Interest Rates and Credit Rationing in U.S. Mortgage Lending*

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Abstract

Recent work on imperfect competition in lending markets focuses on the interest rate margin, despite the importance of credit rationing in lending. I estimate a structural model of bank competition in interest rates and credit rationing using U.S. mortgage data. I use the estimated model to show how banks optimally trade-off interest rates and credit rationing, and illustrate its policy relevance by examining the magnitude and the form of banks' pass through – to clients – of a cut in funding costs. I find that banks pass through their lower funding cost by not only cutting interest rates but also relaxing credit rationing. There is substantial heterogeneity in the pass through in both margins and this is mainly explained by heterogeneity in two different types of banks' costs: funding cost of originating mortgages and cost of processing applications. Lastly, I quantify the importance of adverse selection and moral hazard in how banks pass through lower funding costs through credit rationing. I find that moral hazard is the more important friction in the U.S. mortgage market, where shutting down moral hazard almost completely erases the pass through in the credit rationing margin.

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1 Introduction

Credit rationing is a universal feature of lending markets: lenders have the right to reject potential borrowers they deem too risky.[1] In mortgage lending, credit rationing is important to policy makers because of the strong interest in home ownership, and how mortgage lending can affect financial stability and economic activity.

Different factors affect credit rationing or the extent to which loan applications get rejected. Credit rationing entails that demand for loans is greater than supply. Given excess demand from borrowers at a given interest rate, various frictions such as adverse selection and moral hazard prevent lenders from profitably raising interest rates to clear the market because doing so would raise the riskiness of the borrowers and thereby lower profitability (Stiglitz and Weiss, 1981). In addition, lenders lowering credit rationing to fight for market share is widely attributed as a contributor to the 2008 financial crisis (see Financial Crisis Inquiry Report 2011). Despite the fundamental importance of the relationship between interest rates and credit rationing in understanding credit markets, empirical work on the relationship between the two margins is somewhat limited.

In this paper, I estimate a structural model of imperfect competition in mortgage lending using U.S. mortgage data and use the estimated model to understand how banks trade-off interest rates and credit rationing. In particular, to demonstrate the importance of understanding this trade-off for policy questions, I use the estimated model to study the pass through of a cut in banks' cost of funding mortgages and show that banks adjust substantially in both the interest rate and credit rationing margins.

I define credit rationing as rejected mortgage applications. Previous papers have measured credit rationing as rejected loan applications, including Agarwal et al. (2017), Cuesta and Sepúlveda (2019), and Jappelli (1990). The proportion of accepted applications or acceptance probability is my measure of credit rationing, where a higher acceptance probability means lower credit rationing. I document several stylized facts to motivate my analysis. First, there is substantial cross-sectional variation in acceptance probabilities across markets in the U.S. This variation has two dimensions: variation across markets for a given bank, and variation across banks for a given market. I show that there are systematic differences across banks, both in the levels of interest rates and acceptance probabilities they set as well as the relationship between the two margins across markets for a given bank. I also show that while the average mortgage interest rate closely mirrors the movements of the 10 Year Treasury Rate, there is substantial heterogeneity around the mean, and that there is

[1] There are some limits such as laws against racial discrimination (e.g. red-lining laws).

also substantial heterogeneity in the data in how interest rates and acceptance probabilities change from year-to-year across markets.

Motivated by this evidence, I develop and estimate a structural model of bank competition in mortgage lending using bank-market-year data. Households choose among competing banks to apply for a mortgage given the offered interest rates and acceptance probability. Characteristics such as ease of access to bank branches in the market differentiate mortgages. Banks compete by simultaneously choosing the optimal interest rates and credit rationing – measured by acceptance probabilities – to offer households.

My modeling contribution is to develop a general framework where banks take into account multiple factors when choosing the optimal acceptance probability. Following the recent literature, the fundamental reason why mortgage applications get rejected in my model is that idiosyncratic cost shocks make some mortgage applications too costly for banks to accept.[2] However, I allow important factors to affect the degree of credit rationing. First, adverse selection and moral hazard in mortgage defaults provide frictions that affect how banks trade-off interest rates with credit rationing. Second, banks take into account how lowering credit rationing by offering higher acceptance probabilities can attract households that, ceteris paribus, prefer to apply to banks with higher acceptance probabilities. Banks balance this incentive to offer higher acceptance probabilities to attract households with the fact that accepting too high a proportion of applications may lower the profitability of accepted mortgages due to adverse selection. As far as I am aware of, my paper is the first to capture this lowering credit rationing to capture market share mechanism in structural models of lending markets. I implement this mechanism using insights from the industrial organization literature (Hotz and Miller, 1993; Aguirregabiria and Magesan, 2013).

Another important innovation of the model is the existence of two types of bank costs: funding cost of originating mortgages and cost of processing applications. The former is only incurred for originated mortgages and reflects the cost of borrowed funds plus regulatory and closing costs associated with originating a mortgage, whereas the latter is incurred for all received applications and represents the cost of processing applications including verifying income and appraising the property.[3] I show that banks cannot lower interest rates or

[2]See Cuesta and Sepúlveda (2019). In addition, Allen et al. (2019) use idiosyncratic cost shocks to rationalize the heterogeneity in interest rates in the Canadian mortgage market.

[3]Fuster et al. (2017) show evidence of "capacity constraints" in processing mortgage applications where an increase in the volume of mortgage applications in a given month leads to a significant increase in the margin between the funding cost and the mortgage interest rate. This is interpreted as banks passing through higher costs of processing mortgages to borrowers at peak times of mortgage demand.

raise acceptance probabilities too much lest they attract more than the optimal amount of applications and incur large processing costs. Interestingly, changes to funding costs have different implications on how banks trade-off interest rates and acceptance probabilities versus changes to processing costs. Namely, a decrease in either cost leads to lower interest rates, but for a decrease in funding costs banks raise acceptance probabilities whereas for a decrease in processing costs banks lower acceptance probabilities. The intuition is that for a decrease in funding costs the profit margins on originated mortgages increase, but for a decrease in processing costs the profit margins decrease so banks accept a lower proportion of applications. In addition, counterfactuals show the importance of both types of costs for explaining the heterogeneity in pass through.

I estimate the model using U.S. data on mortgage applications, originations, interest rates, and defaults at the bank-market-year level for 2009 to 2014. The key identification challenge is the estimation of demand parameters capturing households' sensitivity to interest rates and acceptance probabilities. Correlation between interest rates, acceptance probabilities, and unobservable bank quality over markets imply that standard OLS estimation would misattribute the effect of unobserved bank quality on demand as the causal effects of interest rates and acceptance probabilities respectively, thereby biasing my estimates.

My approach to deal with this endogeneity problem is to use instruments justified by the exclusion restriction that some bank cost shifter variables affect the funding costs of originating mortgages but do not enter the demand equation. Therefore these cost shifters affect interest rates and acceptance probabilities only through their effects on bank funding costs and are not correlated with unobserved bank quality over markets. The cost shifters I use are variables that measure interest expense and the percentage of noncurrent loans on a bank's balance sheet. I argue that an increase in either variable increases the funding cost, the former by increasing the interest rate at which banks must borrow to fund mortgages, and the latter by increasing the riskiness of a bank's assets overall which negatively affects bank equity.[4]

I also estimate two types of bank costs: funding and processing costs. These costs are allowed to vary across banks, markets, and years. The identification idea is that mortgage applications and originated mortgages appear separately in the bank profit function. Independent sample variation in mortgage applications and originated mortgages in conjunction with two first order conditions of optimality – one for interest rates and the

[4]This type of instrument has been used before by Egan et al., (2017).

other for acceptance probabilities – separately identify the two different types of costs.

Demand estimates show that households favor banks with lower interest rates and higher acceptance probabilities, but that households are much more sensitive to interest rates. Due to the low sensitivity of borrowers to acceptance probabilities, I find that in the aftermath of the financial crisis banks in effect did not relax credit rationing to compete for market share. There is also evidence of adverse selection and moral hazard in defaults. An increase in interest rates has a causal effect on increasing default risk, and an increase in acceptance probabilities also increases the riskiness of the pool of accepted mortgages. I also estimate funding and processing costs and find that they vary significantly across banks, markets, and years. Funding costs increase with higher bank interest expense and share of longer maturity assets on balance sheet. Processing costs increase year over year, which reflect findings in Fuster et al. (2017) that in the years after the 2008 financial crisis the cost of processing mortgage applications increased due to increased legal and regulatory burden.

