from observed market shares; second, compute the sequence $\{g(c_j)\}$ using lenders' first-order condition and estimated markups, and finally, recover the cut-off sequence $\{c_j\}$ from the estimated CDF and PDF using the trapezoid approximation.

A lender $j$'s market share consists of borrowers with search costs higher than $c_j$, who sample lender $j$ before any other, more attractive lenders are found. At each search instance, the probability that any particular lender is sampled is $\rho$. Let $S$ denote the size of the market (total number of loans), market shares $ms_j$ for all lenders from 1 to $N-1$ are determined by the CDF $G(c_j)$ via the following system of equations:

$$\begin{aligned}
ms_1 &= S \times \rho[1 - G(c_1)] \\
ms_2 &= S \times \rho\left[1 + \frac{\rho G(c_1)}{1-\rho} - \frac{G(c_2)}{1-\rho}\right] \\
&\dots \\
ms_j &= S \times \rho\left[1 + \frac{\rho G(c_1)}{1-\rho} + \frac{\rho G(c_2)}{(1-\rho)(1-2\rho)} + \sum_{k=3}^{j-1} \frac{\rho G(c_k)}{(1-k\rho+\rho)(1-k\rho)} - \frac{G(c_j)}{1-j\rho+\rho}\right]
\end{aligned} \tag{1.11}$$

The first equation relates the market share of lender 1 (the lowest utility lender) with the cut-off CDF $G(c_1)$. Market shares for all other lenders, up to $N-1$, are represented by the following equations in the system. In total, the system has $N-1$ linear equations, which are used to solve for $N-1$ unknowns $G(c_1), G(c_2), \dots, G(c_{N-1})$.

The cut-off PDF $\{g(c_j)\}$ can be obtained by first calculating the derivatives of market shares with respect to $m_j$ from the above system of equations:

$$\frac{\partial ms_j}{\partial m_j} = -\frac{\rho^3 g(c_1)}{1-\rho} - \frac{\rho^3 g(c_2)}{(1-\rho)(1-2\rho)} - \sum_{k=3}^{j-1} \frac{\rho^3 g(c_k)}{(1-k\rho+\rho)(1-k\rho)} - \frac{(N-j)\rho^2 g(c_j)}{1-j\rho+\rho} \tag{1.12}$$

Substituting this expression for $\partial ms_j / \partial m_j$ into the lenders' first-order condition (equation 1.8) again yields a system of $N-1$ linear equations in $N-1$ unknowns that allows solving for $g(c_1), \dots, g(c_{N-1})$ as a function of estimated markups.

As in Hortaçsu and Syverson (2004), the systems of equations above have one less equation than the number of lenders in the market. Because we assume all borrowers obtain a mortgage, the market share of lender $N$, whose quality is the highest in the market, can be obtained simply by subtracting all other lenders' market shares from the total. The markup of lender $N$ is not used to obtain the cut-off vector; lender $N$'s cut-off has to be zero for all borrowers to obtain a mortgage. The lack of the $N^{\text{th}}$ equation in the systems of equations above does not affect estimation of the search cost distribution; however, it implies that counterfactual results, as explained in Section 1.7, are approximations.

Finally, once $G(c_j)$ and $g(c_j)$ have been calculated, search cost cut-offs $c_j$ are obtained using the trapezoid approximation:

$$c_{j-1} - c_j \approx \frac{2[G(c_{j-1}) - G(c_j)]}{g(c_{j-1}) + g(c_j)} \tag{1.13}$$

Starting with $c_N = 0$, all search cost cut-offs can be solved recursively with the above equation. All search cost cut-offs and their associated CDF values are now identified.

### 1.5.2 Estimation of Markups

Estimating the above model requires data on market shares and lender markups. Market shares are used to compute the search cost CDF at the cut-off levels, while markups are needed to compute the cut-off levels. I compute market shares directly from the Ginnie Mae loan-level data. On the other hand, lender markups are not directly observed and need to be estimated. To do so, I first find a reasonable approximation of the marginal cost of lending, and then use equation 1.2 and the distributional assumption $E[e_i] = 0$ to recover markups.

I approximate the expected value of the marginal cost of lending by breaking it into two components: servicing cost $SC$, and payments $R$ payable to investors who bought the mortgage-backed security:

$$\overline{mc_i} = E[mc_i \mid y_i] = SC + R_i \tag{1.14}$$

I compute payments $R_i$ using the amortization formula and the yield rate $r_i^y$ of the mortgage-backed security to which mortgage $i$ belongs:

$$\hat{R}_i^y = L_i \times \frac{r_i^y}{1 - (1 + r_i^y)^{-360}} \tag{1.15}$$

An alternative to estimating $R$ is to use the coupon rate instead of the yield rate of the mortgage-backed security in the above formula. When the coupon rate is used, this formula calculates the monthly payments, payable to holders of the MBS, such that the loan principal and interest will be repaid in 360 months. A drawback to using the coupon rate, as opposed to the yield rate, is that the coupon rate does not capture variations in the transacted price of the MBS. When a lender sells a MBS to investors, the price could be different to the face value of the MBS. For example, if the price is higher than the face value, the lender would receive an upfront premium; if the price is lower, the lender would be providing an upfront discount. The yield rate adjusts for such variations in transacted price and represents the true monthly cost of the MBS. It would be equivalent to the coupon rate if the mortgage-backed security was bought at par (neither at a premium nor a discount). In computing $\hat{R}_i^y$, I therefore use the yield rate $r_i^y$.

I assume a constant servicing cost $SC$ for all loans. In general, servicing cost differs depending on whether the loan is performing or non-performing (its delinquency status). However, since lenders do not observe the delinquency status of loans at the time of origination, I use a weighted-average of servicing cost between performing and non-performing loans. According to a report by the Urban Institute, annual servicing cost in 2014 amounts to \$158 for a performing loan and \$1,949 for a non-performing loan (Goodman, 2016). During the sampled period, the delinquency rate of residential mortgage loans in the US is about 7.2% according to data published by the Federal Reserve Board.[2] Using this information, I calculate servicing cost to be \$287 per year per loan. In the estimation, servicing cost is measured on a monthly basis, I therefore set $S = \$24$ per month per loan.

[2] Federal Reserve Board (2016), "Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks".

In table 1.5, I show the summary statistics of payments payable to investors, calculated using both coupon and yield rates, the marginal cost, and estimated markups for five lenders with the highest market shares in Texas. Empirically payments $R^c$ (calculated with the coupon rate) are invariably higher than $R^y$ (calculated with the yield rate). The discrepancy between them can be explained because during the sample period most mortgage-backed securities are traded at a premium, hence the yield is almost always lower than the coupon rate.

Table 1.5: Payments to Investors, Marginal Cost and Markup: Top 5 Lenders in Texas

| Lender's Name | Payment $R^c$ (Coupon) | Payment $R^y$ (Yield) | Marginal Cost $R^y + S$ | Markup |
|---|---|---|---|---|
| Wells Fargo | 793.90 | 675.84 | 699.84 | 131.11 |
| | (336.11) | (294.61) | (294.62) | (0.42) |
| PennyMac | 833.09 | 713.48 | 737.48 | 134.86 |
| | (310.13) | (273.95) | (273.95) | (0.66) |
| US Bank | 683.60 | 549.36 | 573.36 | 144.44 |
| | (238.07) | (222.49) | (222.49) | (0.77) |
| USAA Federal Bank | 963.32 | 856.74 | 880.74 | 122.50 |
| | (397.18) | (351.22) | (351.22) | (1.04) |
| JP Morgan Chase | 793.41 | 680.08 | 704.08 | 132.01 |
| | (364.87) | (327.36) | (327.36) | (1.10) |

Payment $R^c$ and $R^y$ refer to payments payable to investors, calculated using (respectively) the coupon and the yield rate of the MBS. Marginal cost is the sum of $R^y$ and servicing cost $S$. Standard deviations are reported in parentheses for $R^c$, $R^y$, and Marginal Cost. For Markup, the standard error of the mean is reported. All variables are measured in dollars.

Once $E[mc_i]$ is obtained, I estimate lender markups using equation (1.2) and the assumption that $E[e_i] = 0$. The estimated markups are then simply the average of differences between monthly payments and marginal costs, calculated for each lender. The last column in table 1.5 shows the estimated markups for the sampled five lenders as well as the standard errors.

Estimated markups are dispersed and vary across lenders. Table 1.6 shows the dispersion in markups, as captured by the coefficient of variation (the ratio of standard deviation over

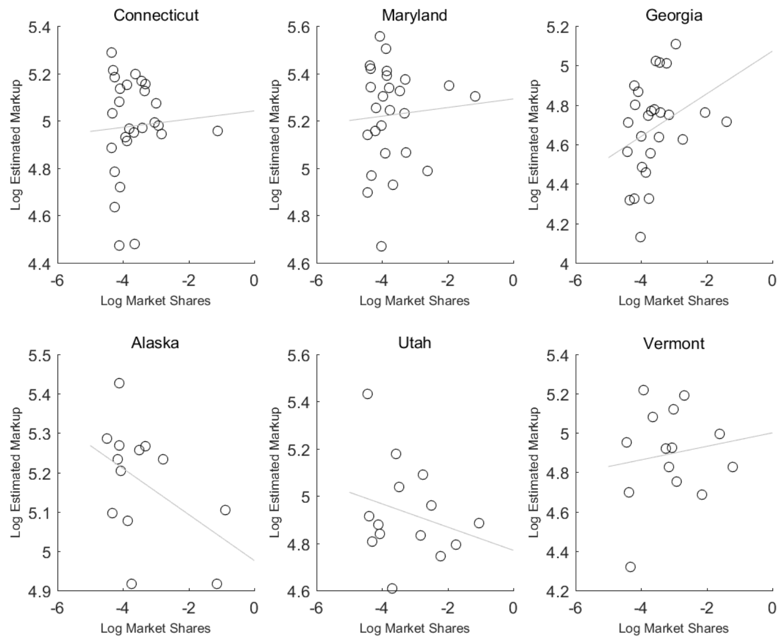
Table 1.6: Dispersion of Markups across Markets

| Market | Number of Lenders | Number of Loans | Average of Markups | Standard Deviation of Markups | Coefficient of Variation |
|---|---|---|---|---|---|
| New York | 23 | 29928 | 176.33 | 72.52 | 0.41 |
| North Dakota | 18 | 2624 | 143.21 | 56.80 | 0.40 |
| South Dakota | 15 | 4081 | 93.89 | 33.39 | 0.36 |
| Washington D.C. | 17 | 1058 | 334.59 | 117.97 | 0.35 |
| Iowa | 20 | 8586 | 90.26 | 24.10 | 0.27 |
| New Jersey | 22 | 18788 | 192.57 | 25.16 | 0.13 |
| Delaware | 19 | 3850 | 161.04 | 20.61 | 0.13 |
| New Hampshire | 24 | 5063 | 152.21 | 16.21 | 0.11 |
| Colorado | 21 | 29239 | 170.77 | 16.35 | 0.10 |
| California | 25 | 97154 | 250.93 | 23.03 | 0.09 |
| National Mean | 20.82 | 21,409.75 | 138.16 | 28.19 | 0.21 |

mean), for ten markets with the highest and lowest degree of variation. The coefficient of variation for markups ranges from a low of 0.09 in California to 0.41 in New York. Across all markets, the mean of this coefficient of variation is about 0.21. This level of dispersion is comparable to that found in other studies of price dispersion. For example, Sorensen (2000), using a sample data on prices of prescription drug in New York, finds the coefficient of variation to be 0.22. In another study by Villas-Boas (1995) on the market for coffee, the coefficient of variation is 0.21. The authors in both of these studies argue that costly consumer search represents a major explanatory factor of price dispersion.

The estimated markups also lends support for quality differentiation among lenders. In Figure 1.1, I graph the log of estimated markups against the log of market shares for the following markets: Connecticut, Maryland, Georgia (three states with the most number of lenders), and Alaska, Utah, and Vermont (three with the least number of lenders). If lenders are homogeneous and the degree of differentiation is negligible, the relationship between markups and market shares should be negative and monotonic; a lender whose price is consistently high should get a lower share and vice versa. However, as graphs in Figure 1.1

Figure 1.1: Scatter Plot of Log Markups against Log Market Shares




show, markups and market shares do not seem to be negatively correlated, suggesting that quality differentiation is a relevant feature of this market.

## 1.6 Results

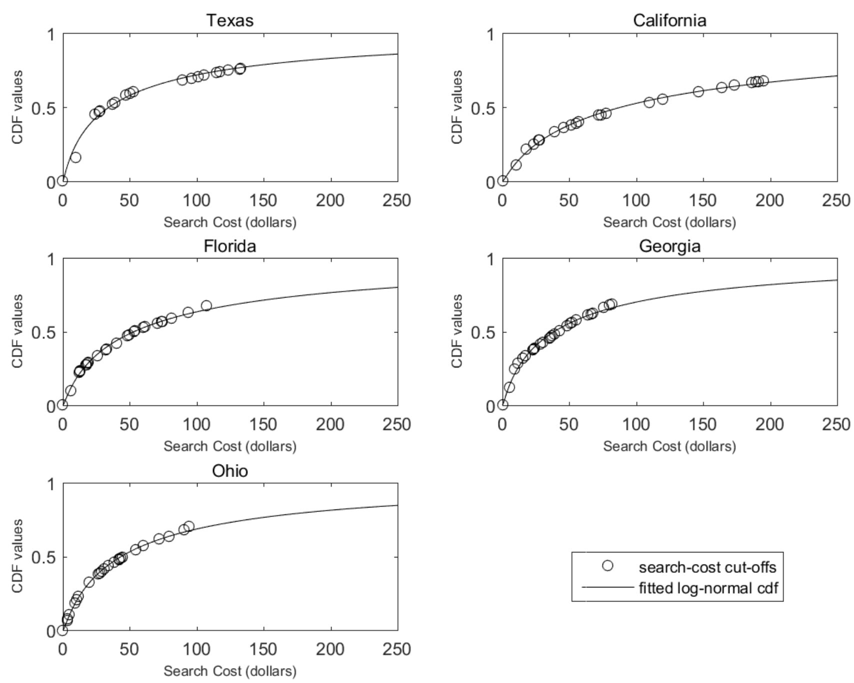
### 1.6.1 Search Cost Distribution

I treat each state as an independent market, and estimate the model separately for all 50 states and the District of Columbia. In each market, the CDF $G(\cdot)$ and PDF $g(\cdot)$ of the search cost distribution are identified at the cut-off points $c_j$. The identification comes from the market share equations (1.11) and lenders' first-order equation (1.8). Having computed $G(c_j)$ and $g(c_j)$, I obtain the cut-off levels $c_j$ from the trapezoid equation (1.13).

Using least-squares approximation, I fit a log-normal CDF over the estimated cut-offs

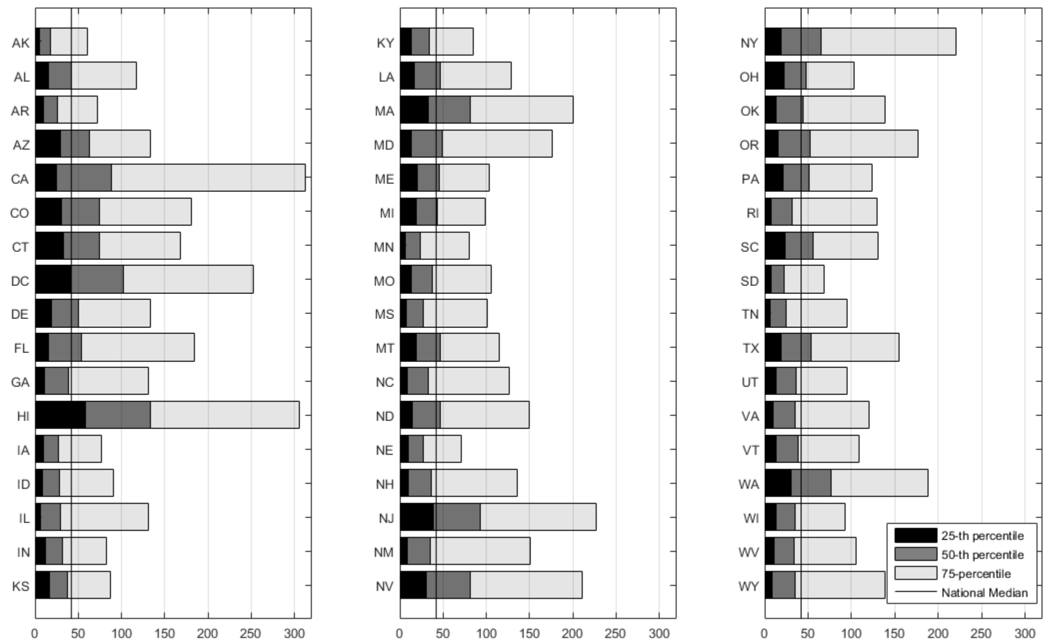
$c_j$ and CDF $G(c_j)$. The fitting of a log-normal CDF is necessary because the search cost distribution is non-parametrically identified only at the cut-off levels, in other words, only at $N$ number of points in its support. The continuity of a log-normal CDF allows for convenient summary statistics across markets and implementation of counterfactuals where the cut-off levels change. I find that the fit is relatively close across all markets.

Figure 1.2: Estimated search cost distribution for five states with the most observations




I report the estimation results of search cost distributions in Figure 1.2 and Figure 1.3. For five largest markets (Texas, California, Florida, Georgia, and Ohio), I show the non-parametrically identified points in the search cost distribution, as well as the fitted log-normal curve. In each plot, from left to right the cut-off points (shown in circles) correspond to lenders in decreasing utility order. The leftmost cut-off is always at the origin because the highest utility lender have a zero search cost cut-off ($c_N = 0$), an implication of assuming no outside option. $c_N = 0$ also follows directly from the cut-off equation (1.10). In a similar vein, the CDF value at the rightmost cut-off $G(c_1)$ is always less than 1. This result arises because all lenders in the data, including lender 1 who provides the lowest utility, have positive market shares. Should $G(c_1) = 1$, there would be no borrower whose search cost is higher than $c_1$. Consequently every borrower who samples lender 1 would choose to search further, and lender 1 would have a zero market share.

Figure 1.3: Estimated interquartile range of search cost across all states




In Table 1.7, I report summary statistics on the distribution of consumer search cost across all 51 markets. Table 1.7 shows the average at the $10^{\text{th}}$, $25^{\text{th}}$, $50^{\text{th}}$, $75^{\text{th}}$, and $90^{\text{th}}$ percentiles of search cost distributions across all 51 markets. The median per-month search cost, averaged across all markets, is around \$42. Compared to the Canadian market, where Allen et al. (2014a) estimate a per-month search cost of about \$20, borrowers in U.S. mortgage markets seem to have higher search costs. According to Table 1.7, a borrower with a \$20 search cost would correspond approximately to the $30^{\text{th}}$ percentile in the search cost distribution. The higher search cost levels in the U.S. reflect institutional differences of this market between the two countries.

Table 1.7: Average of Estimated Search Cost across All States

| Percentiles | Minimum | Maximum | Median |
|---|---|---|---|
| 10 | 1.74 | 28.00 | 5.34 |
| 25 | 5.25 | 58.76 | 13.82 |
| 50 | 17.88 | 133.92 | 42.24 |
| 75 | 60.88 | 312.95 | 129.19 |
| 90 | 170.33 | 972.32 | 325.26 |

I use the empirical bootstrap method to obtain standard errors and confidence intervals around the estimated search cost CDF. Unlike Hortaçsu and Syverson (2004), empirical bootstrap is feasible here because lenders' markups, an input into the model, are estimated and not directly observed. I find that the 95% confidence interval of the search cost CDF is very tight in most markets. The appendix provides a more detailed discussion on the application of the empirical bootstrap method in this setting.

### 1.6.2 The Relationship between Search Cost Distribution and Market Demographics

Estimating the distribution of search costs in separate geographical markets allows us to study the connection between search cost distributions and market-level demographics. According to Goldman and Johansson (1978) and Nishida and Remer (2015), search costs may arise from two factors: (1) the opportunity cost of time and money (phone calls, driving to banks, paperwork etc.), and (2) the cognitive and information-processing capacity of consumers. The former factor presumably varies with household income, while the latter varies with age and education level. As explained in section 1.3.4, I employ data on household income, age and years of education in 2014 from the American Community Survey in order to examine their relationship with search cost distribution. Table 1.3 shows the summary statistics for these demographic variables at the state-level.

To incorporate demographic variables into the estimation, I specify the parameters of the fitted log-normal distributions as:

$$\mu = \beta_0 + X^{\mu}\beta$$

$$\sigma = \gamma_0 + X^{\sigma}\gamma$$

Here, $\mu$ and $\sigma$ refers to the mean and standard deviation of the associated normal distribution. $X^{\mu}$ is a vector of observables containing the average household income, median age, and average years of education in each state. $X^{\sigma}$ contains the standard deviation of these demographic variables. Constant terms $\beta_0$ and $\gamma_0$ are included in both equations. The parametrization of the mean parameter $\mu$ and standard deviation parameter $\sigma$ using, respectively, mean and standard variables follows closely that used by Nishida and Remer (2015).

Table 1.8: The Relationship of State Demographics with Search Cost Distribution

| | Coefficient Estimate ($\hat{\beta}$) | Standard Error | Effect on Median Search Cost ($e^{\mu}$) | Effect on Average Search Cost ($e^{\mu+\sigma^2/2}$) |
|---|---|---|---|---|
| Mean Parameter $\mu$ | | | | |
| Constant | 9.533 | 0.657 | 13,813 | 13,813 |
| Household Income | 0.026 | 0.001 | 1.02 | 1.02 |
| Age | 0.039 | 0.004 | 1.04 | 1.04 |
| Years of Education | -0.707 | 0.057 | 0.49 | 0.49 |
| Std. Dev. Parameter $\sigma$ | | | | |
| Constant | 7.816 | 2.161 | - | 42.89 |
| Household Income | 0.023 | 0.005 | - | 1.03 |
| Age | -0.202 | 0.075 | - | 0.74 |
| Years of Education | -1.291 | 0.356 | - | 0.29 |

The effects on median and average search costs are multiplicative. For example, a $1000 increase in household income would raise the median and mean search cost by a factor of 1.02, or 2%.

I then use non-linear least squares to fit this parametrized log-normal distribution to the search cost cut-offs obtained in section 1.5.1. Coefficient estimates for $\beta$ and $\gamma$ and their associated standard errors are reported in Table 1.8. All estimates are statistically significant. I find that household income and age are positively related to the mean parameter, or equivalently markets with higher incomes and older populations tend to have a higher search cost. On the other hand, years of education and search cost level are negatively related, which confirms the intuition that educated consumers are more sophisticated and therefore have a lower cost of search.

The variance of the search cost distribution is also related to the variance of demographic variables. Markets with high variation in income are associated with a high variation in search costs, which is consistent with the hypothesis that income level captures the opportunity cost of searching. In contrast, an increase in the variance of age and years of education reduces the variance of search costs, an empirical result also documented in gasoline markets by Nishida and Remer.

We can examine the economic significance of changes in income, age, and education on search cost levels. Because of our parametrization, the coefficients in Table 1.8 represent the effects of changes in the independent variables on the parameters $\mu$ and $\sigma$. It is possible to convert these coefficients into more economically meaningful numbers. For example, the third and fourth columns in Table 1.8 show the effects on the median and average search cost levels. Since the median and mean of a lognormal distribution are respectively $e^{\mu}$ and $e^{\mu+\sigma^2/2}$, the effects of changes in $\mu$ and $\sigma$ on the median and mean are multiplicative.[3] A

[3] If a demographic variables $X$ affects the mean parameter $\mu$, I calculate its effects on the median search costs as:

$$\frac{e^{\mu+\hat{\beta}\Delta X}}{e^{\mu}}$$

and its effect on the average search cost as:

$$\frac{e^{(\mu+\hat{\beta}\Delta X)+\sigma^2/2}}{e^{\mu+\sigma^2/2}}$$

If $X$ affects only the standard deviation parameter $\sigma$, then a change in $X$ would affect the average search cost but not the median search cost. Its effect on the average search cost is given by:

$$\frac{e^{\mu+(\sigma+\hat{\gamma}\Delta X)^2/2}}{e^{\mu+\sigma^2/2}}$$

$1000 increase in household income would raise the median and mean search cost by a factor of 1.02, or 2%. Likewise, a one year increase in age raise the median and mean search cost by 4%; a one year increase in the average level of education, however, cuts the median and mean search cost by over 50%. Changes in the standard deviation parameter $\sigma$ only affects average search cost. Standard deviations of income positively affects the average search cost, while standard deviations of age and education negatively affects average search cost. Taken as a whole, these findings suggest a close link between market demographics and the distribution of search costs.

## 1.7 Counterfactual of Search Cost Reductions

### 1.7.1 General Setup

I consider counterfactual scenarios where search costs are reduced by 10, 25, 50, 75, 90 and 100 percents. These scenarios provide a characterization of how search costs affect equilibrium price and quantity in the market. Moreover, by quantifying how welfare changes in each scenario, we also would be able to determine the importance of costly search in this industry, and what can be gained from efforts to reduce search costs.

The Consumer Financial Protection Bureau recently enacted several policies to improve price transparency in the mortgage market. These efforts include initiatives to educate consumers on the benefits on mortgage shopping, regulations to streamline to price quoting process as well as new tools to facilitate price comparisons. We could reasonably presume that many of these initiatives serve to reduce shopping cost, although the exact extent of such reduction is difficult to quantify. A counterfactual with discrete reductions in search costs would be useful as an approximate roadmap.

In each counterfactual scenario, I derive the new price equilibrium that arises from discrete changes in search costs. The actual equilibrium provides the benchmark search cost distribution, from which I derive counterfactual distributions where all search cost levels are reduced by a specified percentage. In solving for the new equilibrium, I keep several model primitives constant. Quality of lenders is invariant, and lenders simply take the quality vector $\delta$ as given. I also do not consider entry and exit explicitly, and the number of lenders does not change across scenario. An exception to this rule occurs when a lender optimally charges zero markup, earns zero profit, and has zero market share, then I do not take its markup into account when calculating the average market-level markup (practically this lender has dropped out of the market).

The equilibrium where search costs are reduced by 100 percent can be solved analytically. Without positive search costs, the model becomes that of price competition with full information and quality differences. Price competition then ensures that only the highest quality lender is able to charge a positive absolute markup. In each market, lender $N$ who provides the highest utility would charge a markup $m_N = \delta_N - \delta_{N-1}$ (the difference between the highest quality and the next best one), while all other lenders $j \neq N$ would charge $m_j = 0$. Because it is now possible for all borrowers to locate the highest quality lender $N$ costlessly, this lender would capture 100% of market share.

For the remaining scenarios where search costs are reduced by a positive factor less than 100 percent, I use numerical methods to approximate the new price equilibrium. Given the search cost distribution and the vector of lender quality, I find the vector of markups that satisfy the systems of equations in (1.11) and (1.12). One drawback of this approach is that there are only $N-1$ equations in each of these systems. For the market shares equations in (1.11), having $N-1$ equations is enough to identify the market share of all $N$ firms, since the last firm's market share must be so that all market shares add up to 1. However, for the equations on the first-order conditions of markups in (1.12), having only $N-1$ equations implies that one cannot solve for the profit-maximizing markup of the $N^{\text{th}}$ firm, which in this case is the highest quality lender.

For lender $N$, we know its profit-maximizing markup at the two extremes of search cost reductions: when search costs are reduced by 0 or by 100 percents. In the intermediating scenarios, I assume that lender $N$'s markup is not affected by search cost reductions and is held constant as in the original equilibrium:

$$m_N^r = m_N^{r=0}$$

where $r$ = 10, 25, 50, 75, 90 denotes the percentage point reductions in search costs, and $m_N^{r=0}$ is lender N's markup in the original equilibrium. For this reason, apart from the two extremes of 0 or 100 percent reductions, all intermediating scenarios can only be viewed as an approximation of the profit-maximizing equilibrium. In Appendix A.4.1, I consider an alternative specification of lender N's markup where it varies proportionally to the magnitude of search cost reductions.

### 1.7.2 Price Effects

I first examine the effects of search cost reductions on optimal markups that lenders charge. Characterizing these price effects is useful because from a theoretical perspective, the relationship between search cost, price level, and price dispersion is not always clear and varies across models and assumptions (Baye et al., 2006).

Regarding average price observed in a market, on the one hand, lower search costs implies more price competition between firms, pulling average price down. On the other hand, when search costs are uniformly reduced by a certain percentage, as in this counterfactual, the variance of search costs is also reduced, pushing average price up. Intuitively, when consumers have lower but more homogeneous search costs, the gain from capturing the low-search cost consumers becomes relatively smaller, and firms have less incentive to set a low price. When search cost becomes completely homogeneous, the Diamond (1971) paradox may arise, in which all firms set the monopoly price.

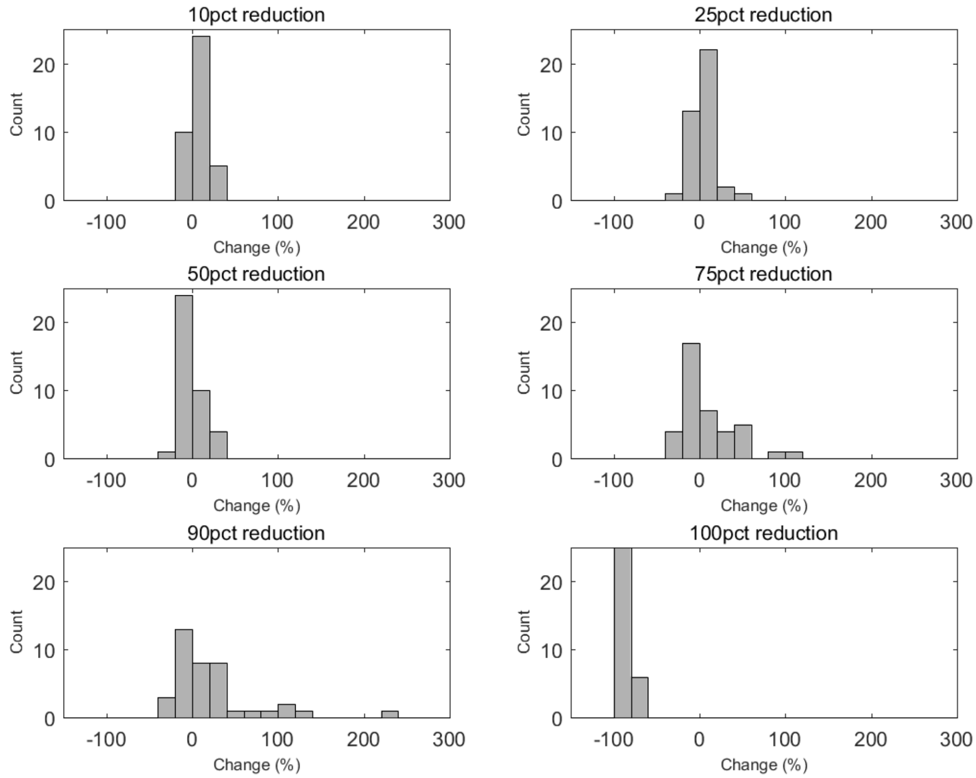
Likewise, the effect of reduced search cost on price dispersion may also be unclear. Models such as Carlson and McAfee (1983) predict that lowering search costs also lowers the variance of prices. In contrast, others such as Stahl (1989) imply a non-monotonic relationship between search cost and price dispersion: as search costs are reduced, price dispersion first increases then decreases. Empirical analysis tend to be mixed, with evidence supporting both theoretical views (Brown and Goolsbee, 2002; Brynjolfsson and Smith, 2000; Ancarani and Shankar, 2004).

I employ average absolute markup as the metric to measure price level and the coefficient of variation (CV) as that of price dispersion. Different geographical markets have different model primitives; namely the benchmark search cost distribution, the number of lenders, as well as the distribution of lender quality all vary across markets. Because of this, there is also variation across markets in lenders' choice of optimal markups when search costs are reduced. However, a general trend of how prices change over all markets can be an informative summary and an indication of how markets would respond to search cost reductions.

In Figure 1.4, I show the frequency count of how average markup would change in each state. There are six panels in this figure, each corresponding to a separate scenario and a separate level of search cost decrease ranging from 10% to 100%. In all cases, the average markup observed in the actual equilibrium is the benchmark, corresponding to a 0% change in the horizontal axis. Histogram bars to the left of zero shows the count of states where average markup has fallen compared to the actual equilibrium.

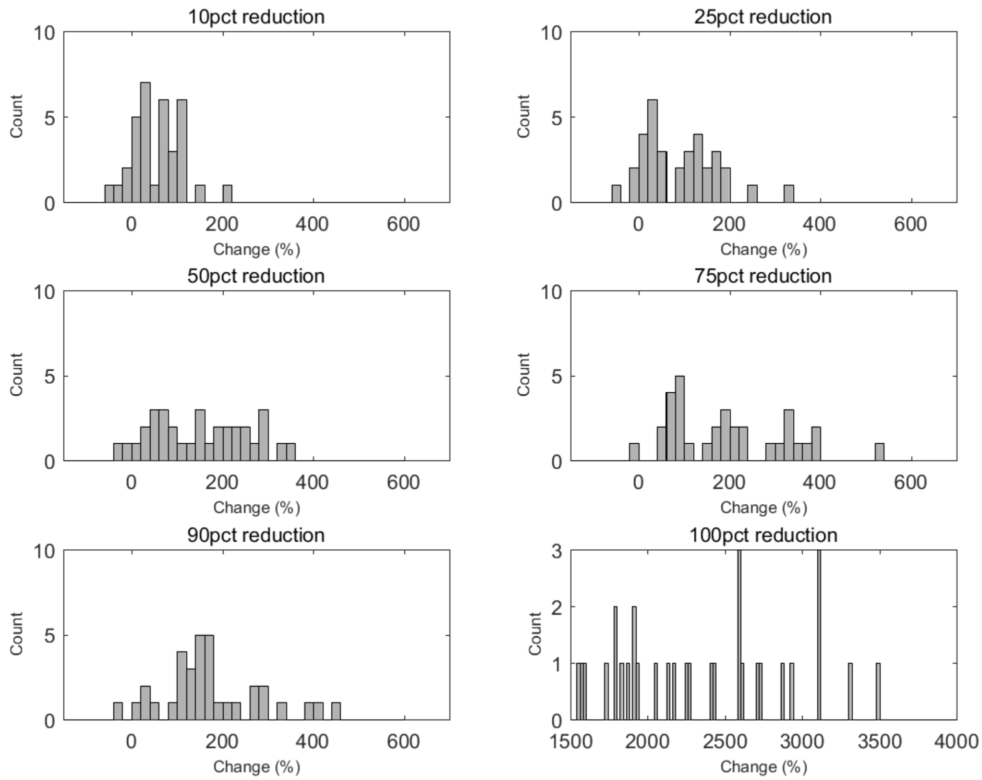
We observe that the distribution of average markup change tends to shift to the right as

Figure 1.4: Distribution of Change in Average Markup following Search Cost Reductions




the level of search cost reduction is increased. More and more states would experience an increase in average price, and the magnitude of increase is also significant, reaching 200% over the original average markup in some cases. However, there is a price decrease in the zero search cost case, since full information implies that only the highest quality lender is charging a positive markup, while all other lenders are charging a zero markup. It appears that price level will tend to rise as search costs are reduced. The incentive to set a low price and capture a larger share of consumers with low search costs disappears as more consumers become informed and consumer search costs are more homogeneous. In Appendix A.4.2, I examine the change in average markups when search costs are reduced, but the variance of search costs is unchanged, and find that under that scenario, lenders are more likely to set lower prices than in the original equilibrium.

Figure 1.5: Distribution of Change in Markup Dispersion following Search Cost Reductions




As for price dispersion, in Figure 1.5, I graph the frequency count of the coefficient of variation of optimal markups charged by lenders in each state. Values on the horizontal axis represents the percentage change in the coefficient of variation compared to the original equilibrium. We observe a non-monotonic relationship between dispersion and search cost reductions. As the magnitude of search cost reduction increases, the coefficient of variation seems to increase, and optimal markups charged become more dispersed at first. The increase is even more significant in the extreme case of 100% reduction, because there would be only one lender with a positive markup while all others charge a zero markup, usually leading to a very high coefficient of variation. Thus the change in price dispersion is monotonic with search cost reductions.

### 1.7.3 Welfare Effects

The model predicts two sources of welfare change following an elimination of search costs. First, there is a gain in the quality of transacted lenders, because borrowers can now more easily find lenders with higher quality. Second, consumer welfare also increases from the saving of direct search cost expenditures, because each search instance would cost less. Here I describe how each of these effects is characterized and discuss the welfare results of the counterfactual.

#### Total Quality

When search costs are reduced, higher quality lenders are more likely to be found by borrowers, and would gain a larger market share. From the market-level perspective, there is an increase in the total quality of lenders, when that quality is weighted by market share. I therefore define total quality as the sum of market share-weighted lender qualities:

$$TQ = \sum_{j=1}^{N} ms_j \delta_j$$

where $j = N$ denotes the highest quality lender, and $ms_j$ and $\delta_j$ are the market shares and quality of lender $j$, respectively. We would expect $TQ$ to increase monotonically as search costs are reduced by an increasing percentage. At the extreme, in the equilibrium with no search costs, only lender $N$ has a positive market share, and total transacted quality would be equal to the quality of lender $N$:

$$TQ^{r=100} = \delta_N$$

**Search Cost Expenditure**

To calculate the amount of search cost expenditures, I rely on structural assumptions in the consumer search problem. The optimal search strategy described in Section 1.4.2 allows us to calculate the expected search cost expenditure for any borrower given her search cost level. For a given market size, it is possible to approximate total expenditures at the market level by first calculating it for each individual borrower.

For a borrower with a search cost level $s_i$, the number of search instances to find a successful match follows a geometric distribution. The probability that the $k^{\text{th}}$ search instance is the first success after $k-1$ failures is:

$$\Pr(X_i = k) = (1-\lambda_i)^{k-1}\lambda_i$$

where $\lambda_i$ denotes the probability of a successful search during each search instances. The mean of this geometric distribution, $E[X]$, represents the expected number of search instances up to and including the first successful match. $E[X]$ is given by $1/\lambda_i$; therefore, the borrower's total search expenditure, inclusive of the final and successful search, is $s_i/\lambda_i$.

To calculate total expenditure for each state-level market, I take $M$ random draws from the borrower's search cost distribution, where $M$ varies across markets and equals the average number of new loans each month over the period October 2013 to March 2015. I calculate the expected search expenditure for each of these randomly drawn borrowers, and then aggregate borrower-level expenditures to approximate the market-level expenditure.

Let $SE$ denote search cost expenditures. A measure for social welfare would then be total quality less search expenditure:

$$SW = TQ - SE \tag{1.16}$$

### Profit

Typically, changes in marginal costs and in market equilibrium quantity and price would also affect social welfare. However, in this setting, these sources of changes are not present. Marginal cost of lending depends on borrower characteristics, and remains the same when search costs are reduced. Market quantity also does not vary, because the model assumes that all borrowers would obtain a mortgage. Absent the change in equilibrium quantity, any changes in equilibrium price would amount to a transfer of surplus between lenders and borrowers.

Because there is no fixed cost, the size of the surplus transfer between lenders and borrowers can be determined by calculating the change in profit of lenders. Under the current assumptions, calculating profit is straightforward because the absolute markup $m_j$ represents the lender $j$'s profit for each loan that it originates. Once optimal markups $m_j$ and market shares $ms_j$ are determined for each counterfactual scenario, profit would simply be:

$$\Pi_j = M \times m_j \times ms_j$$

where $M$ is the market size.

### Results

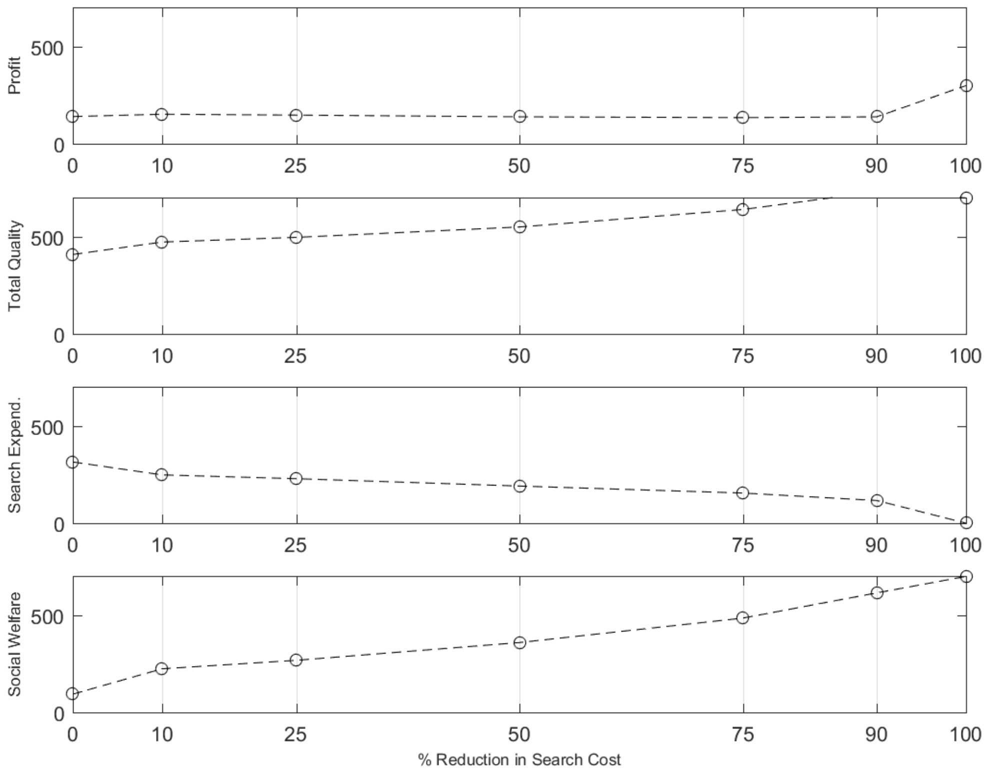
There are two remarks worth discussing before results on welfare calculations are presented. First, for all the welfare quantities listed above, including profit, total quality, and search expenditures, it is possible to measure them either at the loan-level and at a more aggregate (state or national) level. A loan-level basis is useful in separating the effect of market size from the welfare calculations, especially since the model assumes there is no change in equilibrium quantity. In contrast, a market or national level basis provides information on the aggregate effects of search cost reductions, which due to the considerable size of the government-backed mortgage market, can be very significant. Appendix A.2 explains how welfare is calculated at the loan and the national level.