I use the estimated model for three sets of counterfactuals. First, I exogenously vary funding and processing costs in order to illustrate how these two types of costs affect banks' optimal trade-off in interest rates and acceptance probabilities. I find that a decrease in funding costs lead to a decrease in interest rates and an increase in acceptance probabilities, whereas a decrease in processing costs lead to a decrease in both interest rates and acceptance probabilities.

Second, I run a series of counterfactuals studying how banks pass through lower funding costs through interest rates and acceptance probabilities, and how this pass through varies across banks and markets. The model predicts that for a 10% decrease in the cost of funding a mortgage, interest rates fall by 10.4% and acceptance probabilities increase by 7.1% on average. I show that in a model where only the interest rate is endogenous it under-predicts the increase in lending, over-predicts the interest rate pass through and the increase in consumer surplus, and under-predicts the gain to banks. In addition, there is significant heterogeneity across banks and markets in the pass through in both margins. In markets where banks have more market power there is lower pass through in interest rates and acceptance probabilities, but that the heterogeneity in processing costs play the biggest role in explaining the heterogeneity in pass through. In particular, variation in processing costs can explain 78% of the variation in interest rate pass through across banks and markets. Overall, my model predicts that credit rationing will respond substantially to a decrease in funding costs, and that there will be substantial heterogeneity in the pass through in both interest rates and credit rationing across banks and markets.

Third, I quantify the importance of adverse selection and moral hazard in how banks pass through lower funding costs with higher acceptance probabilities. I first look at changes in equilibrium outcomes when I shut down adverse selection and moral hazard respectively. In both cases interest rates and acceptance probabilities increase compared to the observed data, but the increase in both margins is larger when I shut down moral hazard than when I shut down adverse selection. Then, I calculate the counterfactual pass through in interest rates and acceptance probabilities for the cases where there is no adverse selection and no moral hazard respectively. I find that with no adverse selection, the percentage change in acceptance probabilities decreases from 7.073% to 3.789%, whereas with no moral hazard the percentage change in in acceptance probabilities decreases to 0.443%. These results show that moral hazard is the more important friction in U.S. mortgage lending.

Overall, these results yield insight into a fundamental aspect of credit markets: how lenders use the interest rate and credit rationing margins to maximize profits. I show the important policy implications that these insights have on the pass through of lower funding costs by banks to households, and in particular the effects that processing costs, adverse selection, and moral hazard have on the pass through in interest rates and credit rationing.

This paper contributes to three main strands of literature. First, I contribute to the recent literature of structural models of competition in lending markets. These papers focus on the competition in interest rates between lenders in different lending markets such as mortgages (Aguirregabiria et al., 2019; Allen et al., 2019; Benetton, 2019; Tsai, 2019), corporate loans (Crawford et al., 2018; Ioannidou et al., 2019), and personal loans (Cuesta and Sepúlveda, 2019). My paper contributes to this literature by making both interest rates and credit rationing endogenous, and studying how factors such as adverse selection, moral hazard, competition, and funding and processing costs affect credit rationing.

However, my paper is not the first to endogenize credit rationing. Cuesta and Sepúlveda (2019) also study the trade-off between interest rates and credit rationing to study the effect of interest rate caps on personal loans in Chile. My paper differs from their study for at least two reasons. First, my model of credit rationing differs from theirs in that my model allows the possibility of banks lowering credit rationing to fight for market share, whereas they assume that banks always accept profitable loan applications and reject unprofitable ones. In addition, I can identify two different types of bank costs in funding and processing costs which play key roles in the trade-off between interest rates and credit rationing and have different policy implications. Second, my model incorporates both adverse selection and moral hazard whereas their model only captures adverse selection. Third, my paper studies the effect of a different policy change – a decrease in funding costs – on the U.S. mortgage market.

Another paper that endogenizes credit rationing is Agarwal et al. (2017), who study the U.S. mortgage market and document that contrary to the standard search model framework, borrowers that search more obtain more expensive mortgages. They also study the trade-off between interest rates and credit rationing in U.S. mortgage lending, but they estimate a search model to explain why borrowers with similar characteristics differ in search behavior and the interest rates they obtain, whereas I estimate a model of imperfect competition in mortgage lending and focus on the heterogeneity in interest rates and credit rationing across banks and markets. In addition, they do not allow processing costs to vary across banks and markets.

Second, this paper contributes to the literature of empirical studies on credit rationing. Classic references include Cox and Jappelli (1990) and Jappelli (1990). More recent papers include Agarwal et al. (2017), Ambrose et al. (2016), Canales and Nanda (2012), Carbo-Valverde et al, (2012), Cenni et al. (2015), Cowling (2010), Cheng and Degryse (2010), Kirschenmann (2016), and Kremp and Sevestre (2013). I contribute to this literature by being the first to show that changes in processing costs can have different implications than changes in funding costs for credit rationing. According to my estimates, in U.S. mortgage lending a decrease in processing costs leads to more credit rationing whereas a decrease in funding costs leads to less credit rationing.

Third, this paper contributes to the literature on the transmission of monetary policy by financial intermediaries. Previous papers have studied how market power (Scharfstein and Sunderam, 2017) and mortgage contract design (Di Maggio et al., 2017) affect pass through of lower interest rates to mortgage borrowers in the U.S. There are also papers studying interest rate pass through in other settings (Benetton and Fantino, 2019; De Graeve et al., 2007). Finally, some papers show how monetary policy affects loan quantity and lender risk-taking (Agarwal et al., 2018; Drechsler et al., 2017; Jiménez et al., 2014). In this paper, I study how changes in bank funding costs are passed on through changes in mortgage interest rates and credit rationing. I contribute to this literature by showing how credit rationing is an important margin in the pass through of lower funding costs by banks to households, and that the heterogeneity in the pass through in interest rates and credit rationing is driven by heterogeneity in processing costs. In addition, I show that without moral hazard the pass through in the credit rationing margin is trivial.

The rest of the paper is organized as the following. Section 2 describes data sources and descriptive evidence. Section 3 explains the model of demand and supply of mortgages. Section 4 describes identification and estimation. Section 5 presents estimation results. Section 6 discusses counterfactuals. Section 7 concludes.

2 Data and Descriptive Evidence

2.1 Data Sources

The Home Mortgage Disclosure Act (HMDA) data contains application-level information on mortgage applications and originations as well as some information about the applicants such as income, race, and sex as well as where the property is located down to the census tract.[5] All banks that have received a mortgage application in a Metropolitan Statistical Area (MSA) and have assets greater than $10 million or originate more than 100 loans in a year are required to report all mortgage applications and their outcomes, and it is estimated that upwards to 90% of all mortgage applications in the U.S. are observed in HMDA data. As is well known, HMDA lacks some key information such as the term and interest rate of the loan, and the credit score of the borrower.[6]

Fannie Mae and Freddie Mac, two government sponsored enterprises (GSE) that purchase the bulk of mortgages from banks in the U.S., provide loan-level data on 30-year fixed rate mortgages[7] including the interest rate of the loan and borrower credit score. I observe the location of the mortgage to first three digits of the zip code. However, GSE data only discloses the identity of the lending institution for the top few lenders in terms of overall volume due to privacy concerns. Data is available from 2000 onwards, and monthly default status of each loan is available up to present day.

Summary of Deposits (SOD) data includes information on all bank branches of all banks in the U.S. down to the zipcode and how much deposits are in each branch each year. Deposit data is available from 1994 onwards. I use the SOD data to calculate the share of

[5] Data is available from 1990 onwards.

[6] Even with the increasing availability of detailed micro-level data on credit markets such as credit registry data, it is rare for a dataset to have information on credit rationing such as rejected applications. An exception is Agarwal et al. (2017), who use data from one of the two government sponsored enterprises to obtain a sample of 5.36 million mortgage applications from 2001 to 2013 with data on outcomes and detailed information on applicant characteristics. However, this is a small proportion of the overall mortgage lending activity that goes on in the U.S. Cuesta and Sepúlveda (2019) is another exception where they have information on applications for personal loans in Chile.