Second, all welfare numbers are measured on a monthly dollar basis. This measurement unit follows directly from observing mortgage prices and markups in monthly and annual terms instead of in absolute terms. For instance, a loan-level welfare gain of 500 dollars per month means that market participants are each better off by 500 dollars each month for the remaining life of their mortgage contract. Because the expected length of mortgages in the United States is about 84 months, one way to convert measurements to an absolute basis by converting the sum of all monthly dollars in 84 months to a net present value. This approach, even with a positive discount factor, tends to suggest that welfare changes can be very large on an absolute basis. However, the expected length of each mortgage contract, observed privately by market participants, may differ from 84 months.

In Figure 1.6, I show how total quality, search expenditure, profit, and social welfare changes as search costs are reduced discreetly from 0 to 100 percents. Here welfare is measured on the vertical axis and on a loan-level basis. For example, when search costs are cut by 10%, a value of total quality of about 470 dollars means that total transacted quality, as described in the previous section, divided by the number of loans is equivalent to about 470 dollars per month. It is apparent that all the welfare quantities move monotonically and as expected. Total quality increases; search expenditure decreases, and social welfare increases as a result.

Table 1.9 presents the welfare numbers that are used to construct Figure 1.6. I find that welfare gained from reductions in search cost can be considerable, even at a loan-level basis. When search costs are cut by only 10%, social welfare would increase more than two-fold (from 94 dollars per month to 224 dollars per month). This increase is a result from an increase in total quality and a decrease in search expenditure (both having the magnitude

Figure 1.6: Welfare Effects (in dollars) at the Loan Level




of about 60 dollars per month). These calculations suggest that market allocations can be significantly improved even if search costs are reduced by a relatively small percentage.

Change in profit is approximately 10 dollars per month at the 10% reduction level. This change in profit amounts to a transfer from consumers to lenders that follows from an increase in markup when marginal cost is held constant. Although producer surplus increases, consumer surplus does not necessarily have to decrease, thanks to the gain from total quality and the saving in search cost expenditure. The positive change in profit and social welfare imply that both buyers and sellers benefit from search cost reduction.

At the extreme, when search costs are reduced by 100%, search expenditures are zero, and social welfare would increase from 94 dollars per month to nearly 700 dollars per month. If search costs are completely eliminated, an average borrower of government-backed mortgage

Table 1.9: Welfare Effects (in dollars) at the Loan Level

| Search Cost Reduction | 0% | 10% | 25% | 50% | 75% | 90% | 100% |
|---|---|---|---|---|---|---|---|
| Profit | 139 | 151 | 147 | 138 | 134 | 138 | 299 |
| Total Quality | 408 | 472 | 496 | 549 | 639 | 730 | 698 |
| Search Expenditure | 314 | 248 | 228 | 190 | 155 | 116 | - |
| Social Welfare | 94 | 224 | 267 | 358 | 484 | 613 | 698 |

See Appendix A.2 for how welfare quantities are calculated at the loan level.

would experience a utility increase that is equivalent to receiving an additional 600 dollars each month for the rest of his mortgage's life. This result highlights the relevance of costly search in the government-backed mortgage market because put another way, the presence of costly search has reduced his utility by the same amount.

Table 1.10: Total Welfare Effects (in million dollars) at the National Level

| Search Cost Reduction | 0% | 10% | 25% | 50% | 75% | 90% | 100% |
|---|---|---|---|---|---|---|---|
| Profit | 8.46 | 6.61 | 6.41 | 6.04 | 5.85 | 6.03 | 18.11 |
| Total Quality | 24.74 | 20.60 | 21.64 | 23.98 | 27.89 | 31.87 | 42.33 |
| Search Expenditure | 19.05 | 10.82 | 9.97 | 8.32 | 6.76 | 5.08 | - |
| Social Welfare | 5.69 | 9.78 | 11.67 | 15.66 | 21.13 | 26.78 | 42.33 |

Market size in each state is the average number of new loans each month from September 2013 to December 2015. See Appendix A.2 for how welfare quantities are calculated at the national level.

While welfare effects at the loan-level are helpful in separating out the effects of market size, from a policy-making perspective, it is arguably more helpful to measure welfare changes at the aggregate level. In Table 1.10, I show the equivalent welfare results measured at the aggregate nationwide level. In calculating these numbers, I take the market size in each state as the average number of new loans each month during the period from September 2013 to March 2015. The welfare numbers in Table 1.10 can then be interpreted as flow welfare variables across the U.S. government-backed mortgage market, measured in terms of monthly dollars.

I find that search cost reductions can have a significant effect on the flow of welfare. A small 10% reduction in search costs can increase the welfare flow each month from about

5.7 to 9.7 million dollars per month. Furthermore, a complete elimination of search costs increases welfare flow by over 35 million dollars per month. Considering that mortgages in the U.S. have an average life of 84 months, an absolute measure of this welfare change can be even more significant. These calculation results provide a clear theoretical foundation for the benefit of reducing consumer search costs in this industry.

## 1.8 Conclusion

Costly consumer search is relevant in mortgage markets because borrowers often have to go through a prolonged process in order to gather accurate price quotes. The literature, however, does not readily provide information on how large consumer search costs might be, and how much welfare is lost due to the presence of search. Quantifications of search costs and welfare effects are especially important considering the size and scope of mortgage markets in the United States.

In this chapter, I provide one of the first estimates of consumer search costs in this market. The estimated search costs are large: a median borrower stops searching when the expected utility gain from the next search is less than $40 per month. Due to costly consumer search, market welfare is reduced by about $600 per borrower per month. The reduction in welfare occurs because under costly search borrowers spend resources on searching and are matched with lower quality lenders. Given the number of new borrowers in the government-backed mortgage market each month, this welfare reduction corresponds to about $35 million at the national level.

I establish the relationship between market demographics and search cost magnitudes in order to examine the nature of search costs. Results indicate that search costs in this market are related to both the opportunity cost of time and money, as well as an individual borrower's education level. Therefore, policies directed at improving general and financial educations, such as educating consumers on the functioning of mortgage markets, could potentially be fruitful.

I solve a range of counterfactual scenarios to characterize the effects of search cost reductions on social welfare, price dispersion, and price level. I find that following search cost reductions, average prices would increase, but consumers benefit from spending less on search and from finding a better match. As a result, social welfare would increase unambiguously. These results confirm that policies aiming to reduce search costs are beneficial to improve welfare.

# Chapter 2

# Price Discrimination in U.S. Mortgage Markets

## 2.1 Introduction

The market for mortgages in the United States provides lenders with many favorable conditions in order to practice price discrimination. First, interest rates are quoted specifically for each borrower and loan contract. The customer-specific nature of price quoting sets the mortgage market apart from many other consumer products where firms have posted prices common to all customers. By quoting a separate price to each borrower and loan, mortgage lenders can potentially extract surplus on a loan-level basis. Second, mortgages contracts are by nature an exclusive good and cannot be resold by the customer. A price discrimination scheme can therefore be supported because a borrower who receives a low rate would not be able to resell his or her contract to someone who would have received a high rate.

Should lenders practice price discrimination, the ramifications on the mortgage market can be considerable. Market surplus may be redistributed from borrowers to lenders as well as across borrower groups. Given the size of the mortgage market in the US, which measures at 13 trillion dollars in total mortgage debt in 2014, the magnitude of this welfare redistribution would be very significant. The presence of price discrimination is also a sign that the mortgage credit market is less than competitive. Hence, the redistributive effect of discrimination may be compounded by a further decrease in total market welfare. Besides, price discrimination can also affect borrowing decisions. Instead of being determined solely by the cost of lending and borrowers' default risk, interest rates under price discrimination would also reflect many other factors concerning the elasticity of demand, such as the borrowers' search cost, negotiation skill, and outside option. At the macro-level, price discrimination can have macroeconomic consequences, as borrowers who get charged a high price unrelated to cost factors would then have an increased risk of default (Gerardi, Goette and Meier, 2010).

Price discrimination is even more likely considering the high level of search cost that borrowers face in this market. Variations in search costs provides a basis to charge different markups to different borrowers. A high search cost reduces the borrower's willingness to engage in shopping and makes her more likely to accept a higher price. It also affects the number of sampled lenders and the outside option, which provides important bargaining leverage during interest rate negotiations. Provided that lenders have the means to directly or indirectly observe search costs, price discrimination could then be supported: in order to maximize profit, lenders may charge a higher markup to borrowers with a higher search cost.

Even though the institutional setup of the mortgage market is well-suited to price discrimination, it does not necessarily imply that mortgage lenders are adopting this practice. Despite the customer-specific price quoting process, price discrimination may not happen if the market is competitive enough. With little market power, lenders would be forced to charge very close to the marginal cost of lending. An open question is therefore to determine whether price discrimination does in fact exist in the United States mortgage markets.

This chapter analyzes data on recent mortgage loans in the United States and tests if the data is consistent with the existence of price discrimination. Price discrimination is formulated as being driven primarily by variations in search costs across borrowers. The presence of varying search costs implies that in equilibrium borrowers would face different prices from lenders even if marginal cost is held constant. Unlike many other discriminatory practices, this type of discrimination is perfectly acceptable under the current legal and regulatory framework.

In the context of U.S. mortgage markets, not much is known about price discrimination driven by consumer search costs. The literature studying discrimination in consumer credit markets has traditionally focused on illegal activities of discriminating against minority borrowers or those who reside in low-income neighborhoods (Munnell, Tootell, Browne and McEneaney, 1996; Goldberg, 1996). Lawful price discrimination that stems from differences in consumer search cost, on the other hand, has received very little academic attention. An exception is Allen et al. (2014c) who argue that positive search cost is consistent with the pattern of price dispersion they observe in the Canadian mortgage market.

The paper bridges this gap in the literature and provides the first suggestive evidence on the existence of lawful price discrimination in U.S. mortgage markets. I develop a stylized mortgage search model with multiple customer types. Each customer type incurs a different marginal cost of lending and has a different level of search cost. Within each type, there is a fraction of shoppers with zero search cost, as well as non-shoppers with a positive search cost. I solve for the equilibrium price distribution assuming firms are maximizing profit for each customer type. Price discrimination is inherent in this model as lenders find it optimal to vary markup across and within customer types, even if the marginal cost of lending is held constant.

The model demonstrates testable restrictions on distribution of transacted interest rates. The equilibrium features a constant pass-through rate; proportionally an increase in marginal cost corresponds to the same increase in equilibrium transacted rates. On the contrary, a change in search cost has a differential effect that vary positively with the conditional quantile of transacted rates; the effect of search cost is larger at the top quantiles of transacted rates than at the bottom.

The contrasting effects on transacted interest rates between marginal cost and search cost changes provide a basis to test the model. If a loan observable is affiliated with the marginal cost of lending, its marginal effect on the interest rate is constant across all quantiles of transacted rates. On the other hand, if it correlates with the borrower's search cost level, marginal effects would get larger in absolute values as we move up the quantiles of transacted interest rates. A loan observable may also affiliates with both marginal cost and search cost, in which case its marginal effect would vary monotonically across interest rate quantiles.

In order to examine the effects of loan observables on different quantiles of transacted interest rates, I run quantile regressions using recent data on FHA mortgages. The data is obtained from Ginnie Mae for the period from October 2013 to March 2015. FHA mortgages are fully insured, ensuring that variations in default risks are not a relevant factor driving observed price dispersion. The data contains loan-level observations with rich information of loan observables, such as borrower's credit score, the loan-to-value ratio, the loan amount, among others.

The empirical analysis is implemented in two steps. First, in order to determine how each loan observable correlates with marginal cost, I run an OLS regression of mortgage-backed securities yield rate on loan observables. Because lenders borrow from the secondary mortgage market to fund their loan originations, the yield rate represents a good approximation for the marginal cost of lending. Second, I run a quantile regression of transacted interest rates on observed loan variables. Depending on whether the loan observable is determined to be correlated with marginal cost or not, its marginal effects on transacted rates would be either constant or vary monotonically across quantiles. Quantile regression provides a convenient way to examine this hypothesis.

Estimated results are to a large extent consistent with the theoretical model of price discrimination. In a quantile regression of transacted interest rates on loan observables, all marginal effects exhibit patterns predicted by the model. For loan observables that correlate with marginal cost, including credit score, original principal balance, and loan-to-value ratio among others, the marginal effects either vary monotonically across quantiles or equal to a non-zero constant. For those that do not correlate with marginal cost, such as the debt expense to income ratio and the number of borrowers, the marginal effects decrease monotonically or approximately equal to zero at all quantiles. The results support the existence of price discrimination created by costly consumer search in U.S. mortgage markets.

The model combined with the estimation results also provide insight into how each loan observables relate to the level of borrower search costs. Knowing this relationship may be helpful as search costs are for the most part not directly observed. I find that credit score, original principal balance, debt expense ratio, and first-time buyer status, have a negative association with search costs, while an indicator of whether the borrower receives a down-payment assistance and the number of living units in the property being mortgaged are positively associated with search costs.

The presence of price discrimination also suggests that, for policy makers aiming to promote more competition in the banking sector, not only the number of bank but also the search cost of borrowers is relevant. While increasing the number of banks and lending institutions may increase competition, it could also lead to excessive risk-taking and engender systemic financial collapses. If the policy goal is to prevent unfair discrimination of mortgage borrowers, efforts directed at reducing consumer search cost may actually be very useful.

## 2.2 Related Literature

This paper is related to several strands of literature. The theoretical model of mortgage shopping presented in Section 2.5 contains elements similar to many other search-theoretic models where consumers shopping for the best price have to incur a positive search cost for each additional price quote. Some representative papers in this literature include Stigler (1961), Rothschild (1973), Reinganum (1979), Burdett and Judd (1983), Carlson and McAfee (1983), and Rob (1985), and Stahl (1989). A common implication in these models is that price dispersion arises as an equilibrium outcome even when products are homogeneous across sellers. Baye et al. (2006) provide a detailed literature review on many of these search-theoretic models as well as others on consumer search and price dispersion.

Building on the theoretical models, another set of papers aim to develop methodologies to estimate the magnitude of consumer search cost empirically. Hong and Shum (2006) propose a method to recover the distribution of search costs using only data on observed prices. The dispersion in prices, when combined with theoretical results on consumers' optimal stopping rule, reveal how much consumers could have gained from searching further, and provide an estimate for search cost. Among others, Hortaçsu and Syverson (2004) and Wildenbeest (2011) extend this framework to allow for variations in the quality of sellers. These papers provide important insights on how to apply consumer search theory in empirical works.

Related specifically to price dispersion in credit markets, there is also an extensive literature studying the pricing of loan contracts. Many important works in this literature focus on determining the relationship between default risk of debtors and the interest rate they get charged. On the theoretical side, Geanakoplos (2002) and Dubey, Geanakoplos and Shubik (2005) study the effects of default risks on loan terms in a general equilibrium setting. Geanakoplos (2002) proposes a model where price of risky contracts is endogenously determined, and shows that when the probability of default increases, contract price will decrease.

The practice of pricing contracts according to their default risk is commonly referred to as risk-based pricing. Even though risk-based pricing has been identified as a relevant pricing mechanism in credit markets as early as in Riley (1987), only starting in mid-1990s, advances in underwriting models and data processing technology enabled credit lenders to adopt this pricing practice. This adoption is also partially driven by the Community Reinvestment Act which mandates lenders to place greater emphasis on lending to borrowers in lower-income neighborhoods (Canner and Passmore, 1997).

Many empirical papers find evidence of increasing use of risk-based pricing in mortgage markets as wells as in other consumer credit markets. Edelberg (2006) documents how such practice results in an increase in the premium paid per unit of risk. Also as a result, low-risk borrowers increase their debt level as a result of their falling borrowing cost. High-risk borrowers gained access to expanded credit, but also face higher prices. Livshits, MacGee and Tertilt (2011) test the prediction that financial innovations generate entry of lending contracts targeted at high-risk borrowers, which in turn leads to higher default rates and higher price dispersion. Using the Survey of Consumer Finance and data from the Board of Governors, they find evidence consistent with this prediction. Einav, Jenkins and Levin (2013) study the adoption of credit scoring at an auto finance firm and find that risk classification help screen out high-risk borrowers and enable targeting more generous loans toward low-risk borrowers.

The strong relationship between default risk and contract prices, identified by both the theoretical and empirical literature, motivates the choice to focus on fully-insured loans in the paper. Since all sampled loans in the empirical analysis are fully-insured, the observed dispersion in interest rates is therefore more readily attributable to consumer search rather than the variation in default risks. In a series of papers on negotiation and pricing in the Canadian mortgage market, Allen et al. (2014c) and Allen et al. (2014a) also focus on insured loans as a means to eliminate the variation in contract prices driven by default risk heterogeneity.

Finally, this chapter also contributes to the long-standing theoretical and empirical literature of price discrimination in consumer markets. As presented in Tirole (1988), the foundational theory on price discrimination consider scenarios where firms are able to charge customers their maximum willingness-to-pay (first-degree discrimination), offer a menu of prices to which customers self-select (second-degree discrimination), or segment customers and charge a different markup for each customer segment (third-degree discrimination). Recent developments extend the theory to study more explicitly the acquisition of customer information and use of different price and non-price instruments in implementing price discrimination. A review of these recent models is provided in Armstrong (2006). Seen in the light of this extensive theoretical literature, the model outlined in Section 2.5 is very similar to the canonical third-degree price discrimination framework, where multiple customer segments are each charged a different price.

Because price discrimination amounts to selling products with the same marginal cost at different prices to different customers, the main challenge in testing empirically for price discrimination is usually to separate out cost-driven price dispersion from markup-driven price dispersion. An accepted approach in the literature, exemplified by Borenstein and Rose (1994), is to first control for cost or competition, then measure how much price dispersion remains afterward. In more competitive markets, dispersion is more readily attributed to variation in costs of serving customers, whereas in less competitive markets, it could be caused by firms extracting rent from customers. Borenstein and Rose (1994) apply this reasoning to data on airline ticket prices and find evidence consistent with price discrimination. Shepard (1991) provides an alternative test of whether price variations in the retail gasoline market can be attributed to discrimination or cost, and finds that discrimination plays a significant role in pricing. Busse and Rysman (2005) studies the effects of competition on second-degree price discrimination in the market of display advertising on Yellow Pages directories, and find that purchasers of large ads face a lower price than purchasers of small ads in more competitive markets. In the context of employer-provided health insurance markets, Dafny (2010) finds evidence that more profitable employers face higher premium growths, and the growth is higher in more concentrated markets, suggesting the existence of price discrimination. Mortimer (2007) studies optimal pricing decisions under indirect price discrimination and finds that predictions of a price discrimination model are supported by data in the VHS and DVD movie distribution market.

The empirical analysis used in this chapter builds on an alternative approach in contrast to the method described above which hinges on using competition as a control for cost. I derive testable empirical relationships between price and loan observables, and use quantile regression to verify if results are consistent with the model. I find controls for cost empirically by regressing cost proxies on a set of loan observables. This approach is very similar to that proposed by Allen et al. (2014c) who study price discrimination in the Canadian mortgage market.

## 2.3 Background on FHA Mortgages

The sample used in this chapter consists exclusively of mortgages insured by the Federal Housing Administration (FHA). The FHA was established by Congress in 1934 under the National Housing Act, with the main goal of stimulating U.S. mortgage markets after the Great Depression. The FHA program initialized many changes regarding contractual features of mortgages that still persist until the present day. For example, under the FHA program, for the first time borrowers could obtain long-term mortgages with amortization period longer than 20 years. These long-term mortgages gradually became the norm in the industry, replacing those with short terms. Changes introduced by the FHA program helped bring about stability and recovery in the mortgage market after the Great Depression, and contributed to increasing homeownership rates in America.

A key innovation introduced by the FHA program was insurance protection on approved mortgages. The insurance fully protects lenders and mortgage originators in the event of credit default. If a borrower defaults on an FHA-insured loan, the lender would be reimbursed for the remaining principal amount owed. Introduced in the wake of the Great Depression, this insurance helped increase the supply of mortgage credit in the market without requiring the FHA to originate the loans. To this day, the insurance scheme has grown significantly. FHA now insures a range of mortgage types, including single-family, multi-family properties, as well as hospital facilities. At the end of fiscal year 2012, 7.7 million single-family home mortgages with a total outstanding balance of $1.1 trillion are insured by FHA.

FHA mortages are available to borrowers who can credibly demonstrate their ability to repay loans according to the term of their contract. Although FHA borrowers are predominantly low-income families, there is no strict income limit for borrowers seeking FHA-insured loans. Lenders originating FHA loans use a standard credit worksheet to examine the applicant's financial status, funds to close the loans, and other debts and obligations. Most applicants have to demonstrate that their monthly mortgage payments would make up less than 31% of their monthly income, and that their total debt obligations would be less than 43% of gross monthly income. Effective October 4, 2010, the minimum credit score for FHA approval is 500, and there is an increase in down-payment for borrowers with credit scores below 580.

The principal amount of mortgages insured by FHA is subject to a statutory floor and ceiling; these limits vary across areas and the number of living units in the collateral property. For instance, in December 2013 - a time period observed in our sample, FHA approve loans in the range of $271,050 to $729,750 in high-cost areas as defined by the Department of Housing and Urban Development (HUD). The down-payment on FHA mortgages is lower than that of conventional mortgages with the minimum being at 3.5%. In return to providing insurance for mortgages with such a low down-payment, FHA charges borrowers an insurance premium. In 2014, annual mortgage insurance premiums cannot exceed 1.55% of loan balance, and upfront premiums cannot exceed 3%.

## 2.4 Data Sources and Sample Description

### 2.4.1 Ginnie Mae MBS Disclosure Data

The primary dataset in this chapter is constructed from monthly mortgage-backed securities data disclosed by Ginnie Mae. In order to improve transparency and attract global capital, beginning in October 2013 Ginnie Mae began releasing loan-level data of mortgages that belong to active mortgage-backed securities. Mortgages securitized by Ginnie Mae originate exclusively from four government-backed mortgage programs, administered by the Federal Housing Administration, the Department of Veterans Affairs, the Office of Public and Indian Housing, and the Department of Agriculture. Respectively these loans are abbreviated FHA, VA, PIH, and RD, and they differ from conventional loans in several dimensions, including targeted borrower demographics and credit requirements.

In this chapter, I focus only on the subset of FHA mortgages because these loans are fully insured, and lenders originating FHA loans are protected from borrower credit risks. The unpaid principal amount is fully reimbursed to the lender in case the borrower defaults on a FHA-approved loan. On the other hand, VA, PIH, and RD loans only provide lenders with partial insurance, hence only a fraction of the unpaid principal amount can be reimbursed. The full insurance feature of FHA loans alleviates concerns of risk-based pricing and ensures that dispersion in interest rates is not predominantly driven by variation in borrower default risks.

The loan-level data disclosed by Ginnie Mae contains fairly rich information. For each observation, contractual data, such as the original principal amount, the loan-to-value, and the term of the loan, are included. Some information about the borrower financial situation, such as her credit score and her ratio of debt expense to income, is also observed. Data on the lender or banking institution that originates the loan as well as its geographical location is also included. Moreover, because Ginnie Mae identifies the mortgage pool to which each loan belongs, it is possible to use this pool-level information to retrieve secondary-market data about each observed loan, such as the coupon and yield rates of the mortgage-backed security created by the loan.

### 2.4.2 Bloomberg Mortgage-backed Security Data

I supplement the primary loan-level Ginnie Mae dataset with data on yields of mortgage-backed securities collected from Bloomberg. In some empirical specifications presented later in Section 2.6.3, an approximation of the marginal cost is needed. Data on the secondary mortgage market would be very useful for that purpose. The rate at which mortgage lenders borrow funds from the secondary market can be used as a measure for the marginal cost of lending, an approach also employed by Scharfstein and Sunderam (2014).

The loan-level Ginnie Mae dataset provides information on the coupon rate of the mortgage-backed security to which each individual mortgage in the sample belongs. The coupon rate shows the face interest rate that investors of the MBS are entitled to, and is one measure of the marginal cost of lending used in Section 2.6.3. However, because it is the face interest rate, the coupon rate is only accurate insofar as the security is traded at par, a requirement that does not necessarily hold for many of the Ginnie Mae mortgage-backed securities during the sampled time period. For this reason, I additionally employ the yield rates, which adjust for the initial transaction price of the security. I match yield rates with

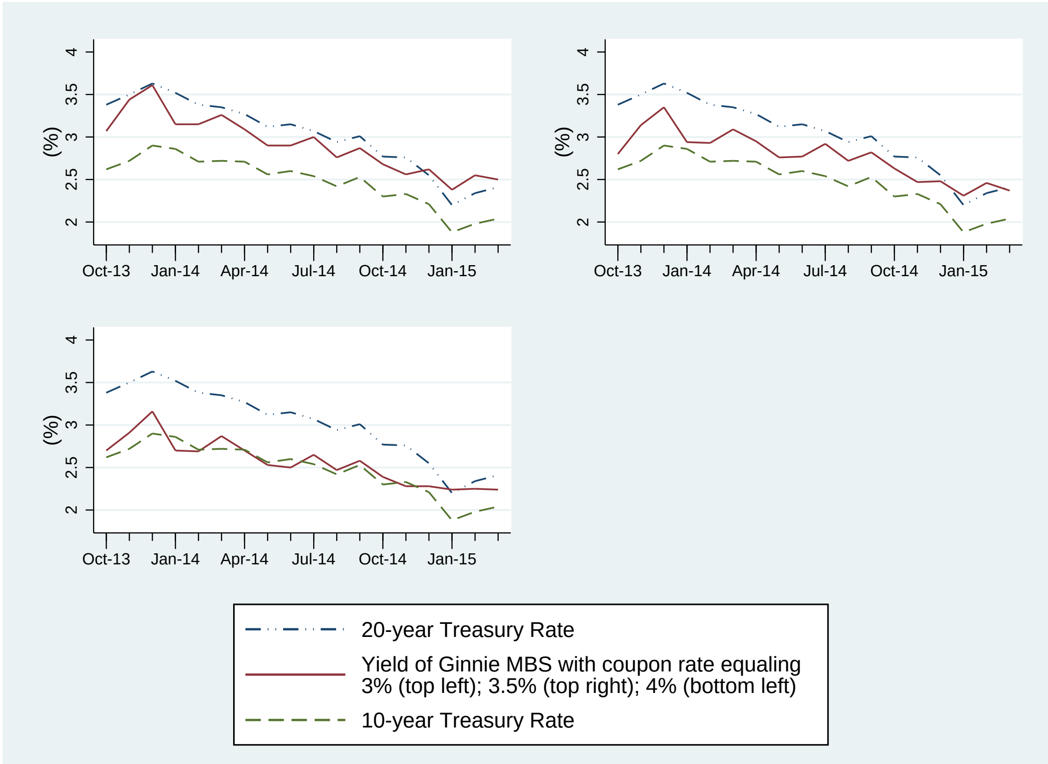



Figure 2.1: Ginnie Mae MBS Yield and the Treasury Rate

loans using the observed coupon rate and issuance date.

The collected yield rates suggests that Ginnie Mae MBS are effectively risk-free investments for investors in the secondary market. In Figure 2.1, I graph the time series of yield rates of Ginnie Mae MBS compared to the Treasury rates. The figure shows that Ginnie Mae MBS yield rates typically fall between the 10-year and 20-year Treasury rates. This observation is consistent with investors regarding Ginnie Mae MBS as risk-free as Treasury bonds but with a different maturity date. The maturity date of Ginnie MBS is determined by the prepayment and refinance propensity of its underlying mortgages, which may be reasonably regarded as being between 10 and 20 years.

### 2.4.3 Sample Description

Using the Ginnie Mae loan-level dataset, I make several restrictions in order to arrive at the final sample. The Ginnie Mae dataset contains loans insured by agencies other than the Federal Housing Administration, but these loans are only partially insured and hence are dropped from the sample. I also exclude refinances and focus only on loans that are new home purchases. The interest rate of refinanced loans are likely dependent on the interest rate of the original loan, which is unfortunately unobserved. I also keep only loans with a common 30-year amortization schedule and a fixed interest rate. Discount points may also affect the distribution of transacted interest rates in ways that are unrelated to price discrimination; therefore I drop loans where the borrower opts to purchase discount points.

Using these restrictions, the Ginnie Mae loan-level dataset consists of 790,994 observations. The empirical analysis calls for quantile regressions, but running quantile regression on such a large dataset would be prohibitively slow. Therefore, I choose a random 5% sample of 39,550 observations in order to make the estimation feasible.

Table 2.1: Summary Statistics of Continuous Variables

| Variables | Measurement Unit | Observations | Mean | Median | Standard Deviation |
|---|---|---|---|---|---|
| Transacted Interest Rate | basis points | 39,550 | 425.25 | 425.00 | 35.44 |
| Credit Score | n/a | 39,468 | 682.63 | 675.00 | 44.80 |
| Original Principal Balance | $1000 | 39,550 | 178.63 | 157.00 | 93.98 |
| Loan-to-Value | % | 38,479 | 95.33 | 96.50 | 4.55 |
| Debt Expense Ratio | % | 38,091 | 40.87 | 41.75 | 8.94 |
| Coupon Rate of MBS | basis points | 39,550 | 387.45 | 400.00 | 37.79 |
| Yield Rate of MBS | basis points | 38,824 | 256.27 | 255.00 | 30.81 |

Tables 2.1 and 2.2 report the summary statistics for continuous and discrete variables observed for each loan contract. Transacted interest rate, which is a measure of contract price, average at 425 basis points with a standard deviation of around 35 basis points. Hence, even for a sample of fully insured loans, there is evidence of dispersion in transacted interest rates. As variation in default risk is eliminated, observed price dispersion can be plausibly

attributed to other factors. As argued in Chapter 1, other factors that drive observed price dispersion may include variations in marginal costs, lender quality, and search costs of borrowers.

Table 2.2: Summary Description of Discrete Variables

| Loan Observables | Values | % of Contracts |
|---|---|---|
| Number of Borrowers | One | 62.31% |
| | Two | 36.26% |
| | Three | 1.24% |
| | Four | 0.19% |
| Down-Payment Assistance | No | 88.97% |
| | Yes | 11.03% |
| First-time Homebuyer | No | 32.51% |
| | Yes | 67.49% |
| Number of Units | One | 97.52% |
| | Two | 1.98% |
| | Three | 0.32% |
| | Four | 0.17% |
| Origination Source | Broker | 13.23% |
| | Correspondent | 54.15% |
| | Retail | 32.62% |

For each loan, the data also provide information on the credit score of the borrower, the loan's original principal balance, the loan-to-value ratio, the total debt to income ratio of the borrower. Additionally, I also observe discrete variables such as the number of borrowers undersigning the contract, a dummy indicating if the borrower receives gift funds for the down payment, a dummy indicating if the borrower is a first-time homebuyer, the number of units in the mortgaged property, and the origination channel of the mortgage. These are loan observables that I will later use in our empirical analysis.

## 2.5 A Model of Mortgage Shopping

### 2.5.1 Overview

In order to motivate the empirical approach, here I describe a stylized model of consumer search in mortgage markets.[1] The model is related to that of Stahl (1989); in the presence of positive consumer search costs, price dispersion arises as an equilibrium mixed strategy adopted by firms. To allow for price discrimination, I specify multiple consumer types who differ in their level of search costs and get charged different levels of markup in equilibrium. The analytical solution of the equilibrium price distribution is based on Janssen, Moraga-González and Wildenbeest (2005). The model produces restrictions on comparative statics of prices that later will be used as motivations of the empirical analysis.

Let us consider a geographical market and suppose there is a continuum of consumers in this market. Each consumer demands exactly one mortgage and has an inelastic demand $D(p) = 1$. A more flexible demand specification does not qualitatively change the central results as long as the revenue function $pD(p)$ has a unique maximum at $\hat{p}$, and that for all $p < \hat{p}$, $pD(p)$ is strictly increasing.

Each consumer belongs to a specific type $\theta$ that incurs a marginal cost $c_\theta$ on lenders. For each consumer type, there is a fraction $\mu_\theta > 0$ of consumers who have a zero search cost and are referred to as shoppers. The rest $1 - \mu_\theta$ fraction of consumers have a positive search cost $s_\theta > 0$. The inclusion of shoppers aims to capture the population of consumers who derive intrinsic satisfaction from shopping. For each type $\theta$, non-shoppers have a common search cost, hence the search cost distribution is degenerate, and the model can be seen as a special case of Stahl (1996). Each borrower type can be fully described by the three parameters $\mu_\theta$,

[1]This model borrows heavily from Michael Grubb's lecture notes in his Graduate Industrial Organization class at Boston College. Prof. Grubb's generously provided these lecture notes to me, for which I am very thankful.

$s_\theta$, and $c_\theta$.

Let $N$ denote the number of different mortgage lenders in the market, who all have an identical production function. I assume that the mortgage product is homogeneous across lenders, but mortgages can have differing marginal costs that are induced by variations in the borrowers' cost parameter $c_\theta$. This cost parameter $c_\theta$ is fixed throughout the shopping occasion; the model therefore posits that the borrower has already decided on all non-price dimension of the mortgage contract prior to shopping. Terms such as the downpayment size, the loan-to-value ratio, the length of the mortgage, as well as borrower's characteristics such as income and credit score are all fixed, and the borrower is only searching along the price dimension.

Furthermore, the assumption of homogeneous lenders also implies that any quality variations across mortgage lenders will not be considered. In reality, quality differentiation across lenders may be present and is a potential source of price dispersion. However, the homogeneity assumption greatly simplifies the solution of the model by allowing the focus on symmetric equilibria.

Lenders will simultaneously choose prices $(p_1, \ldots, p_N)$. To facilitate solving the model, each consumer type is regarded as a separate sub-market, and strategic interactions between lenders are confined to within sub-markets only. The price vector then can be more precisely described with the subscript $\theta$: $(p_{\theta 1}, \ldots, p_{\theta N})$. However, since solving the model is mechanically the same across sub-markets, from here on I will omit the subscript $\theta$ in solving for the equilibrium price vector. The solution presented below can be seen as being applicable across all sub-markets.

I adopt a Symmetric Nash Equilibrium (SNE) solution concept. A SNE solution is plausible since lenders are homogeneous and would follow the same strategy in equilibrium. The choice of solution concept is an implicit assumption about what consumers know prior to search. Under a SNE, consumers are assumed to know the equilibrium CDF of posted price $F(p)$, but not the empirical distribution of prices actually being charged. Papers that adopt a SNE solution concepts include Burdett and Judd (1983) and Stahl (1989). On the other hand, Salop and Stiglitz (1977) and Rob (1985) adopt a Stackelberg paradigm, in which firms move first and set prices, after which consumers are informed of the empirical price distribution before engaging in search. The SNE concept is chosen in this chapter since it is natural to assume that mortgage borrowers should have no information regarding actual prices without searching.

### 2.5.2 Borrowers Problem

Prior to searching, borrowers know the CDF of the posted price distribution, denoted here on by $F(p)$. Let $\left[\underline{p}, \bar{p}\right]$ denote the support of this CDF. To learn the actual price that each lender charges, borrowers have to visit that lender. The visit is free for shoppers and incurs a cost $s$ for non-shoppers. Borrowers search with perfect recall and without replacement. The first visit is free for all borrowers, ensuring that all borrowers participate in the market.

Because shoppers have zero search cost, they will always search and find the firm offering the lowest price in the market. On the other hand, consider the non-shoppers who have positive search cost. As quality differentiation acorss lenders is assumed away, borrowers' utility is a function of price only. In this setting, the optimal strategy is to search until a price $p$ lower than the reservation price $r$ is found (Weitzman, 1979). This reservation price satisfies:

$$
\begin{aligned}
s &= \int_{\underline{p}}^{r} D(p)F(p)\,dp \\
&= \int_{\underline{p}}^{r} F(p)\,dp
\end{aligned}
$$

The equality defines the reservation price because it is the price at which the benefit of the marginal search equals to the cost of searching. The second line follows because of inelastic demand $D(p) = 1$.

It is possible to show that in equilibrium, $\bar{p} \leq r$, or that the whole support of the posted price distribution is less than the reservation price. The claim that $\bar{p} \leq r$ can be established by contradiction. Suppose that $\bar{p} > r$ is an equilibrium, then a firm charging $\bar{p}$ would always induce consumers to search; its consumers would always find a better price elsewhere, and the firm would have zero profit. However, by deviating to $\underline{p}$ instead, the firm would earn a positive profit. This positive profit at $\underline{p}$ is guaranteed because as shown in Appendix B.1, any equilibrium will necessarily have $\underline{p} > c$. Thus a firm charging $\bar{p} > r$ is not maximizing profit, a contradiction to $\bar{p} > r$ being an equilibrium.

Since $\bar{p} \leq r$, non-shoppers would always only search exactly once: they are guaranteed to find a satisfying price from the very first search. In equilibrium, only shoppers would search more than once. The implication that only shoppers search makes the model thematically similar to other consumer search models, such as Varian (1980), in which each firm has a captive customer population and compete against each others for the informed customers. In the mortgage search model presented here, each firm has an equal chance of capturing a non-shopper regardless of the price it charges. Setting a lower price makes it more probable that the firm can also capture the shoppers, who would only buy from the lowest price lender. In these types of models where a captive consumer segment exists alongside with informed consumers, a pure strategy Nash Equilibrium is unobtainable (Anderson and Renault, 2016). However, a mixed strategy NE exists.

### 2.5.3 Equilibrium

In this model, the existence of a symmetric mixed strategy price equilibrium is shown in Stahl (1996). Let us then consider a price equilibrium $F$ as a SNE. Again denote the support of $F$ by $\left[\underline{p}, \bar{p}\right]$.

If a lender charges price $p$, it has a $(1-F(p))^{N-1}$ probability of being the lowest price lender and capture the shoppers. On the other hand, because non-shoppers do not search, this lender will capture $1/N$ of the fraction of non-shoppers. Equilibrium profit as a function of price would be:

$$\pi(p) = (p-c)\left[\mu(1-F(p))^{N-1} + \frac{1-\mu}{N}\right]$$

Note that the above equation describes profit in a given market segment (sub-market) even though the segment subscript $\theta$ has been suppressed. Solving this equation for $F(p)$ yields:

$$1 - F(p) = \left(\frac{\frac{\pi(p)}{p-c} - \frac{1-\mu}{N}}{\mu}\right)^{\frac{1}{N-1}}$$

Two special cases arise when the price charged is at the bounds of the price support:

$$\pi(\bar{p}) = (\bar{p}-c)\left[\frac{1-\mu}{N}\right]$$
$$\pi(\underline{p}) = (\underline{p}-c)\left[\mu + \frac{1-\mu}{N}\right]$$

In a mixed strategy equilibrium, $\pi(p) = \pi(\underline{p}) = \pi(\bar{p})$. Substituting $\pi(p)$ by $\pi(\bar{p})$ in the equation for $1-F(p)$:

$$1 - F(p) = \left[\left(\frac{1-\mu}{\mu}\frac{1}{N}\right)\left(\frac{\bar{p}-c}{p-c} - 1\right)\right]^{\frac{1}{N-1}} \tag{2.1}$$

Solving the above equation for $p$ yields:

$$p = c + \frac{\bar{p} - c}{1 + \frac{\mu}{1-\mu} N (1-F)^{N-1}}$$

Using $F(\underline{p}) = 0$, I obtain the lower-bound of the price support:

$$\underline{p} = c + \frac{\bar{p} - c}{1 + \frac{\mu}{1-\mu} N} \tag{2.2}$$

The final step involves solving for the upper-bound of the price support. Once a consumer samples $\bar{p}$, the expected price saving from the next search would be $\bar{p} - E[p]$. Because shoppers are indifferent to search once they sample $\bar{p}$, the optimal stopping rule is satisfied and we have $\bar{p} - E[p] = s$. Janssen et al. (2005) presents a solution for $\bar{p}$ by characterizing $E[p]$.[2] More specifically, letting

$$A = \int_0^1 \frac{1}{1 + \frac{\mu}{1-\mu} N x^{N-1}} \, dx$$

yields

$$\bar{p} = c + \frac{s}{1 - A} \tag{2.3}$$

Equations (2.1), (2.2), and (2.3) jointly characterize the price distribution in a symmetric mixed strategy Nash equilibrium. Although the subscript $\theta$ is omitted, we should view this equilibrium as occurring separately in each market segment $\theta$.

[2] I learned of this technique from Michael Grubb's lecture notes. See also the previous footnote.