[7] Freddie Mac data also contains 10 and 20-year fixed rate mortgages.

bank branches each bank has in a year-MSA. In addition, I obtain bank cost shifters from the Uniform Bank Performance Report (UBPR) data, which contains measures of bank performance derived from Call Reports data. I also obtain conforming loan limits from FHFA. Finally, I use the American Community Survey (ACS) data to count the number of households in each MSA per year. I use this information to calculate market size, with a market defined as an MSA.

In order to merge application information from HMDA data with information about loan characteristics from GSE data, I aggregate loan-level data from HMDA and GSE data to bank-MSA-year unit of observation. For both HMDA and GSE data I identify to which bank the mortgage application or originated mortgage was for. Once the proportions and averages of mortgage and borrower characteristics are calculated at the bank-MSA-year unit of observation for HMDA and GSE data, HMDA and GSE variables are merged. SOD bank branch network data is aggregated and merged at year-MSA-bank level.

Because GSE data only discloses the identity of the bank for top sellers in terms of volume whereas HMDA data discloses the identity of the bank for every mortgage application, I focus my analysis on the top 5 banks in terms of volume in both HMDA and GSE data for much of my sample: Bank of America, Citigroup, JP Morgan Chase, and Wells Fargo, and US Bank. These top 5 banks lend mortgages extensively across the U.S. and are therefore ideal for studying their response to variation in demand and default risk across the country. Non-bank lenders such as Quicken Loans are not included because bank cost shifter variables from UBPR data are only available for banks.

Because I only have data on interest rates from GSE data, I drop applications from HMDA data that are not GSE-eligible. Merging conforming loan limits from FHFA to HMDA data, I drop all applications whose loan size is above the conforming loan limit before I aggregate loans at the bank-MSA-year level.[8][9] After aggregating and merging HMDA and GSE data, I drop bank-MSA-year observations where all or none of the mortgage applications were originated. I also drop all bank-MSA-year observations where the bank received less than 100 applications, and then I keep observations from MSA-years where at least 4 of the top 5 banks have observations in that MSA-year.[10] The regression sample runs from 2009 to

[8] Starting in 2009 the GSEs instituted minimum FICO scores for GSE-securitization eligibility. Unfortunately HMDA does not report credit scores so I assume that all mortgage applications below the loan conforming limit are GSE-eligible.

[9] I assume that interest rates from GSE data are broadly representative of the interest rates that HMDA applications in my regression sample had.

[10] This is done to ensure that there are enough observations per MSA-year fixed effect which will be included in all regression specifications.

Table 1: Summary Statistics

$N = 6052$	mean	std	min	50%	max
Mkt. Shr.	0.0067	0.0067	0.0002	0.0046	0.1131
Interest Rate	0.0431	0.0049	0.0262	0.0437	0.0540
Acc. Prob.	0.4357	0.1628	0.0144	0.4399	0.9064
Branch Shr.	0.0515	0.0602	0.0000	0.0278	0.4130
Defaults	0.0346	0.0278	0.0000	0.0303	0.5000
FICO	761.5258	11.0080	665.0000	762.8578	817.0000
LTV	69.9372	4.9598	26.0000	70.2441	94.0000
DTI	31.3539	2.1686	11.0000	31.3356	40.1434

Notes: Table shows summary statistics for key variables of interest. Variables at bank-MSA-year unit of observation.

2014[11], includes 281 MSAs, and has 6,052 bank-MSA-year observations.

Table 1 shows summary statistics of the key variables of interest. The average interest rate is 0.0431 and the average acceptance probability is 0.4357. The table shows considerable variation in acceptance probabilities, ranging from 0.0144 to 0.9064. The proportion of mortgages that defaulted, defined as 1 month or more delinquent in payment within two years of origination[12], is on average 0.0346, with one outlier in Idaho Falls, ID in 2012 where half the mortgages defaulted for Citigroup. FICO scores averages are high at 761.5258 and reflects the fact that these are coming from originated mortgages. Market share, defined as the number of applications to a bank-MSA-year over the total number of households in the MSA-year, is small with an average market share of 0.0067. The share of bank branches a bank has a MSA-year is on average 0.0515. There are numerous MSA-years where a bank originates mortgages in the MSA-year but has a zero bank branch share.

[11] Due to concern about preponderance of subprime loans in the HMDA data before the recent financial crisis in the U.S., I only use data from 2009 onwards to keep the sample more representative of prime-eligible applications.

[12] The literature typically defines default as 2 or 3-month delinquency on loan payments. I define defaults as 1-month or more delinquent in order to avoid zeros in defaults since in my estimation all observations with defaults equal to 0 or 1 will be dropped. The proportion of mortgages 1-month or more delinquent is highly correlated with the proportion of mortgages 2-month or more delinquent. I discuss this issue further in the estimation section.

2.2 Descriptive Evidence

I use the proportion of mortgage applications accepted or acceptance probabilities as my measure of credit rationing, where a lower acceptance probability means higher credit rationing. Acceptance probabilities are calculated at the bank-MSA-year level. Panel (a) of figure 1 shows that there is substantial cross-sectional variation in acceptance probabilities. There also some systematic differences between the banks. For example, US Bank seems to have higher acceptance probabilities while Citigroup seems to accept a lower proportion of applications and have lower average interest rates. This variation in interest rates and acceptance probabilities across the U.S. and across banks are key features of the data that this paper tries to explain, and the structural model helps to decompose this variation across demand and supply factors. Panel (b) of figure 1 shows that the relationship between interest rates and proportion of applications accepted differ across banks. JP Morgan, Bank of America, and Citigroup has a positive correlation between interest rates and proportion of applications accepted whereas US Bank and Wells Fargo has a negative relationship. As explained later, these differences across banks in the relationship between interest rates and acceptance probabilities can be explained by funding and processing cost heterogeneity. [13]

Panel (a) of figure 2 shows the distribution of bank-MSA-year average interest rates per year as well as the year-average interest rate and the 10-year Treasury rate which is a benchmark rate for 30-year fixed rate mortgages. Despite the correlation coefficient of the year-average mortgage interest rate and the Treasury rate being 0.925, there is considerable heterogeneity in the bank-MSA-year average interest rates per year. There is also considerable heterogeneity in the yearly changes in interest rates and proportion of applications accepted for a given bank-MSA-year. This can be seen from panel (b) of figure 2, which plots the percentage change in bank-MSA-year average interest rates and proportion of applications accepted from 2010 to 2011. The figure shows that there is substantially more cross-sectional variation in the percentage change in acceptance probabilities than in average interest rates. Numerous factors could explain this heterogeneity in the interest rate and acceptance probability margins, such as differences in market power and cost differences across banks and MSAs. I use my structural model to explain the heterogeneity in pass through across banks and MSA-years.