### 2.5.4 Comparative Statics

In this section, I examine several comparative statics of prices that later will be used in the empirical analysis. These comparative statics are derived for transacted instead of posted prices, as the data on mortgage contracts only reveal transacted prices. In order to derive the CDF of transacted prices, consider a consumer $i$ who obtains a transacted price $p_i^{trans}$. The probability that this transacted price is less than a certain value can be written as follows:

$$\begin{aligned}\Pr(p_i^{trans} < x) &= \Pr(i \in \text{shoppers}) \times \Pr(p^{min} \leq x \mid i \in \text{shoppers}) \\ &\quad + \Pr(i \in \text{non-shoppers}) \times \Pr(p^{posted} < x \mid i \in \text{non-shoppers})\end{aligned}$$

Therefore, let $F^{trans}$ denote the CDF of transacted prices, $F^{min}$ the CDF of the minimum posted price, and $F^{posted}$ the CDF of posted prices. The CDF of transacted prices can then be expressed as a function of the fraction of shoppers $\mu$ and the other two price CDFs:

$$\begin{aligned}F^{trans} &= \mu F^{min} + (1-\mu)F^{posted} \\ &= \mu \left\{ 1 - \left[ \left( \frac{1-\mu}{\mu N} \right) \left( \frac{s}{\gamma(p-c)(1-A)} - 1 \right) \right]^{\frac{N}{N-1}} \right\} + \dots \\ &\quad + (1-\mu) \left\{ 1 - \left[ \left( \frac{1-\mu}{\mu N} \right) \left( \frac{s}{\gamma(p-c)(1-A)} - 1 \right) \right]^{\frac{1}{N-1}} \right\} \end{aligned} \tag{2.4}$$

Consider an implicit function defining transacted prices $p^{trans}$ in terms of marginal cost $c$, search cost $s$, fraction of shoppers $\mu$, and quantile value $\tau$. By definition of a CDF, this implicit function holds true for each quantile value $\tau \in (0, 1)$:

$$F^{trans}(p^{trans}, c, s, \mu) - \tau = 0$$

Applying the Implicit Function Theorem on the above function produces the relevant comparative statics of transacted prices. The resulting comparative statics are provided below, and a more detailed derivation of these results can be found in Appendix B.2. In all mathematical expressions here on, prices refer exclusively to transacted prices. I therefore omit the superscript "*trans*" for conciseness.

$$\frac{\partial^2 p}{\partial c \partial \tau} = 0 \tag{2.5}$$
$$\frac{\partial^2 p}{\partial s \partial \tau} > 0 \tag{2.6}$$
$$\frac{\partial^2 p}{\partial \mu \partial \tau} < 0 \tag{2.7}$$

As Appendix B.2 also shows, closed form solutions can be obtained for the first derivative of transacted price with respect to marginal cost and search cost. In particular, we have:

$$\frac{\partial p}{\partial c} = 1 \tag{2.8}$$
$$\frac{\partial p}{\partial s} = \frac{p - c}{s} \tag{2.9}$$

Taken together, the above equations imply that as quantile values $\tau$ increases, the first derivative of transacted prices with respect to marginal cost remains unchanged, the first derivative with respect to search cost increases, and the first derivative with respect to fraction of shoppers decreases. The direction of change of these first derivatives across quantiles forms the theoretical basis that motivates our use of quantile regressions in the empirical analysis.

As shown in Appendix B.3, equation (2.9) implies that transacted price is linear in marginal cost and search cost.[3] We can expressed transacted price as:

$$p = c + \beta(\tau, N, \mu)s \tag{2.10}$$

for some $\beta(\tau, N, \mu) = \frac{\partial p}{\partial s}$. The linearity lends further support for the use of quantile regres-

[3]Thanks to Michael Grubb for suggesting and actually proving the linear relationship between transacted price, marginal cost, and search cost.

sions, where transacted price are assumed to be linear in the independent variables.

In Appendix B.4, I simulate a dataset of transacted interest rates, search cost, and marginal cost. I then show that equations (2.8) and (2.9) can be supported by running the appropriate quantile regressions on the simulated data. Results in this appendix suggest that the theoretical model, in the form of equations (2.8) and (2.9) can be tested using observational data.

## 2.6 Empirical Analysis

### 2.6.1 Empirical Specification of the Model

In this section, I discuss a few further specification issues of the model that was developed in Section 2.5 before applying it to the data. Let $X$ denote the set of loan-level variables observed in the data. The conditional quantile function (CQF) of transacted prices $p$ can then be defined given the vector of regressors $X$:

$$Q_\tau(p \mid X) = F_p^{-1}(\tau \mid X)$$

where $F_p^{-1}$ is the inverse of the CDF of transacted prices that was derived in equation (2.4). A standard quantile regression would specify the conditional quantile function as a linear model with parameters $\beta_\tau$ to be estimated:

$$\begin{aligned} Q_\tau(p \mid X, \beta_\tau) &= X\beta_\tau \text{ for each } \tau \in (0,1) \\ &= \sum X_k \beta_{k\tau} \end{aligned} \tag{2.11}$$

where the subscript $k$ indexes each specific regressor $X_k$. For ease of notation, let

$$p_\tau \equiv Q_\tau(p \mid X, \beta_\tau)$$

The main empirical goal is assessing how the coefficients $\beta_\tau$ vary across different quantiles. In order to achieve this objective, I first write $\beta_\tau$ as a partial derivative of transacted prices with respect to a loan observable $X_k$, holding other observables fixed. Applying the chain rule with respect to marginal cost $c$, fraction of shoppers $\mu$, and search cost $s$ then yields:

$$\beta_\tau = \frac{\partial p_\tau}{\partial X_k} = \frac{\partial p_\tau}{\partial c}\frac{\partial c}{\partial X_k} + \frac{\partial p_\tau}{\partial \mu}\frac{\partial \mu}{\partial X_k} + \frac{\partial p_\tau}{\partial s}\frac{\partial s}{\partial X_k} \tag{2.12}$$

How the coefficients $\beta_\tau$ vary would depend on how each of the terms in the above equation change across quantiles. The analysis so far has established the sign of changes in the partial derivatives of prices with respect to model parameters $c$, $\mu$, and $s$. More specifically, in equations (2.5), (2.7), (2.6), and in Appendix B.2, we showed that as quantile value $\tau$ increases, $\partial p_\tau/\partial c$ is constant, $\partial p_\tau/\partial \mu$ is negative and decreasing, and $\partial p_\tau/\partial s$ is positive and increasing.

Depending on the sign and magnitude of the remaining derivatives, $\partial c/\partial X_k$, $\partial \mu/\partial X_k$, and $\partial s/\partial X_k$, we would expect different directions of change in $\beta_\tau$ across quantiles. These partial derivatives with respect to $X$ represent the mapping between observable data $X$ and model parameters $c$, $\mu$, and $s$. The magnitude of these partial derivatives can be interpreted as how $X_k$ is affiliated with $c$, $s$, and $\mu$.[4] These parameters are not observed; as a result, it is difficult to assess this mapping empirically and quantify it.

In order to test the model's predictions, I make a few empirical assumptions on the derivatives of $c$, $\mu$, and $s$ with respect to $X$. Specifically, I assume that across all quantile

[4]See Krishna (2002) for definition of affiliation between random variables.

values $\tau$:

$$\frac{\partial c}{\partial X_k} = T_{ck}$$
$$\frac{\partial \mu}{\partial X_k} = T_{\mu k}$$
$$\frac{\partial s}{\partial X} = T_{sk}$$

for some constants $T_{ck}$, $T_{\mu k}$, and $T_{sk}$. Changes in certain loan and borrower observables, such as credit score or loan-to-value ratio, are almost certainly associated with changes in the lending cost, as well as changes in how likely the borrower would search for mortgages. The above assumption allows for such changes in the model parameters $c$, $\mu$, and $s$ to happen as a result of changing loan observables, but restrict the rate-of-change to be constant across all quantiles of transacted price. The stable relationship between $c$, $\mu$, $s$, and observables $X$ allows us to build upon qualitative results of Section 2.5 to derive predictions on the estimated quantile regression coefficients.

Particularly regarding the partial derivative with respect to the fraction of shoppers $\mu$, I further assume that $T_{\mu k} \approx 0$, or equivalently:

$$\frac{\partial \mu}{\partial X_k} \approx 0 \text{ for all } X_k \tag{2.13}$$

In other words, the fraction of shoppers is relatively stable across different values of observables $X$. As loan observables such as credit score, loan-to-value, and original loan balance vary, borrowers would be classified as belonging to different customer segments $\theta$. I maintain that across observed values of these loan characteristics, the fraction of customers with zero search cost remains near a constant.

To provide evidence in support of this assumption, I calculate the fraction of shoppers $\mu$ and examine how it varies across values of loan observables. To this end, I rely on data provided in a report by the Consumer Financial Protection Bureau and Federal Housing Finance Agency (2017). This report presents summary statistics gathered from the National Survey of Mortgage Originations (NSMO). This survey is administered using a representative sample of mortgage borrowers who report to Experian, one of the three national credit repositories. I focus on a particular data item in this report, namely the percentage of borrowers who applied to only one lender during the mortgage shopping occasion.

In order to calculate the implied fraction of shoppers $\mu$ from this data, first recall that in the equilibrium characterized in Section 2.5, non-shoppers would search exactly once, and shoppers may search once or more. Shoppers, having a zero search cost, would only stop searching when they find the lowest price in the market. Therefore, the population of borrowers who apply at one lender would consists of all non-shoppers as well as some shoppers who happen to find the lowest market price in their very first search. The probability of finding this lowest price is $1/N$ in the first search, where $N$ is the total number of lenders in the market. Letting $H$ denote the percentage of all borrowers who apply to one lender, we have:

$$\begin{aligned} (1-\mu) + \frac{\mu}{N} &= H \\ \mu &= \frac{N(1-H)}{N-1} \end{aligned} \tag{2.14}$$

Setting $N = 20$, the average number of lenders observed in each state, I calculate the fraction of shoppers $\mu$. Table 2.3 reports how $\mu$ varies across values of three loan characteristics that are observed in both the sample and in the NSMO report: credit score, the loan's original principal balance, and a dummy indicating if the borrower is a first-time homebuyer.

In Table 2.3, the implied fraction of shoppers stays at a relatively constant level for all the three reported loan characteristics. The range of variation of $\mu$ is about 5.2 ($= 27.1 - 21.9$) percentage points across values of credit score, 7.9 percentage points across values of original

Table 2.3: Variation in the Fraction of Shoppers across Loan Observables

| Loan | Values | Fraction of Borrowers | Fraction of Borrowers who (NMSO Survey Data) | Calculated Fraction ($\mu$) |
|---|---|---|---|---|
| Credit | $< 620$ | 3.4% | 76.7% | 24.5% |
| Score | $620 - 679$ | 49.1% | 74.3% | 27.1% |
| | $680 - 719$ | 25.3% | 75.8% | 25.5% |
| | 720+ | 19.2% | 79.2% | 21.9% |
| Original | $< 50$k | 1.1% | 83.2% | 17.7% |
| Principal | 50k $-$ 150k | 44% | 78.6% | 22.5% |
| Balance | 150k $-$ 300k | 44.9% | 77.2% | 24.0% |
| | 300k+ | 9.4% | 75.7% | 25.6% |
| First-time | Yes | 67.5% | 71.0% | 30.5% |
| Homebuyer | No | 32.5% | 76.7% | 24.5% |

Data for the fraction of borrowers who apply at one lender come from the National Survey of Mortgage Originations in 2014. The corresponding fraction of shoppers are calculated using equation (2.14) assuming $N = 20$.

principal balance, and 5.5 percentage points across groups of first-time buyers and non-first-time buyers. The degree of variation of $\mu$ actually present in the data may even be smaller, because as indicated in the third column of Table 2.3, the majority of loan observables tend to concentrate near their central values. Hence the variation in $\mu$ calculated using the bounds would likely be an overstated representation of the actual variation. The small degree of variation in $\mu$ across values of loan observables provides suggestive evidence for the assumption in equation (2.13).

### 2.6.2 Predictions of the Model

Once equation (2.13) is specified, predicting the changes in $\beta_\tau$ across quantiles amounts to determining only $\partial c/\partial X_k$ and $\partial s/\partial X_k$ for each loan observable $X_k$. The quantile regression coefficient $\beta_{k\tau}$ can now be expressed as:

$$\begin{aligned}\beta_{k\tau} &= \frac{\partial c}{\partial X_k} + \frac{\partial p_\tau}{\partial s}\frac{\partial s}{\partial X_k} \\ &= T_{ck} + \frac{\partial p_\tau}{\partial s} T_{sk} \qquad (2.15)\end{aligned}$$

where $T_{ck}$ and $T_{sk}$ denote the partial derivatives of $c$ and $s$ with respect to $X_k$, which are assumed to be constants. The above equation is a simplification of equation (2.12) using the assumption that $\partial\mu/\partial X_k = 0$ and a result shown earlier that $\partial p_\tau/\partial c = 1$. As argued in Section 2.5.4 and Appendix B.3, the linearity of transacted price in $T_{ck}$ and $T_{sk}$ is supported by the theoretical model.

For each specific loan observable, $T_{ck}$ and $T_{sk}$ may either be zero or non-zero. Therefore, there are four different possible scenarios. Because $\partial p_\tau/\partial s$ is increasing across quantiles $\tau$, using equation (2.15) it is now possible to make testable predictions on how $\beta_{k\tau}$ would vary across quantiles $\tau$ of transacted price.

Table 2.4 presents these testable predictions. There are four possible combinations of values for $T_{ck}$ and $T_{sk}$ based on the zero and non-zero classification, but only three possible outcomes for the quantile regression coefficients $\beta_\tau$. If $T_{ck} = T_{sk} = 0$, then loan observable $X_k$ is unrelated with $c$, $s$, and $\mu$, and therefore would be irrelevant in determining transaction price. It follows that the regression coefficient $\beta_{k\tau}$ should be zero across all quantiles of transacted price. If $T_{ck} \neq 0$ and $T_{sk} = 0$, then $X_k$ is correlated only with the marginal cost parameter but not the search cost parameter. Equation (2.15) would then implies that $\beta_{k\tau} = T_{ck}$, so the regression coefficients $\beta_{k\tau}$ should equal to a non-zero constant across all quantiles. Finally, consider the case when $T_{sk} \neq 0$, or $X_k$ is correlated with the search cost parameter. Because $\partial p_\tau/\partial s$ is increasing, $\beta_{k\tau}$ should be either increasing or decreasing monotonically across quantiles depending on the sign of $T_{sk}$.

Based on the information presented in Table 2.4, one natural way to test the model predictions is to distinguish between cases that $\beta_{k\tau}$ is constant versus otherwise. The distinction occurs depending on whether each loan observable is correlated with search cost $s$ or not. If we can reasonably establish that a variable $X_k$ is correlated with search cost, then its coefficient in a quantile regression of transacted price should vary monotonically. On the contrary, if $X_k$ is deemed to be not correlated with $s$, then its coefficient should be constant, zero and non-zero included. This approach, based on the determining how each loan observable relates with search cost level, is straightforward and clean in its predictions on regression coefficients. It is, however, difficult to implement since borrowers' search cost $s$ is not observed in the data.

Table 2.4: Predictions of the Model

| Values of $T_{ck}$ | Values of $T_{sk}$ | Predictions on Estimated Coefficients $\beta_\tau$ |
|---|---|---|
| Zero | Zero | $\beta_\tau = 0$ for all $\tau$ |
| Zero | Non-Zero | $\beta_\tau$ varies monotonically as $\tau \uparrow$ |
| Non-Zero | Zero | $\beta_\tau =$ Non-Zero Constant for all $\tau$ |
| Non-Zero | Non-Zero | $\beta_\tau$ varies monotonically as $\tau \uparrow$ |

Predictions in the right-most column refer to how quantile regression coefficients $\beta_\tau$ would change as quantile values $\tau$ is increased. More details are provided in Sections 2.5 and 2.6 of the paper.

I therefore pursue an alternative strategy that consists of first determining empirically the relationship between a loan observable and a measure of marginal cost. I then implement a quantile regression of transacted price and verifying if the estimated regression coefficients are consistent with those outlined in Table 2.4. For any loan observable $X_k$, a quantile regression of transacted price should produce coefficients that either vary monotonically or equal to a constant. Whether that constant is zero or non-zero has to be consistent with whether $X_k$ is associated $c$ or not. If $X_k$ is determined to be not related to $c$, then the constant outcome refers exclusively to zero. On the other hand, if $X_k$ is retlated to $c$, then the constant regression coefficients should be non-zero. In all cases, estimated coefficients should not exhibit non-monotonic variations across quantiles.

The model's prediction regarding the quantile regression coefficients $\beta_{\tau k}$ of transacted rates on loan observables $X_k$ could be summed up in the following proposition, which can be obtained immediately from the fact that $\beta_{k\tau} = T_{ck} + (\partial p/\partial s)T_{sk}$.

**Proposition.** *Given a loan observable $X_k$ and marginal cost $c$:*

- $\beta_k = 0$ *across all quantile values* $\tau$ *implies that marginal cost do not vary with* $X_k$.

- $\beta_k \neq 0$ *and constant across all quantile values* $\tau$ *implies that marginal cost do vary with* $X_k$.

- *If* $\beta_k$ *does not fit into either of the above cases (i.e. when* $T_{sk} \neq 0$*), it has to vary monotonically with* $\tau$ *(monotonically increasing if* $T_{sk} > 0$ *or monotonically decreasing if* $T_{sk} < 0$*).*

I adopt the above testing strategy primarily due to its feasibility. Whereas search cost levels are not observed, some measures of marginal cost are. In particular, I observe the yield rate of the mortgage-backed security for which each sampled loan is serving as the collateral. Using the MBS yield rate as a proxy for the marginal cost of lending, I estimate the relationship between loan observables and the cost parameter, and verify if results from a quantile regression of transacted price would be consistent with the model.

### 2.6.3 Identifying Determinants of Marginal Cost

In order to implement the test outlined in Section 2.6.2, the first step is to determine which loan observables $X_k$ is associated with marginal cost $c$ in the sense that the derivative value $T_{ck}$ is non-zero. To this end, a simple OLS regression of marginal cost measurements on loan observables should suffice; however, since the marginal cost of lending is not directly observed, a proxy for it is necessary.

Given that mortgage lenders operate as middle-men channeling funds from the secondary mortgage market to borrowers in the primary market, useful proxies for marginal cost could be obtained from the rates that lenders borrow to fund their loans. To this end, I employ historical yield rates of mortgage-backed securities from Bloomberg, and match it with the sampled Ginnie Mae loans using the original date and coupon rate. As described in Section 2.4.2, the yield rate accounts for sale price of the mortgage-backed security at the time of sale from the lender to investors. This sale price could be different than the face value of the MBS, and needs to be accounted for in determining the true cost of borrowing funds from the secondary market. Because the yield rate accounts for variations in sale price, it is arguably a better measure of marginal cost than the coupon rate.

I then run the following OLS regression of yield rate on loan observables:

$$
\begin{aligned}
yield = {} & \beta_0 + \beta_1 credscore + \beta_2 opb + \beta_3 ltv + \beta_4 debtexp + \beta_5 numborrow \\
& + \beta_6 downassist + \beta_7 firstbuy + \beta_8 numunit + \beta_9 controls + error
\end{aligned}
\tag{2.16}
$$

where *credscore* refers to the borrower's FICO credit score; *opb* is the loan's original principal balance measured in thousands of dollars; *ltv* is the loan-to-value ratio; *debtexp* is the borrower's ratio of total debt expense to income; *numborrow* is the number of borrowers undersigning the contract; *downassist* is a dummy variable indicating if the borrower receives gift funds for the down; *firstbuy* is a dummy indicating if the borrower is a first-time homebuyer; *numunit* is the number of units in the real estate property being mortgaged; *controls* refer to additional controls in the regression, including a set of dummies indicating the origination channel (broker, retail, or correspondent), state, and month of origination. The regression is run separately using either the coupon or yield rate of mortgage-backed securities as the dependent variable.

In the above regression, loan observables whose coefficient is non-zero would correspondingly have non-zero partial derivative value $T_{ck}$. According to the model's predictions in Section 2.6.2, in a quantile regression of transacted interest rate, these same loan observables would have coefficients that either vary monotonically or equal to a non-zero constant across all quantiles. On the other hand, observables not varying with marginal cost would have coefficients that change monotonically across quantiles or equal to zero. I run the regression in equation (2.16) and distinguish between independent variables that have statistically significant coefficients and those who do not. In order to examine economic significance, I run an additional regression, almost identical to that in in equation (2.16), but using variables standardized by their mean and standard deviation.

Results of these regressions are presented in Table 2.5. Most statistically significant estimates, except that for the first-time homebuyer indicator, are signficant at the 1% level. This indicates evidence that the partial derivative of marginal cost with respect to statistically signifcant variables is non-zero. These variables include: credit score, original principal balance, loan-to-value, down payment assistance dummy, first-time homebuyer status, and number of units. On the other hand, debt expense to income ratio and number of borrowers do not seem to be correlated with marginal cost. Together the independent variables explain about half the variation in the yield rate ($R^2 = 0.50$).

In the standardized specification, as expected, the statistical significance of estimates is consistent with results in the non-standardized regression. In the standardized regression, coefficient estimates represent the effects of a one standard deviation increase in the explanatory variable on the explained variables yield and coupon rates, which are also standardized. Loan-to-value ratio and number of units, despite being highly statistically significant, seem to exhibit little economic significance. A one standard deviation change in loan-to-value, for instance, is associated with a .014 standard deviation reduction in yield rates.

Estimates in Table 2.5 suggest that many loan characteristics are related to the yield rate of Ginnie Mae mortgage-backed security. This relationship exists even though Ginnie Mae mortgage-backed securities typically trade near the risk-free rate, as shown in Section 2.4.2. I speculate that, the explanation behind these seemingly contradictory observations is that loan characteristics affect the prepayment risk of mortgages, and consequently the price and yield rate of MBS. If a certain loan characteristic is positively correlated with prepayment probability, then it will be negatively correlated with the term structure of the mortgage.