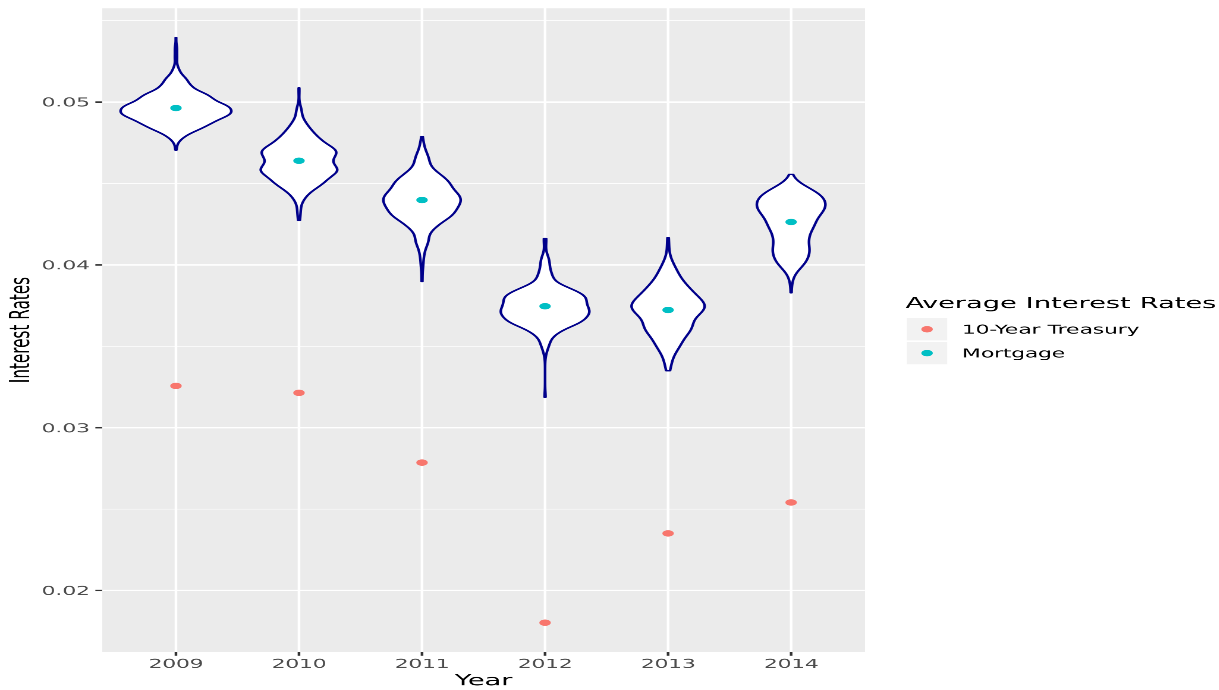
[13] Appendix A shows that this cross-sectional variation in interest rates and acceptance probabilities is not driven by differences in the composition of borrowers.

Figure 1: Bank-MSA-Year Level Variation in Interest Rates and Credit Rationing

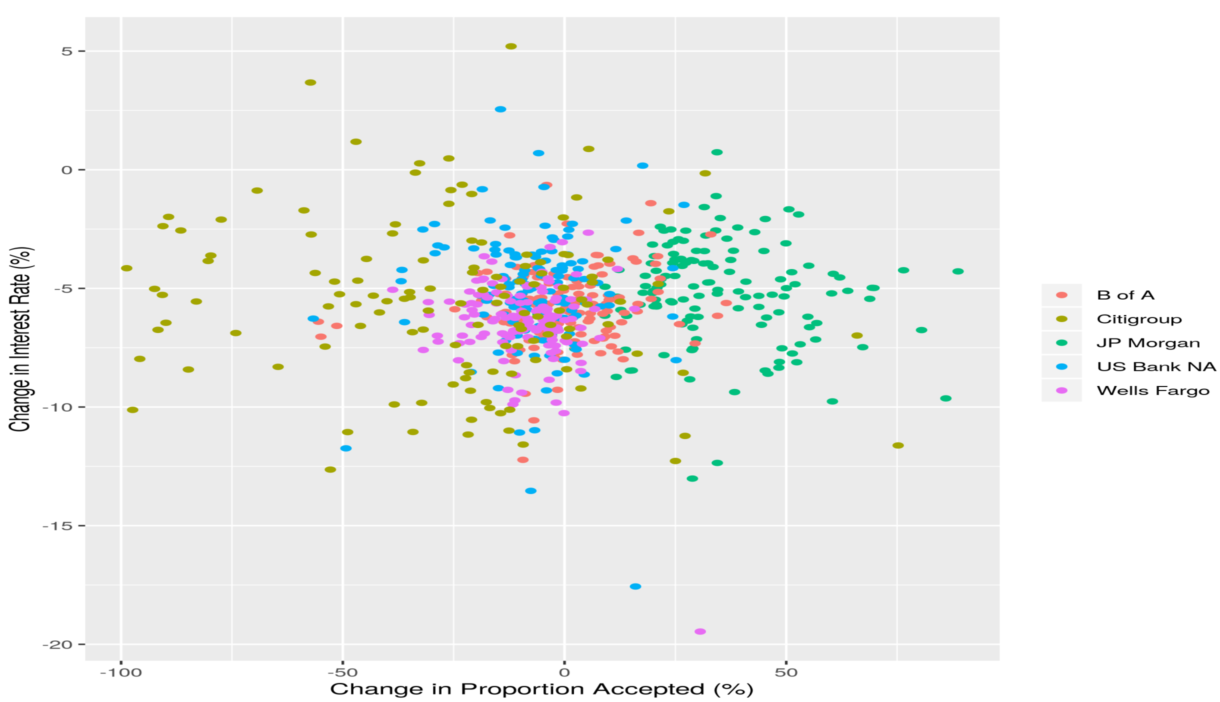
Notes: Figure shows bank-MSA-year level variation in interest rates and credit rationing. Panel (a) plots bank-MSA average interest rates and proportion of applications accepted for the top 5 banks in the U.S. with different colored dots indicating different banks. In panel (b), for each bank the relationship between interest rates and proportion of applications accepted is shown with a linear line of fit.

Figure 2: Descriptive Evidence on Pass Through

(a) Interest Rate Heterogeneity per Year



(b) Pass Through Heterogeneity



Notes: Panel (a) shows the distribution of bank-MSA-year average interest rates per year as well as the yearly average mortgage interest rate and 10-year Treasury rate. Panel (b) plots the percentage change in bank-MSA-year average interest rates and proportion of mortgage applications accepted from 2010 to 2011.

3 A Model of the Mortgage Market with Credit Rationing

I develop a model of the U.S. mortgage market where banks compete to attract mortgage applications by simultaneously posting the interest rate at which households can obtain a mortgage as well as the probability at which the bank will accept applications. First, I describe a household's mortgage application decision. Second, I describe a household's mortgage default decision and how I incorporate adverse selection and moral hazard into the model. Third, I describe banks' optimal choice of interest rates and acceptance probabilities. Fourth, I describe the equilibrium of the model.

3.1 Demand for Mortgages by Households

The model is a one-shot game where in each market banks compete for mortgage applications and households make application decisions. For a given household each bank b in the market[14] offers interest rate i_b and acceptance probabilities a_b. The utility of applying for a mortgage to bank b is:

$$u_b = \alpha_i \cdot i_b + \alpha_a \cdot a_b + X_b \cdot \alpha_X + \xi_b + \varepsilon_b \tag{1}$$

Households have linear preferences over interest rates and acceptance probabilities.[15] X_b is a vector of exogenous observable characteristics that affect the utility of applying to bank b, and one of the key variables is the share of bank branches that bank b has in the market. This captures how households are more willing to apply to a bank that has a higher share of bank branches because it increases the convenience of applying for a mortgage to a bank that is easy to access its bank branches, and may also capture how it is also more valuable to purchase other banking services with a more accessible bank. A higher share of bank branches increases the market power of a bank.[16] X_b also includes bank and MSA-year

[14] In the estimation of the model the definition of a market is an MSA. However, the definition of the market could be more narrowly defined as a combination of geographic location and a particular group of households according to common characteristics that are observable and common knowledge to all the banks, such as a group of high or low credit score households.

[15] Household utility could increase in acceptance probability if there are search or application costs. See Cuesta and Sepúlveda (2019) for a more explicit incorporation of application costs in a model where households apply for consumer loans.

[16] The share of bank branches could also be a proxy for the proportion of households that have a bank as

fixed effects. ξ_b represents unobserved quality of the bank, and ε_b is an idiosyncratic error term. The household utility of not applying to any bank is normalized to $u_0 = \varepsilon_0$. As is common in the literature, I assume that a household's choice of which property to buy with the mortgage is fixed and does not vary across which bank they apply to.

The conditional choice probability of a household choosing to apply to bank b is:

$$q_b = Pr\Big(u_b > u_{b'}, \forall b' \neq b\Big) \tag{2}$$

Re-application decisions by rejected households could be incorporated into the current demand model framework by assuming that each time a household is rejected it re-draws idiosyncratic errors for all alternatives in its new choice set (all banks in the market except the banks that previously rejected the household plus not applying for a mortgage) and then the household chooses its new utility-maximizing alternative. However, due to data limitations[17] I make the restrictive assumption that households only apply once per year. This assumption implies that I will over-exaggerate the welfare cost of a rejected application to a household because I do not allow the possibility of the household receiving utility from subsequent stages in their re-application process. However, this assumption allows me to use a standard discrete choice model framework to characterize household behavior in a parsimonious way, and it allows me to use estimation techniques well-established in the industrial organization literature to identify the key demand model parameters. The important demand model parameters are the sensitivity of households to interest rates and acceptance probabilities respectively. These parameters will determine the nature of competition in mortgage lending, which will have important implications for how banks adjust interest rates and credit rationing in response to changes in funding and processing costs. In particular, the sensitivity of demand with respect to acceptance probabilities determine the extent to which banks compete by lowering lending standards to fight for market share, and my demand model allows me to estimate this critical elasticity in a data-driven way.

their home bank. Allen et al. (2019) shows how banks have market power over consumers that have their main banking services with them due to brand loyalty.

[17]HMDA data contains roughly 90% of mortgage applications in the U.S. but it does not track households across applications.

3.2 Mortgage Default

There are two key frictions that household default behavior could impose on how banks trade-off interest rates and credit rationing. One is moral hazard in defaults where a rise in interest rates has a causal effect in increasing default probability. The other friction is adverse selection, where a household's unobserved willingness to apply for a mortgage is correlated with its unobserved default risk. My model allows for both frictions in the following way. For households that obtain a mortgage, the probability of default is:

$$d_b = Pr\left(\delta_i \cdot i_b + \delta_a \cdot a_b + V_b \cdot \delta_V + \eta_b + \nu_b > 0\right) \tag{3}$$

d_b is the probability of default. I allow moral hazard in default by including interest rates i_b in the default probability. Moral hazard exists if $\delta_i > 0$, which means that higher interest rates increases the probability of default. I also capture adverse selection by including a_b in the default probability, where adverse selection exists if $\delta_a > 0$. The idea is that an increase in the proportion of accepted applications may lead to an unobservably more risky pool of originated mortgages. As a result, I allow for the possibility that the acceptance probability has a causal effect on the default probability. V_b is a vector of exogenous characteristics that affect household probability of default, including average credit or FICO scores, loan-to-value (LTV) and debt-to-income (DTI) ratios, and bank and year-MSA fixed effects. η_b summarizes unobserved factors that affect default probability and is observed by banks before they offer interest rates and acceptance probabilities. ν_b is an idiosyncratic error term.

3.3 Supply of Mortgages by Banks

Banks compete to attract mortgage applications by simultaneously choosing interest rates and acceptance probabilities to offer households. I describe the main factors that affect the trade-off between interest rates and acceptance probabilities.

3.3.1 Ex-Ante Mortgage Profit

For each household in the market, bank b observes ex-ante mortgage profitability π_b:

$$\pi_b = PV_b(i_b, d_b) - mc_b \tag{4}$$

π_b is the profitability of the mortgage observed by bank b before they receive an application which is the difference between the present value of the mortgage and the cost of funding the mortgage. An originated mortgage with interest rate i_b and default probability d_b has a present value of $PV_b(.)$[18], and for each originated mortgage bank b incurs a funding cost mc_b. With moral hazard, there is a trade-off in raising interest rates for profitability of the mortgage since on the one hand raising rates has the direct effect of raising payments from the mortgage, but on the other hand may decrease the present value by increasing the default probability by increasing the monthly payment burden for the borrower:

$$\frac{dPV_b}{di_b} = \underbrace{\frac{\partial PV_b}{\partial i_b}}_{>0,\text{ Increases payments}} + \underbrace{\frac{\partial PV_b}{\partial d_b} \cdot \frac{\partial d_b}{\partial i_b}}_{<0,\text{ Moral hazard}} \tag{5}$$

Adverse selection implies that π_b decreases in a_b:

$$\frac{dPV_d}{da_b} = \frac{\partial PV_b}{\partial d_b} \cdot \frac{\partial d_b}{\partial a_b} < 0 \tag{6}$$

3.3.2 Expected Profit of Mortgage Applications

Once a bank receives a mortgage application, the application is processed which reveals information about the actual profitability of originating the mortgage. For example, income verification may reveal warning signs or property appraisal may conclude that the property is over-valued. This is represented by an idiosyncratic cost shock e_b.[19] The ex-post profits are:

$$\begin{cases} \pi_b + e_b & \text{, if } y_b = 1 \\ 0 & \text{, if } y_b = 0 \end{cases} \tag{7}$$

Where, y_b is an indicator for accepted applications (originated mortgages). The ex-ante profit of rejecting a mortgage application is normalized to 0. These cost shocks – only observed after an application comes in – represent random variation in funding, regulatory, and administrative costs.[20]

A key innovation of this paper is that I do not assume that banks always accept ex-post profitable mortgages and reject ex-post unprofitable mortgages. Instead, I allow banks to

[18] I assume that $PV_b(.)$ is known by the econometrician and is a simple accounting expression.

[19] Agarwal et al. (2017) assumes a similar structure where banks first post interest rates and then screen borrowers.

[20] Idiosyncratic cost shocks have been used to rationalize screening and interest rate variation in previous papers including Agarwal et al. (2017); Allen et al. (2019); and Cuesta and Sepúlveda (2019)

adjust its lending standards to allow for the possibility of banks lowering lending standards to fight for market share. In my model, banks accept and reject mortgage applications according to a decision rule which they commit to at the beginning of the year and that households can observe. As I explain below, this is equivalent to banks posting the acceptance probability. Let the decision rule be of the following form:[21]

$$y_b = 1 \Leftrightarrow \rho_b(\pi_b) + e_b > 0 \tag{8}$$

Where $\rho_b : \mathbb{R} \rightarrow \mathbb{R}$. $\rho_b(.)$ implies a probability of acceptance $a(\rho_b) \equiv Pr\Bigg(\rho_b(\pi_b) + e_b > 0\Bigg)$. The expected profit of receiving a mortgage application is the probability that the bank accepts the application times the expected profit conditional on acceptance:

$$E\pi_b = a(\rho_b) \cdot \Bigg(\pi_b + \mathbb{E}[e_b|\rho_b(\pi_b) + e_b > 0]\Bigg) \tag{9}$$

It could be natural to consider that a bank will accept a mortgage application if and only if it is ex-post profitable ($y_b = 1 \Leftrightarrow \pi_b + e_b > 0$). Indeed, this will maximize the expected profit of receiving an application. However, this simple decision rule does not take into account that the acceptance decision not only affects the expected profit of a mortgage application ($E\pi_b$), but has an externality effect on total expected profits for a bank. Accepting additional applications increases the acceptance probability, which attracts more applications since households, ceteris paribus, prefer to apply to banks with higher acceptance probabilities.[22] This implies that a bank could increase its total expected profits by accepting more than just the ex-post profitable applications in order to attract more applications at the expense of reducing the expected profit per application received.[23] Therefore, I do not assume that banks always accept ex-post profitable and reject ex-post unprofitable mortgage applications but instead allow banks to choose decision rules that will take into account this externality effect.

[21] I derive the optimal decision rule in Appendix B.

[22] To illustrate, define $\tilde{\rho}_b(\pi_b) \equiv \pi_b$ which implies that the bank accepts applications iff $\pi_b + e_b > 0$. Define another decision rule as $\rho'_b(\pi_b) \equiv \pi_b + p$ where $p > 0$ and the bank accepts applications iff $\pi_b + p + e_b > 0$. This decision rule ρ'_b represents bank b accepting all mortgage applications that would have been accepted under $\tilde{\rho}_b$ as well as accepting additional applications rejected under $\tilde{\rho}_b$, namely applications with cost shock $\pi_b + p > -e_b > \pi_b$. It is easy to see that $a(\rho'_b) \equiv Pr(\pi_b + p + e_b > 0) > a(\tilde{\rho}_b) \equiv Pr(\pi_b + e_b > 0)$.

[23] This trade-off will be made explicit in the following sub-section.

I use the fact that $\mathbb{E}[e_b|\rho_b(\pi_b)+e_b>0]$ is only a function of the probability that $\rho_b(\pi_b)+e_b>0$ or $a(\rho_b)$[24] to represent $E\pi_b$ as a function of the acceptance probabilities $a_b \equiv a(\rho_b)$ instead of as a function of the decision rule ρ_b:

$$E\pi_b = a_b \cdot \Big(\pi_b + \sigma \cdot g(a_b)\Big) \tag{10}$$

Where $\sigma \cdot g(a) \equiv \mathbb{E}[e_b|\rho_b(\pi_b)+e_b>0]$ and σ is the variance of e_b. From here on I will describe the bank problem as choosing interest rate i_b and acceptance probability a_b.