Table 2.5: Regression of MBS Yield Rate on Observables

| Dependent Variable | Yield Rate | Yield Rate (Standardized) |
|---|---|---|
| Credit Score | 0.11*** | 0.16*** |
| | (0.003) | (0.004) |
| Original Principal Balance | 0.031*** | 0.094*** |
| | (0.001) | (0.006) |
| Loan-to-Value | -0.097*** | -0.014*** |
| | (0.025) | (0.004) |
| Debt Expense Ratio | -0.0075 | -0.0022 |
| | (0.013) | (0.004) |
| Number of Borrowers | 0.12 | 0.0020 |
| | (0.224) | (0.004) |
| Down-Payment Assistance | -2.93*** | -0.030*** |
| | (0.383) | (0.004) |
| First-time Homebuyer | 0.49* | 0.0074* |
| | (0.246) | (0.004) |
| Number of Units | -1.98*** | -0.014*** |
| | (0.542) | (0.004) |
| Origination Channel Fixed Effects | Yes | Yes |
| State Fixed Effects | Yes | Yes |
| Month-Year Fixed Effects | Yes | Yes |
| Observations | 36,305 | 36,305 |
| $R^2$ | 0.50 | 0.50 |

Standard errors in parentheses. In the standardized specification, all variables, including the independent variables, are standardized around their mean.

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

An increase in this observed characteristic will lower the price of the MBS and increase its yield.

For the three loan characteristics (credit score, principal balance, and loan-to-value) whose relationship with prepayment has been analyzed in the previous literature, the evidence is supportive of the above explanation. For instance, LaCour-Little (1999), using data from an anonymous loan-servicing firm, documents that loan size and borrower's credit score are positively associated with prepayment probabilities. The author also finds that current-level loan-to-value ratio has a positive association with prepayment, although loan-to-value ratio at the time of origination does not. In another study of prepayment loan characteristics, Peristiani, Bennett, Monsen, Peach and Raiff (1997) find that an increase in loan-to-value ratio decreases prepayment probabilities; their result is consistent with the results in Table 2.5 and suggests that loan characteristics may ultimately affect yield rates through their association with prepayment risk.

Since there is no clear basis on which to evaluate the magnitude of economic significance, I use statistical significance in determining if a loan variable is correlated with marginal cost. In the next section, I use this information to verify if a quantile regression of transacted interest rates produce results that are consistent with what the model predicts in Table 2.4.

### 2.6.4 Quantile Regression Results

I run the following quantile regression of transacted interest rate on loan observables:

$$\begin{aligned} Q_\tau(p \mid \beta_\tau) = \beta_{0\tau} &+ \beta_{1\tau} credscore + \beta_{2\tau} opb + \beta_{3\tau} ltv + \beta_{4\tau} debtexp + \beta_{5\tau} numborrow \\ &+ \beta_{6\tau} downassist + \beta_{7\tau} firstbuy + \beta_{8\tau} numunit + \beta_{9\tau} controls \end{aligned} \tag{2.17}$$

for quantile values $\tau \in \{0.05, 0.25, 0.5, 0.75, 0.95\}$. Explanation of independent variables are given in Section 2.6.3. The quantile regression shows the marginal effects of covariates on the conditional quantile function of transacted interest rate, as described in equation (2.11). Results of this quantile regression are presented in Table 2.6. Below I discuss the results concerning each covariate and to what extent they support the theoretical model outlined in Section 2.5.

Table 2.6: Quantile Regression of Interest Rates on Observable Loan Characteristics

| | Q(0.05) | Q(0.25) | Q(0.50) | Q(0.75) | Q(0.95) |
|---|---|---|---|---|---|
| Credit Score | -0.11*** | -0.17*** | -0.16*** | -0.19*** | -0.21*** |
| | (0.005) | (0.003) | (0.004) | (0.005) | (0.010) |
| Original Principal Balance | -0.03*** | -0.04*** | -0.04*** | -0.05*** | -0.06*** |
| | (0.004) | (0.003) | (0.003) | (0.003) | (0.006) |
| Loan-to-Value | 0.20*** | 0.19*** | 0.13** | 0.15** | 0.21*** |
| | (0.06) | (0.03) | (0.05) | (0.06) | (0.06) |
| Debt Expense Ratio | 0.06* | 0.05** | 0.02* | -0.04 | -0.10* |
| | (0.03) | (0.02) | (0.01) | (0.02) | (0.05) |
| Number of Borrowers | 0.17 | 0.17 | -0.19 | -0.35 | 0.18 |
| | (0.51) | (0.40) | (0.39) | (0.47) | (0.80) |
| Down-payment Assistance | 2.36** | 4.43*** | 7.16*** | 7.67*** | 5.51*** |
| | (1.01) | (0.90) | (0.86) | (1.13) | (1.46) |
| First-time Homebuyer | -0.41 | -0.03 | 0.01 | -0.44 | -2.51** |
| | (0.59) | (0.35) | (0.41) | (0.51) | (1.07) |
| Number of Units | -0.93 | 1.30 | 3.47*** | 5.32*** | 8.14*** |
| | (1.04) | (0.96) | (0.74) | (0.92) | (2.49) |
| Origination Channel Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| State Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Month-Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 36,963 | 36,963 | 36,963 | 36,963 | 36,963 |

Standard errors in parentheses.

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

*Credit Score*

A one unit increase in the borrower's FICO credit score is associated with a 0.16 basis point decrease in median transacted rates, with lower effects in the lower quantiles and larger effects in the upper quantiles. The estimated coefficients decrease monotonically throughout the quantiles, from 0.11 in the .05 regression to 0.21 in the .95 regression. A Wald test rejects that the coefficients are equal at the 1% level. As discussed in Section 2.6.3, credit score is likely to be correlated with marginal cost, and a pattern of monotonic decrease across quantiles is consistent with predictions of theoretical model.

*Original Principal Balance*

In the median regression, a $1000 increase in the loan amount is associated with a .04 basis point decrease in the transacted interest rates. The magnitude of this coefficient estimate may seem small at first, but could be economically meaningful as the principal balance is typically several hundreds of thousands of dollars. The average loan amount is around $178,000 with a standard deviation of about $93,000. The estimated coefficients also show a pattern of monotonic decrease, with the largest values being -.03 in the .05 quantile regression, and the smallest being -.06 in the .95 quantile regression. All estimates are statistically different, and a test would reject that these coefficients are constant across quantiles. As original principal balance is shown to be correlated with marginal cost, this result also lends support to the model.

*Loan-to-Value Ratio*

Estimated coefficients for the loan-to-value ratio shows a different pattern compared to those obtained for credit score and original principal balance. The estimated coefficients seem to display a non-monotonic pattern across quantiles, with the lowest estimate being .13 in the median regression. The estimates seem to increase in both lower and upper quantiles to .20 in the .05 quantile regression, and .21 in the .95 quantile regression. However, a Wald test shows that a null hypothesis that coefficients across quantiles are all equal produces a p-value of 0.68 and thus cannot be rejected. Furthermore, a separate Wald test rejects the null that all coefficients are equal to 0, with a p-value less than $10^{-4}$. Hence, the estimated coefficients for the loan-to-value ratio is likely to be a non-zero constant across quantiles. Because the loan-to-value ratio is shown to be correlated with marginal cost, this pattern of estimated coefficients is also consistent with the model.

*Debt Expense to Income Ratio*

This is the only loan variable whose estimated coefficients seem to change signs as the quantile value is increased. The margainal effect of this loan osbervable on interest rate declines from an increase of 0.06 basis points in the .05 regression to virtually zero in the .75 regression. In the .95 quantile regression, the marginal effect become becomes negative and significant; a one percentage point increase in the debt expense to income ratio is associated with a -.10 basis point change in transacted interest rate at the very top quantile. All coefficient estimates, except that of the .75 regression, are significant at the 10% level. As the debt expense to income ratio is shown not to be correlated with marginal cost, this pattern of monotonic decrease also fits with the model.

*Number of Borrowers*

The number of borrowers undersigning the mortgage loan does not seem to affect the transacted interest rate at any of the quantile considered. Table 2.6 shows that the estimated coefficient for this loan observable is not statistically significant in any of the columns. The point estimate ranges from -.35 in the .75 quantile regression to .18 in the .95 quantile regression. A Wald test assuming that all the coefficients are all simultaneously equal to zero yields a p-value of .75; the null hypothesis therefore cannot be rejected. As the number of borrowers is one of the two covariates that are insignificant in the marginal cost regression, the non-significance of its coefficient estimates in Table 2.6 is another evidence in support of the model.

*Down Payment Assistance*

This covariate is correlated with marginal cost according to results in Table 2.5. Its marginal effects on transacted interest rate must therefore vary monotonically or equal a non-zero constant across quantiles. Results in Table 2.6 confirm this prediction. Whether the borrower receives a down payment assistance seems to be strongly associated with all quantiles of transacted interest rate. The coefficient estimates for this independent variable increases steadily from 2.36 in the .05 quantile regression to 7.67 in the .75 quantile regression. At first sight, there seems to be a decrease at the very top quantile; the coefficient estimate in the .95 quantile is 5.51. However, a Wald test cannot reject the hypothesis that the estimates are equal at the .75 and .95 quantiles. It is then plausible to argue that the coefficient estimates follow a monotonic pattern of increasing values across quantiles, which is consistent with the model.

*First-time Homebuyer Status*

The coefficient estimates for this loan observable is statistically indistinguishable from zero at most quantiles of transacted rates, before becoming significant at the very top quantile. In the .95 quantile regression, a borrower who is a first-time homebuyer would receive a rate that is 2.51 basis points lower than a borrower who is a repeated homebuyer. Therefore, the quantile coefficients for first-time homebuyer status also express a pattern of monotonic decrease as we move up the quantiles. Even though in Section 2.6.3 it cannot be determined unambiguously if this loan observable is correlated with marginal cost, a pattern of monotonic variation across quantiles ensures consistency with the model in either case.

*Number of Units*

Given that this loan variable is a correlate of marginal cost, one would expect its quantile regression coefficients to be increasing or a non-zero constant. The .05 and .25 coefficient estimates for the number of units is statistically indistinct from zero. However, as the higher quantiles of transacted rates are considered, the coefficients becomes significant and also express a pattern of monotonic increase. In the median regression, having an additional unit in the mortgaged property would increase interest rate by 3.47 basis points. The marginal effect is extended to 5.32 and 8.14 basis points respectively in the .75 and .95 regressions. A Wald test rejects the hypothesis that all coefficients are equal with a p-value of $10^{-4}$. I conclude that the coefficient estimates are monotonically increasing across quantiles, an outcome that is consistent with the model.

*Summary*

Estimates from a quantile regression of transacted interest rates on loan observables have so far largely supported predictions of the model. For six of the observables under consideration: credit score, original principal balance, debt expense to income ratio, down payment assistance, first-time buyer, and number of units, the coefficient estimates shows a monotonic pattern across quantile. The coefficients of loan-to-value, a loan observable that correlates with marginal cost, are likely to be a non-zero constant. The coefficients of number of borrowers, which does not correlate with marginal cost, is approximately zero throughout all quantiles.

In theory, one can also examine the pattern of coefficient estimates for control variables included in the regression equation 2.17. These control variables include indicators for the origination channel, the state where the property is located, and the monthly date of origination. I decide to omit a more detailed discussion on the estimates regarding these control variables in order to focus on more economically meaningful loan observables.

A concise summary of quantile regression results and how they conform with the model is provided in Table 2.7. I conclude from this exercise that the model of mortgage shopping and price discrimination is supported by the data and the empirical analysis. It is therefore likely that borrowers in the U.S. government-backed mortgage markets are discriminated because of their search costs.

Table 2.7: Conformity of Regression Results with the Model's Predictions

| Loan Observables | Observable Affiliated with Marginal Cost? | Cross-Quantile Relationship of Estimated Coefficients | Results Conform with Model? |
|---|---|---|---|
| Credit Score | ✓ | ↓ | ✓ |
| Original Principal Balance | ✓ | ↓ | ✓ |
| Loan-to-Value | ✓ | Non-zero Constant | ✓ |
| Debt Expense Ratio | X | ↓ | ✓ |
| Number of Borrowers | X | Approx. Zero | ✓ |
| Down-Payment Assistance | ✓ | ↑ | ✓ |
| First-Time Buyer | ✓ | ↓ | ✓ |
| Number of Units | ✓ | ↑ | ✓ |

### 2.6.5 Relationship between Loan Observables and Search Cost

The estimation results combined with the model provide additional insights into the relationship between loan observables and consumer search costs. Taking the derivative of equation (2.15) with respect to $\tau$, we have:

$$\frac{\partial \beta_{k\tau}}{\partial \tau} = \frac{\partial^2 p_\tau}{\partial s \partial \tau} T_{sk}$$

The above equation implies that:

$$\hat{T}_{sk} = \frac{\partial \hat{\beta}_{k\tau}/\partial \tau}{\partial^2 p_\tau / \partial s \partial \tau}$$

Because $\partial^2 p_\tau / \partial s \partial \tau > 0$, as shown in Appendix B.2, the sign of $\hat{T}_{sk}$ should be the same as the sign of $\partial \hat{\beta}_{k\tau}/\partial \tau$. Hence, from Table 2.6, it is straightforward to determine if a loan observable is positively or negatively related to search cost. Table 2.8 displays the results of this exercise.

Most loan observables under consideration turns out to be negatively correlated with search cost. The results conform with casual observations about the market for mortgages in the US. Borrowers with a higher credit score and a lower debt expense ratio may be more financially educated and therefore have smaller search cost for mortgages. Likewise,

Table 2.8: Relationship between Loan Observables and Search Cost

| Loan Observables | $\partial\hat{\beta}_{k\tau}/\partial\tau$ | Relationship with Search Cost |
|---|---|---|
| Credit Score | $-$ | $-$ |
| Original Principal Balance | $-$ | $-$ |
| Loan-to-Value | 0 | 0 |
| Debt Expense Ratio | $-$ | $-$ |
| Number of Borrowers | 0 | 0 |
| Down-Payment Assistance | $+$ | $+$ |
| First-time Buyer | $-$ | $-$ |
| Number of Units | $+$ | $+$ |

borrowers who have a higher original principal balance are likely to be more motivated to engage in shopping. Perhaps interestingly, I also find that the loan-to-value ratio and the number of borrowers undersigning the contract most likely are not correlated with search costs. Whether the borrower obtains a down-payment assistance and the number of units seem to be increasing with search costs. The results, even though only suggestive in nature, may be helpful for businesses and policy-makers as search costs are rarely observed directly.

## 2.7 Conclusion

In this chapter, I formulate a theoretical model of mortgage pricing that includes elements of consumer search and price discrimination. The model is then tested using recent data on government-backed mortgages from September 2013 to December 2015. Estimates from a quantile regression of transacted interest rates on loan observables are consistent with predictions of the economic model.

I conclude in light of this evidence that the price distribution observed in U.S. mortgage markets is consistent with the practice of price discrimination by mortgage lenders. Borrowers with a higher search cost are charged a higher markup compared to those with a lower search cost, even when marginal cost is held constant. The paper is one of the first to provide evidence of economic discrimination in the context of mortgage markets in the United States.

We know from economic theory that the presence of price discrimination can have important implications on market welfare. Compared to the case of uniform pricing, price discrimination can change total welfare level, as well as redistribute welfare between groups of consumers and firms. Given that price discrimination is likely to exist in U.S. mortgage markets, a potential future research avenue would be to quantify the welfare effects of discrimination and inform policies concerning this industry.

# Appendix A

# Appendices for Chapter 1

## A.1 Standard Errors of Search Cost Cut-offs

The estimation described in Section 1.5 identifies $N$ search cost cut-offs in any given market with $N$ lenders (including the cut-off of the highest quality lender, which is always 0). Observed market shares identify the CDF values at the cut-offs $G(c_j)$, and markups identify the cut-off levels for the $N-1$ lenders excluding the highest quality one. A question naturally arises about how precise the estimated cut-offs and their CDF values are.

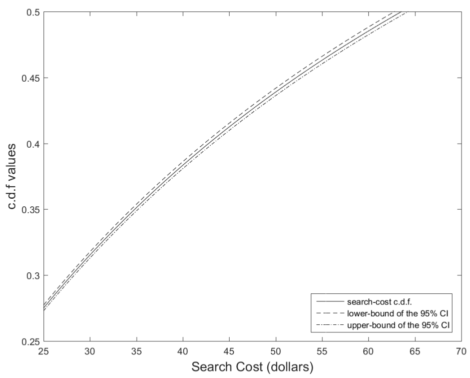
In order to provide some information regarding the preciseness of our estimation procedure, I employ the empirical bootstrap method to obtain standard errors around the estimated search cost cut-offs. This section outlines how bootstrap samples are created and the resulting estimates of standard errors.

The starting point is the loan-level dataset described in Section 1.3.2. For each lender in each state, I keep the number of loans fixed, but replaced each original loan observation with another one randomly drawn from the sample. Because the number of loans for each lender is kept unchanged, the market shares of lenders are kept fixed throughout the bootstrapping procedure. On the other hand, estimated markups may change because randomly drawn loan observations may have different interest rates and are tied with mortgage-backed securities with a different market yield rate.

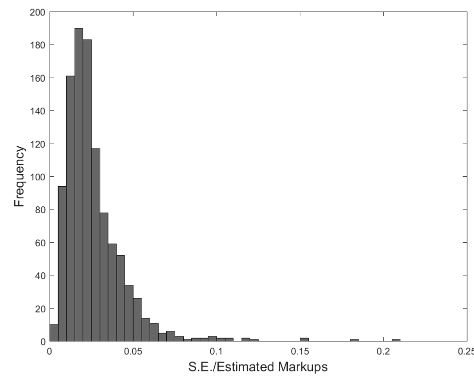
Keeping market shares fixed is necessary as observed markets at the state level have many small lenders with low market shares who may disappear from the bootstrapped sample otherwise. However, as market shares identify $G(c_j)$, these values also be constant across different bootstrapped samples. Bootstrapping with fixed market shares allows us only to examine errors in the cut-off values $c_j$. In other words, we examine the asymptotic scenario when the number of customers at each lender approaches infinity, but the relative shares are the same. The bootstrapped confidence intervals represents the range over which our procedure is likely to contain the true values of the cut-offs.

With the above caveats, I create 200 bootstrapped random samples from the loan-level data and estimate cut-off $\hat{c}_j$ separately for each sample. I compute the deviations in these bootstrapped estimates $\hat{c}_j$. The range between the 2.5 and 97.5 percentiles of these deviations represent the 95% confidence interval around our original estimates.

The estimated confidence intervals from this process are extremely tight. In Figure A.1a, the search cost distribution in Texas and its 95% confidence intervals are zoomed in around the median search cost value. The dashed lines represent the upper and lower bound of the CDF. Both the lower and upper bounds, as well as the original CDF curve, are obtained by fitting a log-normal CDF around estimated $\hat{c}_j$. As shown in this figure, both curves are very close to each other and to the original CDF estimate. The tightness of the confidence intervals suggests that there is little variation in the estimated markups of lenders across bootstrapped samples. Figure A.1b confirms the preciseness of estimated markups. I calculate the standard errors of estimated markets and graph a histogram of computed standard errors divided by estimated markups. For the majority of lenders, the standard error is less 5% of the estimated markup. Because estimated markups seem to be precise, tight confidence intervals around estimated search cost cut-offs can be explained.




(a) A Portion of the 95% Confidence Intervals of Search Cost in Texas




(b) Histogram of S.E. divided by Estimated Markups

Figure A.1: Estimated Standard Errors of Search Cost Cut-offs

## A.2 Calculations of Profit, Quality, and Search Expenditure

### A.2.1 Profit

Let $M_s$ denote the number of loans in a state-level market $s$. Absolute markup $m_{js}$, as described in Section 1.4, can be viewed as the profit for each loan that lender $j$ in state $s$ originates. Therefore, total expected profit for lender $j$ is:

$$\Pi_{js} = M_s \times ms_{js} \times m_{js}$$

where $ms_{js}$ denotes the market share of lender $j$. Conceptually, the above equation is exactly equation 1.7 in the text with the state-level subscript $s$ added in for clarity. Then, average profit per loan across all lenders in each state would be:

$$\overline{\Pi}_{ijs} = \frac{\sum_{j=1}^{N_s} \Pi_{js}}{M_s}$$

At the national level, I calculate average profit per loan as the market size weighted average of $\overline{\Pi}_{ijs}$ across all 51 markets:

$$\overline{\Pi}_{ij} = \frac{\sum_{s=1}^{51} M_s \times \overline{\Pi}_{ijs}}{\sum_{s=1}^{51} M_s}$$

The numerator in the above formula is total profit at the national level.

### A.2.2 Quality

In order to measure welfare effects resulting from a gain in the quality of lenders in the counterfactuals, I first weight quality by market share and obtain total transacted quality at the state-level:

$$Q_s = M_s \sum_{j=1}^{N_s} ms_{js}\delta_{js}$$

Per-loan transacted quality can be obtained by dividing $Q_s$ by the number of loans $M_s$:

$$\overline{Q}_s = \sum_{j=1}^{N_s} ms_{js}\delta_{js}$$

To obtain per-loan transacted quality at the national level, I calculate the market size weighted average of $\overline{Q}_s$ across all 51 markets:

$$\overline{Q} = \frac{\sum_{s=1}^{51} M_s \times \overline{Q}_s}{\sum_{s=1}^{51} M_s}$$

The numerator in the above formula is total quality at the national level.