3.3.3 Total Expected Profits

Assuming constant returns to scale (thereby ignoring loan amount), the total expected profits of bank b is:

$$\Pi_b(i,a;\mathbf{i}_{-b},\mathbf{a}_{-b}) \equiv \underbrace{q_b(i,a;\mathbf{i}_{-b},\mathbf{a}_{-b})}_{\text{Probability of application}} \times \underbrace{a \cdot \Big(\pi_b + \sigma \cdot g(a)\Big)}_{\text{Exp. profit from application}} - \underbrace{C_b(q_b)}_{\text{Processing costs}} \tag{11}$$

Where, q_b is the probability of a mortgage application to bank b, $a \cdot (\pi_b + \sigma \cdot g(a))$ is the expected profit of receiving an application, and $C_b(.)$ is the cost of processing a mortgage application regardless of whether it is accepted or rejected. $\mathbf{i}_{-b}$ and $\mathbf{a}_{-b}$ are vectors of other banks' interest rates and acceptance probabilities respectively. The probability of the household applying to bank b depends not only on bank b's offered interest rate and acceptance probability, but the interest rates and acceptance probabilities of all other banks that offered the household a mortgage. Note that this competition to attract applications from households is the only source of strategic interaction between banks in my model. I assume that $C_b(.)$ is increasing in q_b, implying that processing costs increase with the volume of mortgage applications.

The first order condition for i_b is:

$$\begin{aligned} FOC_i \equiv & \underbrace{\frac{\partial q_b}{\partial i_b}}_{\text{Competing for applicants}} \cdot a_b \cdot \Big(\pi_b + \sigma \cdot g(a_b)\Big) \\ & + q_b \cdot a_b \cdot \Big(\underbrace{\frac{\partial PV_b}{\partial i_b}}_{\text{Increases payments}} + \underbrace{\frac{\partial PV_b}{\partial d_b} \cdot \frac{\partial d_b}{\partial i_b}}_{\text{Moral hazard}} \Big) - \underbrace{\frac{\partial C_b}{\partial q_b} \cdot \frac{\partial q_b}{\partial i_b}}_{\text{Processing costs}} = 0 \end{aligned} \tag{12}$$

[24] Shown in Hotz and Miller (1993) and others.

The first order condition for a_b is:

$$
\begin{aligned}
FOC_a \equiv & \underbrace{\frac{\partial q_b}{\partial a_b}}_{\text{Competing for applicants}} \cdot a_b \cdot \Big(\pi_b + \sigma \cdot g(a_b)\Big) \\
& + q_b \cdot \Bigg(a \cdot \underbrace{\frac{\partial PV_b}{\partial d_b} \cdot \frac{\partial d_b}{\partial a_b}}_{\text{Adverse selection}} + \pi_b + \sigma \cdot \underbrace{G'(a)}_{\text{Cost shocks}}\Bigg) - \underbrace{\frac{\partial C_b}{\partial q_b} \cdot \frac{\partial q_b}{\partial a_b}}_{\text{Processing costs}} = 0
\end{aligned}
\tag{13}
$$

Where, FOC_i and FOC_a denote first order conditions with respect to interest rate i and acceptance probability a respectively, and $G(a) \equiv a \cdot g(a)$ and $G'(a)$ denote the partial derivative w.r.t. a. The two first order conditions reveal the tension between attracting applications and maximizing the profitability of mortgages in the optimal choice of i and a. For example, in FOC_i it can be seen that on the one hand banks need to balance the trade-off in raising interest rates between higher payments and moral hazard, but on the other hand banks must also lower interest rates in order to attract households. Similarly for FOC_a, there is tension between the need to attract applications by increasing a with the need to maximize the expected profitability of applications by reducing adverse selection and optimizing expected cost shocks conditional on acceptance. The incentive to attract applications, and how the probability of a household applying to bank b is affected by competition from other banks, is the mechanism through which banks may become more willing to originate mortgages as competition increases. Finally, in both margins banks need to keep in mind processing costs. Decreasing i or increasing a increases q, which increases processing costs. Therefore, banks cannot lower i or raise a too much lest they incur too much processing costs.

Therefore, there are four main reasons why there is credit rationing in my model. First, moral hazard may prevent profitable increases in the interest rate for a given level of default risk, thereby limiting the number of interest rate-acceptance probability pairs that banks are indifferent between. Second, adverse selection implies that it may be profitable to reject applications to decrease the default risk of accepted applications. Third, ex-post idiosyncratic cost shocks imply that banks may not want to commit to accepting all applications to avoid really negative cost shocks. Fourth, processing costs may incentivize banks to accept a lower proportion of applications to avoid attracting too many applicants.

3.4 Equilibrium

For a given market, vectors of interest rates $\mathbf{i}$ and acceptance probabilities $\mathbf{a}$ form an equilibrium if each bank b maximizes total expected profits given other banks' interest rates $\mathbf{i}_{-b}$ and acceptance probabilities $\mathbf{a}_{-b}$:

$$(i_b, a_b) = \arg\max_{(i,a)} \Pi_b(i, a; \mathbf{i}_{-b}, \mathbf{a}_{-b}) \tag{14}$$

Because the total expected profits of a bank is not strictly concave or quasi-concave, only the existence of a mixed strategies equilibrium via Theorem of the Maximum and Kakutani fixed point theorem can be proven. For estimation I assume that the observed data is a result of equilibrium in pure strategies and for counterfactuals I check that equilibrium in pure strategies exist.

4 Estimation

This section describes identification and estimation of the demand, default, and supply parameters of the model. I use GSE and HMDA data merged at the bank-year-MSA level.

4.1 Demand

I assume that idiosyncratic errors ε in demand in equation (2) are distributed Extreme Value Type I (EVI), resulting in the following equation for the probability of an application to bank b in year-MSA t:

$$q_{b,t} = \frac{exp\Bigg(\alpha_i \cdot i_{b,t} + \alpha_a \cdot a_{b,t} + X_{b,t} \cdot \alpha_X + \xi_{b,t}\Bigg)}{1 + \sum_{b'} exp\Bigg(\alpha_i \cdot i_{b',t} + \alpha_a \cdot a_{b',t} + X_{b',t} \cdot \alpha_X + \xi_{b',t}\Bigg)} \tag{15}$$

I estimate a logit demand model where the estimation equation is the following:

$$ln(q_{b,t}/q_{0,t}) = \alpha_i \cdot i_{b,t} + \alpha_a \cdot a_{b,t} + X_{b,t} \cdot \alpha_X + \xi_{b,t} \tag{16}$$

Where for bank b and year-MSA t, $q_{b,t}$ is the market share of applications, $i_{b,t}$ is the average interest rate, $a_{b,t}$ is the acceptance probability (proportion of applications accepted),

$X_{b,t}$ is a vector of exogenous characteristics which include bank branch share and bank and year-MSA fixed effects, and $\xi_{b,t}$ are unobservables that affect households' willingness to apply to bank b in year-MSA t. $q_{0,t}$ is the share of the outside option of not applying for a mortgage. I assume that all households in a market are identical net of the idiosyncratic errors and that they face the same interest rate and acceptance probability from a given bank. The endogeneity problem with OLS estimation of the above estimating equation is that $i_{b,t}$ and $a_{b,t}$ will be correlated with unobservables $\xi_{b,t}$. $\xi_{b,t}$ captures the unobservable quality of a bank in a year-MSA that affects household utility. For example, if Wells Fargo branches have superior customer service than other competitors in the year-MSA and therefore can charge higher interest rates, not accounting for this correlation between $i_{b,t}$ and $\xi_{b,t}$ will lead to a positive bias in the estimate of α_i. Similarly, a bank with superior unobservable quality may not need to accept as high a proportion of applications in order to attract mortgage applicants and so there may be a negative correlation between $a_{b,t}$ and $\xi_{b,t}$ which leads to a negative bias in the estimate of α_a.

I address the endogeneity problem in the estimation of equation (16) by combining a rich set of bank and year-MSA fixed effects with instrumental variables estimation using funding cost shifter instruments. The rationale for the instruments is that the cost shifters are excluded from the demand equation since they do not directly affect demand and only indirectly affect demand through their effect on $i_{b,t}$ and $a_{b,t}$. This is because the cost shifters affect the funding cost of originating mortgages, and so variation in the cost shifters will lead to variation in funding costs which affect banks' choice of $i_{b,t}$ and $a_{b,t}$. I use the cost shifter variables Interest Expense and Noncurrent Loans from UBPR data as instruments for $i_{b,t}$ and $a_{b,t}$ assuming that these bank cost shifters affect bank profits but are excluded from the demand equation.[25] The effect of Interest Expense on the funding cost of banks is obvious, where higher interest expense leads to a higher cost of borrowed funds and higher funding cost of originating mortgages. Therefore, in general a higher interest expense should lead to higher interest rates and lower acceptance probabilities since it is lowering the profit from any given mortgage. The intuition behind Noncurrent Loans is that a higher share of noncurrent loans – loans past due or in nonaccrual – increases the riskiness of a bank's overall loan portfolio. This increases the likelihood that bank equity is negatively affected which increases the costliness of adding additional loans to its balance sheet and this will increase the funding cost of originating mortgages. This instrument allows me to use exogenous

[25] Interest Expense (UBPRE002): interest expense as a percentage of average assets. Noncurrent Loans (UBPR7414): percentage of loans 90 days past due or in nonaccrual.

variation in bank financial distress overwhelmingly driven by loans made in the past and also non-mortgage related loans.[26] These cost shifter variables vary at the bank-year level.

4.2 Defaults

I assume that the idiosyncratic error term ν in equation (3) is distributed EVI. The equation for the probability of default is:

$$d_{b,t} = \frac{exp\bigg(\delta_i \cdot i_{b,t} + \delta_a \cdot a_{b,t} + V_{b,t} \cdot \delta_V + \eta_{b,t}\bigg)}{1 + exp\bigg(\delta_i \cdot i_{b,t} + \delta_a \cdot a_{b,t} + V_{b,t} \cdot \delta_V + \eta_{b,t}\bigg)} \tag{17}$$

The estimation equation for the logit default model is the following:

$$ln(d_{b,t}) - ln(1 - d_{b,t}) = \delta_i \cdot i_{b,t} + \delta_a \cdot a_{b,t} + V_{b,t} \cdot \delta_V + \eta_{b,t} \tag{18}$$

Where, $d_{b,t}$ is the proportion of mortgages that defaulted, $i_{b,t}$ and $a_{b,t}$ are interest rates and acceptance probabilities respectively, $V_{b,t}$ are exogenous variables including the average FICO scores, LTV and DTI ratios, and bank and year-MSA fixed effects, and $\eta_{b,t}$ are unobservables affecting default probability across banks and year-MSAs. The key parameters of interest are δ_i and δ_a, which represents the moral hazard and adverse selection respectively. If $\delta_i > 0$, then a higher interest rate would increase the default probability of the household due to moral hazard, and if $\delta_a > 0$, then a higher acceptance probability leads to a higher default probability due to adverse selection. The endogeneity problem in estimating δ_i and δ_a is that banks observe $\eta_{b,t}$ before setting $i_{b,t}$ and $a_{b,t}$ but it is unobserved by the econometrician. I use bank branch share as an exogenous demand shifter and the bank funding cost shifters discussed above as instruments for $i_{b,t}$ and $a_{b,t}$, where the bank branch share and bank cost shifters are excluded from the default equation but affect $i_{b,t}$ and $a_{b,t}$ by affecting demand and bank funding costs respectively. In addition, I also include the same rich set of bank and year-MSA fixed effects also included in demand estimation,

One problem with estimating equation (18) is that there are 1,608 observations out of 6,052 that will drop out of the regression sample because they have $d_{b,t} = 0$. This may introduce sample selection bias because the observations that drop out will have less default

[26] See Egan et al., (2017).

risk than the observations that remain. In order to include all 6,052 observations I follow Gandhi et al. (2013) use a Laplace transformation of the variable $d_{b,t}$ and estimate:

$$ln(d_{b,t} + \tau) - ln(1 - d_{b,t} - \tau) = \delta_i \cdot i_{b,t} + \delta_a \cdot a_{b,t} + V_{b,t} \cdot \delta_V + \eta_{b,t} \tag{19}$$

Where, $\tau = 0.001$. This will prevent $d_{b,t} = 0$ observations from dropping out of my regression sample.

4.3 Supply

The key objects of interest in the supply model are the ex-ante profitability of mortgages $\pi_{b,t}$ and processing costs $C_{b,t}(q_{b,t})$. $\pi_{b,t} = PV_{b,t}(i_{b,t}, d_{b,t}) - mc_{b,t}$ is the present value of a mortgage with interest rate $i_{b,t}$ and default probability $d_{b,t}$ minus the funding cost $mc_{b,t}$. I make the following parametric assumptions for these objects:

$$\begin{aligned} PV_{b,t} &= i_{b,t} \cdot (1 - d_{b,t}) \\ -mc_{b,t} &= W_{b,t} \cdot \beta_W + \omega_{b,t} \\ C_{b,t}(q_{b,t}) &= c_{b,t} \cdot q_{b,t} \end{aligned} \tag{20}$$

I assume that the present value of a mortgage with interest rate $i_{b,t}$ and default probability $d_{b,t}$ is approximated by $i_{b,t} \cdot (1 - d_{b,t})$.[27] The funding cost of originating a mortgage is $-mc_{b,t} = W_{b,t} \cdot \beta_W + \omega_{b,t}$ where $W_{b,t}$ includes the two funding cost shifter variables and bank and year-MSA fixed effects. $\omega_{b,t}$ is the unobserved component of the funding cost that varies across banks and markets. Processing costs are linear in application probability $q_{b,t}$ and are allowed to vary across banks and year-MSAs, reflecting heterogeneity in efficiencies across banks, and regulatory burden across different jurisdictions and across time.

I assume that the idiosyncratic cost shocks e in equation (7) follows EVI, which jointly with the assumptions of logit demand and defaults imply the following first order conditions for the bank problem:

[27] Allen et al., 2019; Benetton, 2019 utilize similar approximations.

$$FOC^i_{b,t} \equiv \alpha_i \cdot (1 - q_{b,t}) \times \left[a_{b,t} \cdot \left(\pi_{b,t} + \sigma \cdot g(a_{b,t}) \right) - c_{b,t} \right] + a_{b,t} \cdot (1 - d_{b,t}) \cdot (1 - \delta_i \cdot d_{b,t} \cdot i_{b,t}) = 0$$

$$FOC^a_{b,t} \equiv \alpha_a \cdot (1 - q_{b,t}) \times \left[a_{b,t} \cdot \left(\pi_{b,t} + \sigma \cdot g(a_{b,t}) \right) - c_{b,t} \right] - \delta_a \cdot a_{b,t} \cdot i_{b,t} \cdot d_{b,t} \cdot (1 - d_{b,t}) + \pi_{b,t} + \sigma \cdot G'(a_{b,t}) = 0 \tag{21}$$

Where $g(a) \equiv \frac{\gamma - ln(1-a)}{a} + ln(1-a) - ln(a)$, γ is the Euler-Mascheroni constant, $G(a) \equiv a \cdot g(a)$, and $G'(a) = ln(1-a) - ln(a)$. Given demand (α) and default (δ) estimates, I have three unknowns in $\pi_{b,t}$[28], $c_{b,t}$, and σ in the two first order conditions. Note that $FOC^i_{b,t}$ and $FOC^a_{b,t}$ together identify $\pi_{b,t} + \sigma \cdot G'(a_{b,t})$ since $\alpha_a \cdot FOC^i_{b,t} - \alpha_i \cdot FOC^a_{b,t} = 0$ yields the following expression:

$$\kappa_p \equiv \delta_a \cdot a_{b,t} \cdot i_{b,t} \cdot d_{b,t} \cdot (1 - d_{b,t}) + \frac{\alpha_a \cdot a_{b,t} \cdot (1 - d_{b,t}) \cdot (1 - \delta_i \cdot d_{b,t} \cdot i_{b,t})}{\alpha_i} = \pi_{b,t} + \sigma \cdot G'(a_{b,t}) \tag{22}$$

All objects on the left-hand side of equation (22) are either observed or parameters estimated from demand and default models. Substituting in the expression for $\pi_{b,t}$ and rearranging leads to the following estimation equation for σ:

$$\kappa_p - i_{b,t} \cdot (1 - d_{b,t}) = \sigma \cdot G'(a_{b,t}) + W_{b,t} \cdot \beta_W + \omega_{b,t} \tag{23}$$

There is an endogeneity problem where $G'(a_{b,t})$ is correlated with unobserved $\omega_{b,t}$. Supposing I have a valid instrument for $G'(a_{b,t})$ that is uncorrelated with $\omega_{b,t}$, I could estimate σ as the coefficient of $G'(a_{b,t})$ using linear instrumental variables regression. Then, once σ and β_W are estimated I could substitute them in to one of the first order conditions to obtain estimates of $c_{b,t}$.