### A.2.3 Search Expenditure

As explained in the text, for a given search cost level $s_i$, total expected search cost for borrower $i$ in state $s$ can be computed as:

$$E_{is} = \frac{s_i}{\lambda_i}$$

where $\lambda_i$ is the probability of success during each search instance. If $s_i$ is repeatedly and randomly drawn from a given market's search cost distribution, then market level expenditure would be:

$$E_s = \sum_{i=1}^{M_s} E_{is}$$

Per-loan search expenditure in each state would then be:

$$\overline{E}_s = \frac{E_s}{M_s}$$

Per-loan search expenditure at the national level would be the market size weighted average of $E_s$ across 51 markets:

$$\overline{E} = \frac{\sum_{s=1}^{51} M_s \times \overline{E}_s}{\sum_{s=1}^{51} M_s}$$

The numerator in the above formula is total search expenditure at the national level.

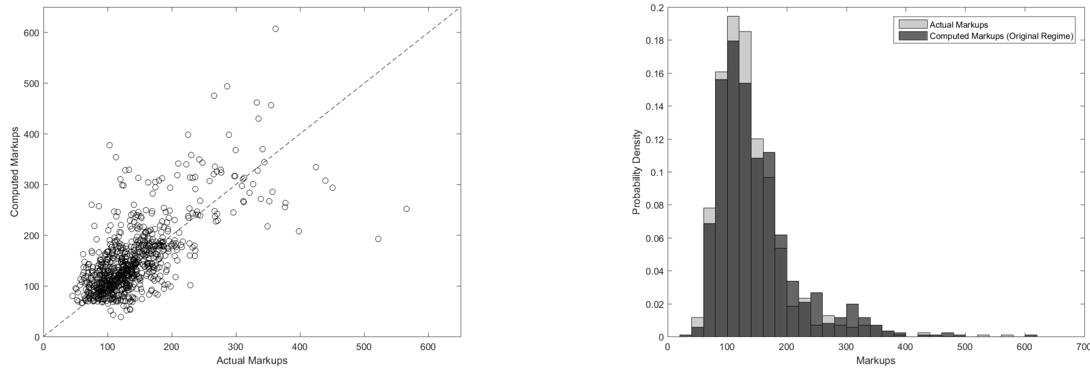
## A.3 Numerical Solver in the Counterfactual of Search Cost Reductions

The primitives of the counterfactual exercise consist of the vector of lenders' quality $(\delta_1, \ldots, \delta_N)$ and the distribution of consumer search cost with its CDF $G(\cdot)$ and PDF $g(\cdot)$. Given these primitives, it is possible to solve for the optimal markups charged by all lenders in the market, except the highest quality one. The first-order conditions of lenders is a system of $N-1$ equations that could be solved for $N-1$ markups. For $j = \{1, \dots, N-1\}$:

$$\frac{\partial ms_j}{\partial m_j} \times m_j + ms_j = 0 \tag{A.1}$$

In the above equation, market shares $ms_j$ depend on the CDF $G(c)$, and the market share derivatives $\partial ms_j / \partial m_j$ depend on the PDF $g(c)$. The optimal stopping rule establishes $c$ as a function of lender quality $\delta$ and markup $m$. Because of this, it is possible to compute profit-maximizing markups for $N-1$ lenders in each market under the counterfactual scenarios of search cost reduction.

Given $G(\cdot)$, $g(\cdot)$ and $\delta$, I solve for optimal markups $m$ using the numerical solver `fsolve` in `MATLAB`. In figure A.2, I evaluate the performance of this numerical method by first computing optimal markups under the original equilibrium with no search cost reductions. How computed markups coincide with the actual, observed markups in the data is an indication of `fsolve`'s reliability. In panel A.2a, I plot the computed markups against the observed markups. This panel shows that at the firm-level, there is some discrepancy between computed and observed markups, although they are clearly positively correlated. In panel A.2b, I graph the histograms of computed and observed markups. I find that their distribution shows similarities. From the two panels, I conclude that while it's difficult to assess the relationship between computed and observed markups at the firm-level, it is still meaningful to talk about them at the distributional level. I therefore employ `fsolve` in order to calculate results for all counterfactual scenarios considered in the main text.




(a) Scatter Plot (b) Histogram

Figure A.2: Computed and Actual Markups in the Original Equilibrium

# A.4 Counterfactual of Search Cost Reductions

## A.4.1 An Alternative Assumption on Markups: Lender $N$'s Markup Varies Proportionally with Search Cost Reductions

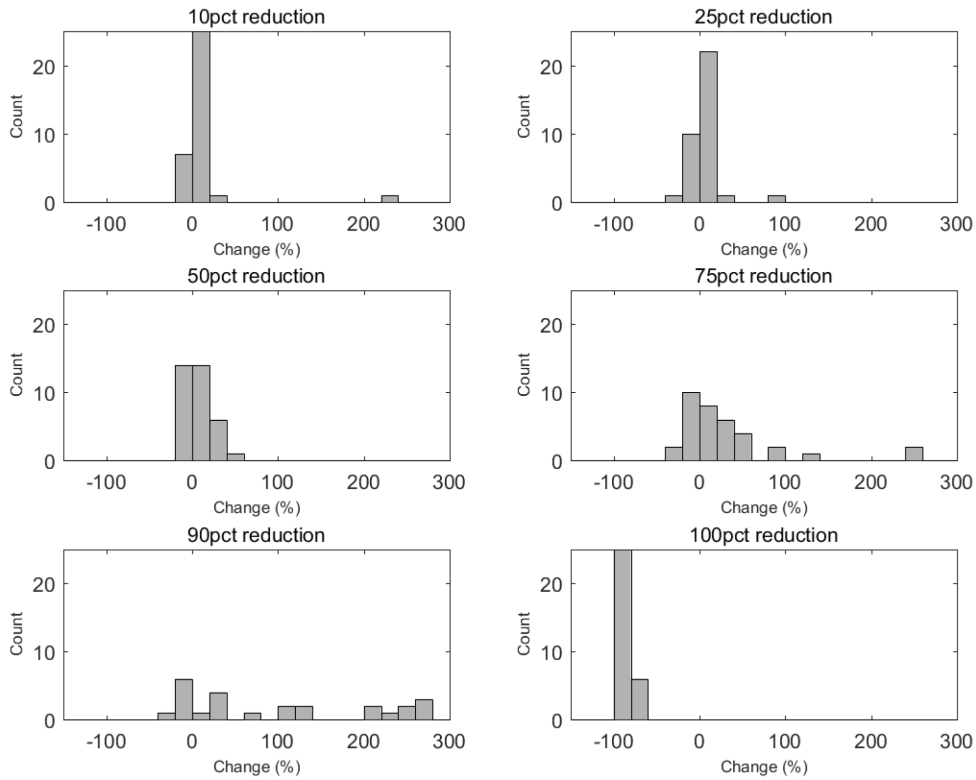
As explained in Section 1.7, the mortgage search model does not impose a first-order condition on the profit-maximizing behavior of the highest quality lender in each market. For this lender (denoted by $N$), we know its profit-maximizing markup at the two extremes of search cost reductions: when search costs are reduced by 0 or by 100 percents. In the main text, I solve the model by assuming that lender $N$'s markup is kept unchanged throughout all the counterfactual scenarios. Here I consider an alternative assumption and specify lender $N$'s markup as varying proportionally with the magnitude of search cost reductions:

$$m_N^r = m_N^{r=0} + (m_N^{r=100} - m_N^{r=0}) \times r/100$$

where $r = 10$, 25, 50, 75, 90 denotes the percentage point reductions in search costs.

In Figures A.3 and A.4 I show the price effects of search cost reductions under this alternative assumption on markups. These price effects are similar to what is presented in

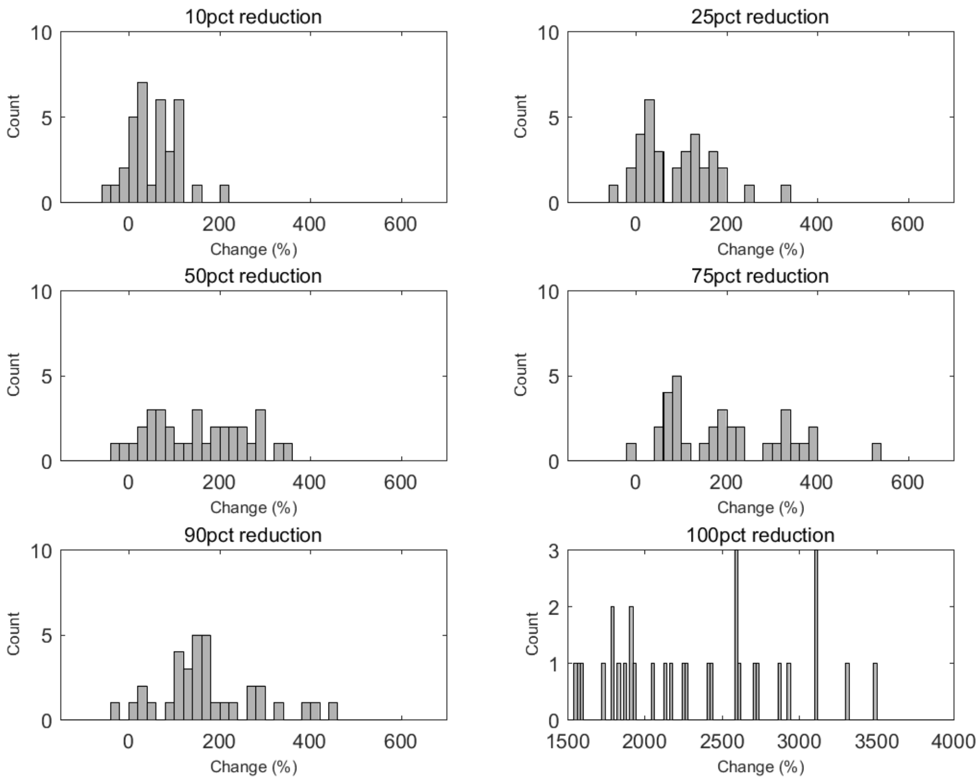
Figure A.3: Distribution of Changes in Average Markup following Search Cost Reductions




Section 1.7. Average markups shows a tendency to increase with search cost reductions up until the extreme case of 100% reductions, where average markups decline. Price dispersion, on the other hand, increases monotonically throughout the counterfactual scenarios, with the most significant increase occurring in the full information scenario. These price effects are qualitatively similar to those derived in Section 1.7. One explanation for the increase of average markups is that the reductions of search costs by a certain percentage make search costs more homogeneous across borrowers, and the model becomes closer to that described by the Diamond paradox where all firms charge the monopoly price (Diamond, 1971).

As for the welfare effects, Tables A.1 and A.2 show calculation results at both the loan level and the national level. We see that the alternative assumption on lender $N$'s markup has a small impact on the welfare numbers. However, the results are qualitatively unchanged, as

Figure A.4: Distribution of Changes in Markup Dispersion following Search Cost Reductions




evidenced in Figure A.5. Profits show a slight increase; total transacted quality also increases, while search expenditure decrease. As a result, social welfare increases monotonously. These qualitative results are also found in Section 1.7.

Table A.1: Welfare Effects (in dollars) at the Loan Level

| Search Cost Reduction | 0% | 10% | 25% | 50% | 75% | 90% | 100% |
|---|---|---|---|---|---|---|---|
| Profit | 139 | 163 | 169 | 188 | 221 | 291 | 299 |
| Total Quality | 408 | 495 | 507 | 539 | 596 | 695 | 698 |
| Search Expenditure | 314 | 226 | 199 | 153 | 106 | 82 | - |
| Social Welfare | 94 | 270 | 308 | 386 | 489 | 614 | 698 |

See Appendix A.2 for how welfare quantities are calculated at the loan level.

Table A.2: Total Welfare Effects (in million dollars) at the National Level

| Search Cost Reduction | 0% | 10% | 25% | 50% | 75% | 90% | 100% |
|---|---|---|---|---|---|---|---|
| Profit | 8.46 | 7.11 | 7.36 | 8.20 | 9.60 | 12.69 | 18.11 |
| Total Quality | 24.74 | 21.58 | 22.07 | 23.46 | 25.94 | 30.28 | 42.33 |
| Search Expenditure | 19.05 | 9.83 | 8.68 | 6.65 | 4.63 | 3.55 | - |
| Social Welfare | 5.69 | 11.75 | 13.40 | 16.81 | 21.31 | 26.72 | 42.33 |

Market size in each state is the average number of new loans each month from September 2013 to December 2015. See Appendix A.2 for how welfare quantities are calculated at the national level.

### A.4.2 An Alternative Assumption on Search Cost Reduction: Reducing the Mean while Keeping the Variance Constant

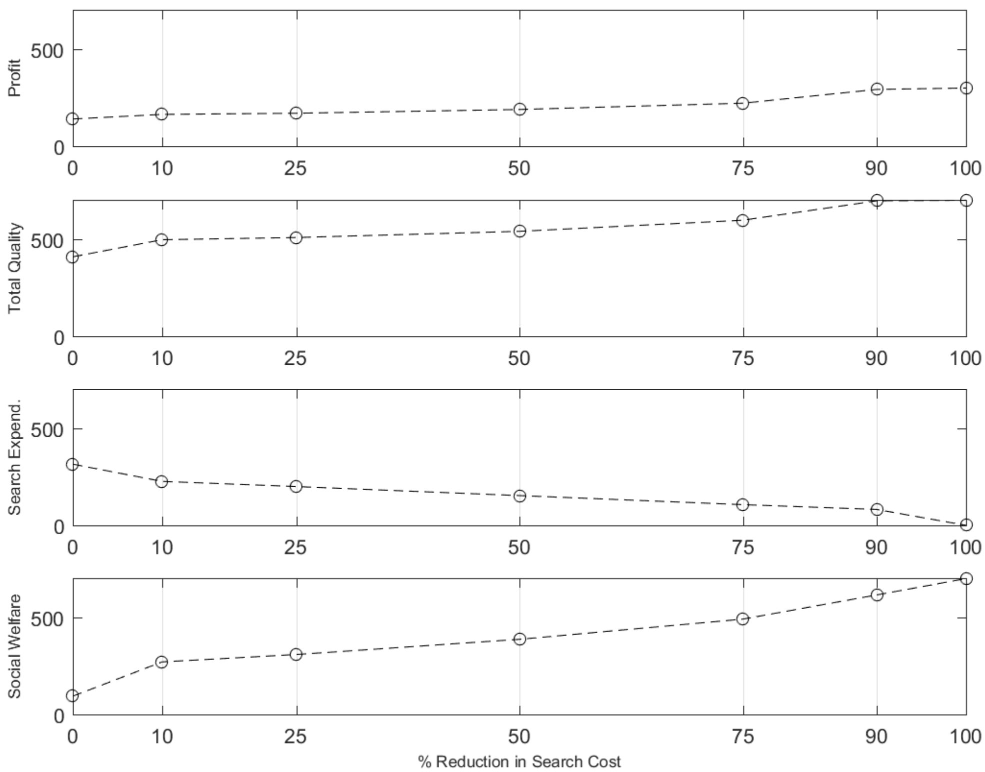
In order to provide additional insights into how search cost reductions affect average markups, I run a counterfactual scenario where the mean of search costs in each market is reduced by 50%, while the variance is kept unchanged.[1] As explained in Section 1.7, a reduction in both the mean and variance of search costs may have opposing effects on average price. Reducing the mean of search costs presumably would foster more intense price competition and lower average price, while reducing the variance makes search costs more homogeneous and induce firms to charge higher prices. This counterfactual provides evidence to support this explanation.

In order to reduce the mean and keep the variance constant, I adjust the parameters of the estimated log-normal distribution of search costs. Specifically, if the parameters of the estimated search cost distribution in the original equilibrium is given by $\hat{\mu}$ and $\hat{\sigma}$, I compute these parameters in the counterfactual as follows.

$$\tilde{\mu} = \hat{\mu} + \frac{\hat{\sigma}^2}{2} - \ln 2 - \frac{\tilde{\sigma}^2}{2}$$
$$\tilde{\sigma} = \sqrt{\ln \frac{(\exp M)^2[\exp(\hat{\sigma}^2) - 1]}{[\exp(M - \ln 2)]^2}}$$

[1] I thank Rich Sweeney for his suggestions on this counterfactual.

Figure A.5: Welfare Effects (in dollars) at the Loan Level




where $M = \hat{\mu} + \hat{\sigma}^2/2$. It can be verified that a log-normal distribution with parameters $(\tilde{\mu}, \tilde{\sigma})$ will have the same variance and half the mean as those of a log-normal distribution with parameters $(\hat{\mu}, \hat{\sigma})$.

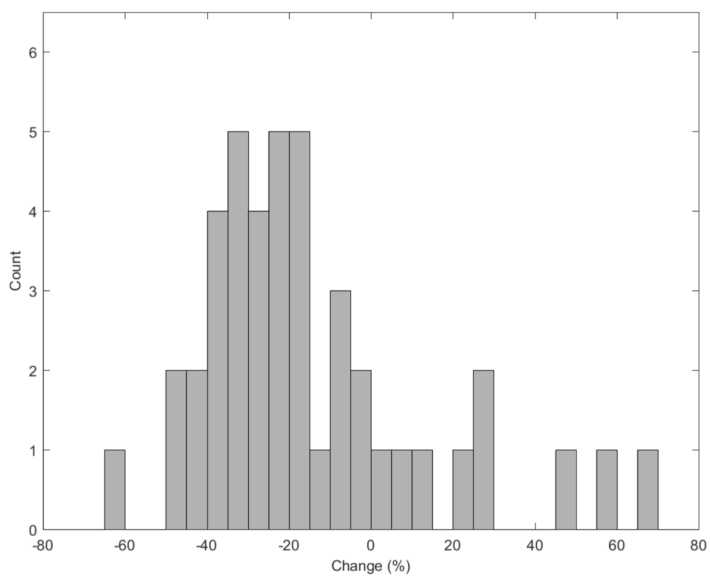
Given the counterfactual search cost distributions with parameters $(\tilde{\mu}, \tilde{\sigma})$, I re-optimize the model and solve for the vector of optimal markups. As in the main text, I assume that in each market, the markup of the highest quality lender is not changed when search costs are reduced. I compute the average markup in each market in the counterfactual, and then calculate the percentage change in average markup relative to the original equilibrium.

Figure A.6 shows a frequency count of how average markups in this counterfactual compare to those in the original equilibrium. When only the mean of search cost is reduced and not the variance, most markets experience a price decline; the histogram is skewed to the left of zero. Out of the 38 markets where the numerical solver succeeds in finding a solution, 29 markets experience decline in average markups. The magnitude of decline ranges from a few percentage points to over 60 percents. Nine markets seem to have price increase in this counterfactual, and some increases can be as significant as nearly 70% over the original markups.

Given the price increase in these nine markets, one may think that the assumption about lender $N$'s markup being constant is not a good approximation in these cases. Alternatively, it's also possible that average markup is related to additional measures of heterogeneity in search costs other than the variance, such as higher moments of the search cost distribution. Unfortunately, both of these explanations for price increase can not readily be tested using the current model and data.

Nevertheless, this counterfactual shows that the majority of markets experience a significant average price decline when only the mean of search costs is reduced. Some of these declines are not observed when both the mean and variance are reduced as in Section 1.7, where 25 out of 39 markets have price decline in the 50% reduction case. Moreover, the magnitude of average markup decline is also higher when the variance of search costs is held constant. In Section 1.7, the average price change is about -2.11% in the 50% reduction case, whereas in the current counterfactual with constant variance, the average price change is -15.1%. Thus, there is good reason to believe that the variance of search costs plays a role in affecting average markups. If search costs become more homogeneous, average markups would tend to rise.

Figure A.6: Distribution of Changes in Average Markup when only the Mean of Search costs is Reduced



# Appendix B

# Appendices for Chapter 2

## B.1 Mixed Strategy Equilibrium

Let $E\pi(p, F)$ be the expected profit when a lender charges $p$ when the equilibrium price distribution is $F$. Similarly to Stahl (1989), we can define a Symmetric Nash Equilibrium (SNE) as follows:

**Definition.** *A distribution $F(p)$ is a Symmetric Nash Equilibrium (SNE) if and only if $E\pi(p, F)$ is equal to a constant for all $p$ in the support of $F$ and not greater than that constant for any $p$.*

**Proposition.** *The model, as described in Section 2.5, has no pure strategy Nash equilibrium.*

*Proof.* This proposition can be proved by arguing that the equilibrium price distribution $F$ is atomless. Suppose otherwise, and $F$ has an atom at $\tilde{p}$, and the strategy of charging $\tilde{p}$ is played with some positive probability. Given this price distribution F, a lender who undercuts $\tilde{p}$ slightly would increase its probability of becoming the lowest price lender and capturing all the demand from shoppers. We have:

$$E\pi(\tilde{p}, F) < E\pi(\tilde{p} - \varepsilon, F)$$

Therefore, a price distribution $F$ with an atom at $\tilde{p}$ cannot be a SNE. Equivalently, the model does not have a pure strategy Nash equilibrium. A pure strategy may exist if shoppers vanish from the model when $\mu_t = 0$ (see Stahl (1996)), but we are excluding this case from our analysis. $\square$

**Proposition.** *There exists a mixed strategy equilibrium in which firms draw prices from an atomless distribution with support* $[\underline{p}, \bar{p}]$ *not containing* $c$.

*Proof.* The proof of existence is presented in Stahl (1996) (Theorem 3.1) and will not be reproduced here. Instead, we will show that the support of $F$ does not contain $c$, or that $\underline{p} > c$.

Suppose to the contrary that $\underline{p} = c$. Let the expected share of customers purchasing from a lender who charges price $p$ be $\Psi(p, F)$. Then we have:

$$E\pi(\underline{p}, F) = (\underline{p} - c)\,\Psi(\underline{p}, F) = 0$$

But the lender charging $\underline{p}$ can profitably increase profit by increasing its price slightly, because $\Psi(\underline{p} + \varepsilon, F) > 0$ for some $\varepsilon > 0$:

$$E\pi(\underline{p} + \varepsilon, F) = (\underline{p} + \varepsilon - c)\,\Psi(\underline{p}, F) > 0$$

Thus, $E\pi(\underline{p}, F) < E\pi(\underline{p} + \varepsilon, F)$ and $F$ is not a SNE, a contradiction. Hence $\underline{p} = c$ is not in the support of $F$. In equilibrium, we should observe $\underline{p} > c$, and lenders are making positive profit. $\square$

## B.2 Partial Derivatives of Transacted Price

As in equation (2.4), the transaction price distribution is given by:

$$
\begin{aligned}
F^{trans} &= \mu \left\{ 1 - \left[ \left( \frac{1-\mu}{\mu N} \right) \left( \frac{s}{\gamma(p-c)(1-A)} - 1 \right) \right]^{\frac{N}{N-1}} \right\} \\
&\quad + (1-\mu) \left\{ 1 - \left[ \left( \frac{1-\mu}{\mu N} \right) \left( \frac{s}{\gamma(p-c)(1-A)} - 1 \right) \right]^{\frac{1}{N-1}} \right\}
\end{aligned}
$$

For each quantile $\tau \in [0,1]$, we can define an implicit function $G$:

$$G(p,c,s,\mu) = F^{trans}(p,c,s,\mu) - \tau = 0$$

Since $F$ is the CDF of transacted prices, by definition $p$ would be increasing in $\tau$. We can use this relationship and the Implicit Function Theorem to evaluate the following partial derivatives:

$$
\begin{aligned}
\frac{\partial p}{\partial c} &= -\frac{\partial F}{\partial c} \Big/ \frac{\partial F}{\partial p} \\
\frac{\partial p}{\partial s} &= -\frac{\partial F}{\partial s} \Big/ \frac{\partial F}{\partial p} \\
\frac{\partial p}{\partial \mu} &= -\frac{\partial F}{\partial \mu} \Big/ \frac{\partial F}{\partial p}
\end{aligned}
$$

The two partial derivatives with respect to marginal cost $c$ and search cost $s$ are algrebaically simple to calculate. We outline the calculation steps below.

$$
\begin{aligned}
\frac{\partial F}{\partial p} &= \mu \frac{N}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}\right)\right]^{\frac{1}{N-1}} \times \frac{1-\mu}{\mu N}\frac{s}{\gamma(1-A)}\frac{1}{(p-c)^2} + \dots \\
&\quad + (1-\mu)\frac{1}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)} - 1\right)\right]^{\frac{2-N}{N-1}} \times \frac{1-\mu}{\mu N}\frac{s}{\gamma(1-A)}\frac{1}{(p-c)^2} \\
\frac{\partial F}{\partial c} &= -\mu \frac{N}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}\right)\right]^{\frac{1}{N-1}} \times \frac{1-\mu}{\mu N}\frac{s}{\gamma(1-A)}\frac{1}{(p-c)^2} - \dots \\
&\quad - (1-\mu)\frac{1}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)} - 1\right)\right]^{\frac{2-N}{N-1}} \times \frac{1-\mu}{\mu N}\frac{s}{\gamma(1-A)}\frac{1}{(p-c)^2} \\
\frac{\partial F}{\partial s} &= -\mu \frac{N}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}\right)\right]^{\frac{1}{N-1}} \times \frac{1-\mu}{\mu N}\frac{1}{\gamma(p-c)(1-A)} - \dots \\
&\quad - (1-\mu)\frac{1}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)} - 1\right)\right]^{\frac{2-N}{N-1}} \times \frac{1-\mu}{\mu N}\frac{1}{\gamma(p-c)(1-A)}
\end{aligned}
$$

The fractions can be simplified to obtain the derivatives with respect to $c$ and $s$:

$$
\begin{aligned}
\frac{\partial p}{\partial c} &= -\frac{\partial F}{\partial c}\bigg/\frac{\partial F}{\partial p} = 1 \\
\frac{\partial p}{\partial s} &= -\frac{\partial F}{\partial s}\bigg/\frac{\partial F}{\partial p} = \frac{p-c}{s}
\end{aligned}
$$

The partial derivate with respect to marginal cost is constant for all values of $\tau$. The partial derivative with respect to search cost is increasing in $p$, and because $p$ is increasing in $\tau$, $\partial p/\partial s$ is increasing in $\tau$ as well. The difference in how these partial derivatives vary with $\tau$ forms the basis of our empirical test, as discussed in Section 2.5.4.

Finally, we consider the derivative with respect to $\mu$, which is more cumbersome to calculate. We have:

$$
\begin{aligned}
\frac{\partial F}{\partial \mu} &= \left\{1-\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}-1\right)\right]^{\frac{N}{N-1}}\right\}+\dots \\
&\quad+\mu\left\{-\frac{N}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}-1\right)\right]^{\frac{1}{N-1}}\times\dots\right. \\
&\qquad\left.\times\left[\left(\frac{1-\mu}{\mu N}\right)\frac{s}{\gamma(p-c)(1-A)^2}\frac{\partial A}{\partial \mu}+\frac{-\mu N-1+\mu}{(\mu N)^2}\left(\frac{s}{\gamma(p-c)(1-A)}-1\right)\right]\right\}+\dots \\
&\quad+(-1)\left\{1-\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}-1\right)\right]^{\frac{1}{N-1}}\right\}+\dots \\
&\quad+(1-\mu)\left\{-\frac{1}{N-1}\left[\left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}-1\right)\right]^{\frac{2-N}{N-1}}\times\dots\right. \\
&\qquad\left.\times\left[\left(\frac{1-\mu}{\mu N}\right)\frac{s}{\gamma(p-c)(1-A)^2}\frac{\partial A}{\partial \mu}+\frac{-\mu N-1+\mu}{(\mu N)^2}\left(\frac{s}{\gamma(p-c)(1-A)}-1\right)\right]\right\}
\end{aligned}
$$

Since a lot of terms in the above equation are repeated (with changing exponents), the partial derivative $\partial p/\partial \mu$ can be written more compactly by first defining:

$$
\begin{aligned}
K_1 &= \left(\frac{1-\mu}{\mu N}\right)\left(\frac{s}{\gamma(p-c)(1-A)}\right) \\
K_2 &= \left(\frac{1-\mu}{\mu N}\right)\frac{s}{\gamma(p-c)(1-A)^2}\frac{\partial A}{\partial \mu}+\frac{-\mu N-1+\mu}{(\mu N)^2}\left(\frac{s}{\gamma(p-c)(1-A)}-1\right)
\end{aligned}
$$

With $K_1$ and $K_2$ defined as above, we can write:

$$
\begin{aligned}
\frac{\partial F}{\partial \mu} &= \left(1-K_1^{\frac{N}{N-1}}\right)-\mu\left(\frac{N}{N-1}K_1^{\frac{1}{N-1}}\times K_2\right)-\left(1-K_1^{\frac{1}{N-1}}\right)-(1-\mu)\left(\frac{1}{N-1}K_1^{\frac{2-N}{N-1}}\times K_2\right) \\
\frac{\partial F}{\partial p} &= \mu\frac{N}{N-1}K_1^{\frac{1}{N-1}}\frac{K_1}{p-c}+(1-\mu)\frac{1}{N-1}K_1^{\frac{2-N}{N-1}}\frac{K_1}{p-c}
\end{aligned}
$$

and obtain $\partial p/\partial \mu$ using the Implicit Function Theorem. Unlike $\partial p/\partial c$ and $\partial p/\partial s$, the expression for $\partial p/\partial \mu$ turns out to be quite challenging to simplify. We therefore adopt a more heuristic approach to examine how $\partial p/\partial \mu$ varies with $p$ and $\tau$.

First, consider the partial derivatives at the price boundaries. From Section 2.5.3, we have that:

$$\bar{p} = c + \frac{s}{\gamma}\frac{1}{1-A}$$
$$\underline{p} = c + \frac{\bar{p}-c}{1+\frac{\mu}{1-\mu}N}$$
$$= c + \frac{s}{\gamma(1-A)(1+\frac{\mu}{1-\mu}N)}$$

It is then straightforward to derive the partial derivatives of price boundaries with respect to $c$, $s$, and $\mu$:

$$\frac{\partial\bar{p}}{\partial c} = 1$$
$$\frac{\partial\underline{p}}{\partial c} = 1$$
$$\frac{\partial\bar{p}}{\partial s} = \frac{1}{\gamma(1-A)}$$
$$\frac{\partial\underline{p}}{\partial s} = \frac{1}{\gamma(1-A)(1+\frac{\mu}{1-\mu}N)}$$
$$\frac{\partial\bar{p}}{\partial \mu} = \frac{s}{\gamma(1-A)^2}\frac{\partial A}{\partial\mu}$$
$$\frac{\partial\underline{p}}{\partial \mu} = \frac{s}{\gamma}\frac{1}{[(1-A)(1+\frac{\mu}{1-\mu}N)]^2}\left[-\frac{\partial A}{\partial\mu}\left(1+\frac{\mu}{1-\mu}N\right)+(1-A)\left(\frac{1}{(1-\mu)^2}N\right)\right]$$

The first three equations confirm our results earlier that the partial derivative of price is constant with respect to marginal cost, and is increasing with respect to search cost (since $1+\frac{\mu}{1-\mu}N > 1$, it follows that $\partial\bar{p}/\partial s > \partial\underline{p}/\partial s$). As for the partial derivative with respect to $\mu$, a sufficient condition ensuring $\partial\bar{p}/\partial\mu < \partial\underline{p}/\partial\mu$ is (this condition depends on the value of $\mu$ and $N$):

$$\frac{\partial A}{\partial\mu}\left(\frac{\mu}{1-\mu}N\right) - (1-A)\left(\frac{1}{(1-\mu)^2}N\right) < 0$$
$$\frac{\partial A}{\partial\mu}\mu(1-\mu) < (1-A)$$

Since $\frac{\partial A}{\partial \mu} < 0$ and $A < 1$, the left-hand side is negative and the right-hand side is positive. For all values of $\mu$ and $N$, the sufficient condition is satisfied, hence $\partial \bar{p}/\partial \mu < \partial \underline{p}/\partial \mu$.

We have established that the partial derivative of price with respect to $\mu$ is smaller at the upper-bound than at the lower-bound of the price support. To check if this $\partial p/\partial \mu$ is indeed decreasing over the whole support of price, we graph it against price for different combinations of values for $N$ and $\mu$. As Figure B.1 shows, the relationship between $\partial p/\partial \mu$ and price is monotonically decreasing over the whole support of price regardless of the values chosen for $N$ and $\mu$. We therefore find it plausible that $\partial p/\partial \mu$ is decreasing in price, and equivalently also in $\tau$, for all values of $N$ and $\mu$.

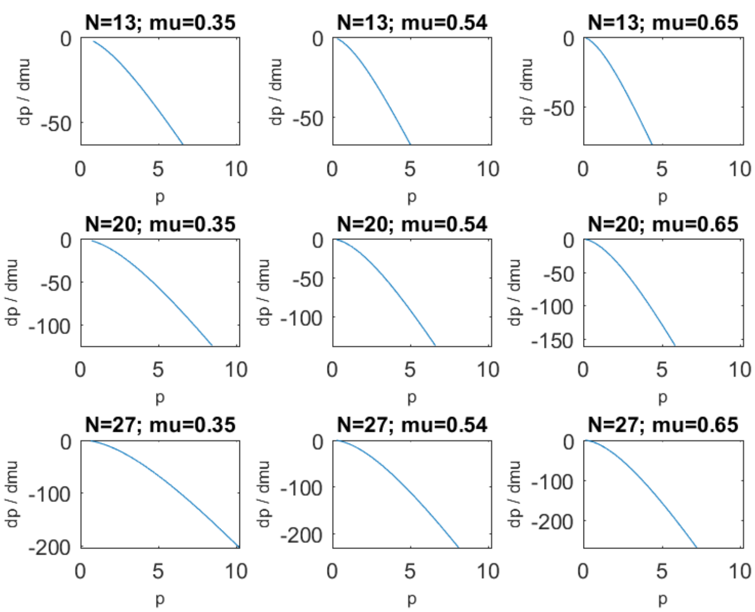



Figure B.1: The Relationship between $\partial p/\partial \mu$ and price

## B.3 Linearity of Quantile Regressions

The first derivative of transacted price with respect to search cost, solved in Appendix B.2, implies that transacted price must be linear in marginal cost and search cost. Consider the differential equation:

$$\frac{p_\tau}{s} = \frac{p_\tau - c}{s}$$

Letting $y = p_\tau$ and $x = s$, we have

$$y = c + y'x$$

Differentiating this equation yields

$$y' = y' + y''x$$

implying that $y'' = 0$ and hence, $y$ must be linear in $x$. Letting $y = \alpha + \beta x$ we have

$$\alpha + \beta x = c + \beta x$$

The above equation is satisfied for any $\beta$ when $\alpha = c$. We can thus express the relationship between transacted price, marginal cost, and search cost as:

$$p_\tau = c + \beta s$$

Thus, the dependence of transacted price on the number of firms $N$ and the fraction of shoppers $\mu$ must occur through $\beta$:

$$p_\tau = c + \beta(\tau, N, \mu)s$$

The above equation shows that the linear form of the quantile regression equations used in the empirical analysis is actually consistent with the modeling assumptions. It is also consistent with our earlier calculations that $\partial p_\tau / \partial c = 1$.

## B.4 Quantile Regressions with Simulated Data

In this Appendix, I use simulated data in order to examine the results of quantile regressions of transacted rates on marginal cost, search cost, and the fraction of shoppers. To generate the data, I set the number of firms $N = 20$, which is the average number of mortgage lenders observed in each state-level market. I also assume that there are 10 different types of consumers and the fraction of shoppers $\mu = 0.25$. I examine three separate scenarios: when marginal cost is constant, positively correlated with search cost, and negatively correlated with search cost.

In each of the scenarios, the generation of simulated data relies on the CDF of transacted prices as given in equation (2.4). I first generate a list of 1000 probability values using a standard uniform distribution with the support $[0, 1]$. For each of these probability values, I solve for the transacted price such that the CDF in equation (2.4) is equal to the given probability value. The calculation is repeated for each of the 10 customer types, and under ideal circumstances, there should be $1000 \times 10 = 10,000$ observations of simulated transacted price in each scenario.

I rely on a numerical method to solve for transacted price given a probability value of the CDF. Specifically, I use the solver `fsolve` in `MATLAB` in order to numerically solve for transacted price, and then drop observations for which the solver fails to obtain a solution. In general, the solver succeeds about half of the times. For this reason, the simulated dataset of transacted price always has less than 10,000 observations in each scenario. The numerical solver is chosen because solving analytically for the transacted price requires inverting the CDF equation. This inversion is difficult given the form of equation (2.4).

In each of the following scenarios, I consider a quantile regression of transacted prices on search cost and fraction of shoppers:

$$Q_\tau(p_i \mid s_i, \mu_i) = \beta_{0\tau} + \beta_{1\tau} s_i + \beta_{2\tau} mc_i \tag{B.1}$$

As predicted by the model, we would expect that as $\tau$ increases, $\beta_{1\tau}$ is increasing and $\beta_{2\tau}$ is approximately equals to 1 (see equations (2.5), (2.7), and (2.6)). These predictions are supported by regression results in all of the three scenarios.

### B.4.1 Scenario 1: Constant and Zero Marginal Cost

In this scenario, the marginal cost parameter is constant and zero ($c_\theta = 0$) for all consumer types $\theta$. I use `MATLAB`'s function `rand` (with the seed set to 2) in order to generate a random sequence of decreasing numbers from 3 to 0.5 to be used as search costs. Table B.1 lists these values of search cost that are then used to simulate the data.

Quantile regression results are presented in Table B.2. We see that the predictions of the model on the quantile regression coefficients are confirmed. All estimates are significant at the 1% level.

Table B.1: Data Generating Parameters

| Consumer Type ($\theta$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Search Cost ($s$) | 2.05 | 1.87 | 1.59 | 1.59 | 1.55 | 1.33 | 1.25 | 1.17 | 1.01 | 0.56 |

Table B.2: Quantile Regression of Transacted Price

| Transacted Price | Q(0.05) | Q(0.25) | Q(0.50) | Q(0.75) | Q(0.95) |
|---|---|---|---|---|---|
| Search Cost | 1.39* | 1.63* | 1.85* | 8.06* | 10.12* |
| | (0.04) | (0.14) | (0.57) | (0.27) | (0.002) |
| Number of Observations | 5102 | 5102 | 5102 | 5102 | 5102 |

*: significant at the 1% level. Standard errors are reported in parentheses.

### B.4.2 Marginal Cost Positively Correlated with Search Cost

I then consider a scenario where marginal costs are chosen such as they are positively correlated with search cost. For the 10 consumer types $\theta$, I generate equally spaced marginal costs ranging from 1 to 28. This range is chosen after heuristic tests in order to maximize the numerical solver's ability to solve for transacted price. Search cost parameters are unchanged from the previous scenario. Table B.3 displays the data generating parameters. Using the data generated with these parameters, I run the quantile regression equation (B.1) and report the results in Table B.4.

Predictions of the model regarding $\partial p/\partial s$ and $\partial p/\partial c$ are again confirmed. The marginal effect of search cost on transacted price is increasing in the quantile value of price. The marginal effect of marginal cost is equal to 1 throughout (the 95% confidence interval of $\beta_{2\tau}$ encompasses 1 in all columns of Table B.4).

Table B.3: Data Generating Parameters

| Consumer Type ($\theta$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Search Cost ($s$) | 2.05 | 1.87 | 1.59 | 1.59 | 1.55 | 1.33 | 1.25 | 1.17 | 1.01 | 0.56 |
| Marginal Cost ($c$) | 28 | 25 | 22 | 19 | 16 | 13 | 10 | 7 | 4 | 1 |

Table B.4: Quantile Regression of Transacted Price

| Transacted Price | Q(0.05) | Q(0.25) | Q(0.50) | Q(0.75) | Q(0.95) |
|---|---|---|---|---|---|
| Search Cost | 1.38* | 2.05* | 4.74* | 9.14* | 10.11* |
| | (0.10) | (0.47) | (1.73) | (0.80) | (0.02) |
| Marginal Cost | 1.00* | 1.00* | 1.01* | 1.06* | 1.00* |
| | (0.004) | (0.02) | (0.08) | (0.04) | (0.001) |
| Number of Observations | 5263 | 5263 | 5263 | 5263 | 5263 |

*: significant at the 1% level. Standard errors are reported in parentheses.

### B.4.3 Marginal Cost Negatively Correlated with Search Cost

Finally, I consider the case when marginal cost is negatively correlated with search cost. I keep the parameter values of search cost and marginal cost from scenario 2, but reorder marginal cost values such that they are decreasing in search cost. Table B.5 lists the data generating parameters, and Table B.6 reports the quantile regression results.

The results in this case are also consistent with predictions of the model regarding $\partial p/\partial s$ and $\partial p/\partial c$. For $\partial p/\partial s$, the only notable estimate is that of the median regression, where the point estimate is about 1. However, this estimate is not significant and has a wide 95% confidence interval (ranging from -4.63 to 6.65). If its true value is closer to the upper-bound of this range, it will ensure that $\partial p/\partial s$ is increasing across quantile values.

The point estimates for $\partial p/\partial mc$, although not remarkably close to 1 in the 0.25, 0.50, and 0.75 regressions, all have confidence intervals that encompasses 1. I therefore cannot reject that their true value is 1 at the 5% level. I suspect that increasing the sample size would bring the point estimates closer to 1, but that can be very expensive in terms of computing power. Nevertheless, even with the current sample size, the model is not rejected.

Table B.5: Data Generating Parameters

| Consumer Type ($\theta$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Search Cost ($s$) | 2.05 | 1.87 | 1.59 | 1.59 | 1.55 | 1.33 | 1.25 | 1.17 | 1.01 | 0.56 |
| Marginal Cost ($c$) | 1 | 4 | 7 | 10 | 13 | 16 | 19 | 22 | 25 | 28 |

Table B.6: Quantile Regression of Transacted Price

| Transacted Price | Q(0.05) | Q(0.25) | Q(0.50) | Q(0.75) | Q(0.95) |
|---|---|---|---|---|---|
| Search Cost | 1.55* | 1.67** | 1.00 | 7.26* | 10.20* |
| | (0.19) | (0.79) | (2.87) | (2.22) | (0.06) |
| Marginal Cost | 1.00* | .97* | 0.83* | 0.91* | 1.00* |
| | (0.007) | (0.03) | (0.11) | (0.09) | (0.002) |
| Number of Observations | 4079 | 4079 | 4079 | 4079 | 4079 |

*: significant at the 1% level; **:significant at the 5% level. Standard errors are reported in parentheses.

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