Instead, I estimate the supply model in the following way. Given a value for σ, say $\hat{\sigma}$, I can use the two first order conditions to solve for $\hat{\pi}_{b,t}(\hat{\sigma})$ and $\hat{c}_{b,t}(\hat{\sigma})$ for every bank-market pair, where the notation represents the dependence of the estimates of mortgage profit and processing cost on $\hat{\sigma}$.[29] Then, with $\hat{\pi}_{b,t}(\hat{\sigma})$ I can obtain estimates $-\hat{mc}_{b,t} = \hat{\pi}_{b,t}(\hat{\sigma}) - i_{b,t} \cdot (1 - d_{b,t})$. Given $-\hat{mc}_{b,t}$, I estimate β_W from the following equation by OLS:

[28] Note that what is really unknown is the funding cost $-mc_{b,t} = \pi_{b,t} - i_{b,t} \cdot (1 - d_{b,t})$.

[29] The exact expressions are derived in Appendix C.

$$- \hat{mc}_{b,t}(\hat{\sigma}) = W_{b,t} \cdot \beta_W + \omega_{b,t} \tag{24}$$

The identifying assumption is that bank cost shifters $W_{b,t}$ are exogenous and uncorrelated with $\omega_{b,t}$, and they include the Interest Expense and Noncurrent Loans variables as well as bank and year-MSA fixed effects. Finally, to pin down the value of $\hat{\sigma}$, I do a grid search over the values of $\hat{\sigma}$ such that in a counterfactual where I lower the funding cost of originating mortgages, the elasticity of interest rates with respect to funding cost on average is equal to 1. Therefore, my estimation approach is based on the moment restrictions: i) cost shifters $W_{b,t}$ are exogenous, i.e., $\mathbb{E}[W_{b,t} \cdot \omega_{b,t}] = 0$, ii) the average elasticity of interest rates with respect to funding cost is equal to 1. To save computational time, I only use observations from 2010 for calculating the pass through counterfactuals.

The second moment restriction is motivated by the fact that the average interest rate closely tracks the 10 Year Treasury Rate, and other papers have shown that this elasticity is equal to 1 (Agarwal et al. (2017) for example). The focus of the paper is not on the average interest rate pass through but in comparing the magnitude of the pass through in credit rationing to the interest rate pass through, as well as the heterogeneity of pass through in interest rates and acceptance probabilities across banks and markets.

5 Results

This section discusses the results of demand, defaults, and supply estimation.

5.1 Demand

Table 2 shows the estimation results of equation (16). The first two columns show OLS and 2SLS estimates of the demand parameters respectively. The first column shows that for OLS estimates, the coefficient on interest rates ($\hat{\alpha}_i$) is not statistically significant from 0 and the coefficient on acceptance probabilities ("Acc. Prob.", $\hat{\alpha}_a$) is negative instead of the expected positive sign. 2SLS estimates show markedly different results, with $\hat{\alpha}_i$ becoming significantly more negative and statistically significant from 0, and $\hat{\alpha}_a$ becoming positive. This is a typical pattern in demand estimation, where the OLS estimates of the coefficient on price can be positive or attenuated and estimation with valid instruments make the price coefficient more negative. This is due to the fact that firms that have products with better unobservable quality can charge higher prices, thereby causing correlation between price and unobservables that significantly bias the price coefficient in OLS estimation. A similar logic follows here, where it seems that banks with better unobservable quality $\xi_{b,t}$ can charge higher interest rates and have lower probabilities of acceptance but still draw applications. Ignoring this correlation between $\xi_{b,t}$, $i_{b,t}$ and $a_{b,t}$ seems to cause significant bias in the demand estimates. For 2SLS estimates, the average own-demand elasticity of interest rate and acceptance probability are 6.637 and -0.3 respectively. 2SLS estimates yield significantly higher interest rate elasticity than OLS estimates, while demand is relatively inelastic with respect to the acceptance probabilities.

5.2 Defaults

Table 3 shows the estimation results for equation (18). The first column shows OLS estimates and the second column shows 2SLS estimates. The key results of interest are that the 2SLS estimates show evidence of adverse selection and moral hazard in U.S. mortgage lending. The effect of moral hazard on defaults is stronger with an elasticity of -3.45 versus the effect of adverse selection on defaults with an elasticity of -0.62. However, the coefficient estimate for adverse selection is statistically significant whereas the coefficient estimate for interest rate is not. Going from OLS to 2SLS estimates flips the signs for the coefficients of both interest rates and acceptance probabilities. The direction of movements in $\hat{\delta}_i$ and $\hat{\delta}_a$ estimates going from OLS to 2SLS are as expected. Banks are likely to not raise interest rates or acceptance probabilities as much where default probability is unobservably higher, and so not accounting for this source of endogeneity is likely to underestimate the $\hat{\delta}_i$ and $\hat{\delta}_a$ parameters, which is exactly what table 3 shows. Finally, other loan characteristics including average FICO, LTV, and DTI ratios all have expected signs. Higher FICO decreases default probability whereas higher LTV and DTI increase default probability. .

5.3 Supply

Figure 3 plots the distributions of processing costs ($c_{b,t}$) and funding costs ($mc_{b,t}$) per bank in 2010. It shows there is variation in funding and processing costs within and across banks. In particular, there is substantial heterogeneity across markets in funding and processing costs for each bank. For both funding and processing costs, I conjecture that the cost heterogeneity across markets is driven by two main factors: heterogeneity in the bank productivity for processing and closing loans, and heterogeneity in regulatory burden or costs. For example, it is well-known that the cost of securitizing a mortgage to the GSEs depends on the FICO

Table 2: Estimates of Demand Parameters

	OLS	2SLS	Interest Rate	Acc. Prob.
Interest Rate	-11.48*	-155.1**		
	(6.263)	(69.58)		
Acc. Prob.	-0.712***	0.697**		
	(0.0629)	(0.289)		
Branch Shr.	6.488***	6.012***	0.000668**	0.414***
	(0.144)	(0.221)	(0.000327)	(0.0312)
Noncurrent Loans			0.000248***	-0.0420***
			(0.0000284)	(0.00272)
Interest Expense			0.00216***	0.0451
			(0.000333)	(0.0319)
Constant	-4.981***	0.663	0.0413***	0.666***
	(0.274)	(3.115)	(0.000279)	(0.0266)
Bank FE	x	x	x	x
MSA-Year FE	x	x	x	x
N	6052	6052	6052	6052
Interest Rate El.	0.580	6.637		
Acc. Prob. El.	0.114	-0.30		

Notes: Standard errors in parentheses. Unit of observation is bank-MSA-year. The first two columns show OLS and 2SLS estimates respectively, and the third and fourth columns show the first stage regressions of the 2SLS regression. The coefficients on Interest Rate and Acc. Prob. (acceptance probabilities) are as expected with household utility decreasing in interest rates and increasing in acceptance probabilities. Branch Shr. – a bank's share of total bank branches in the market – also increase household utility in applying to the bank. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Evidence of Adverse Selection and Moral Hazard in Defaults

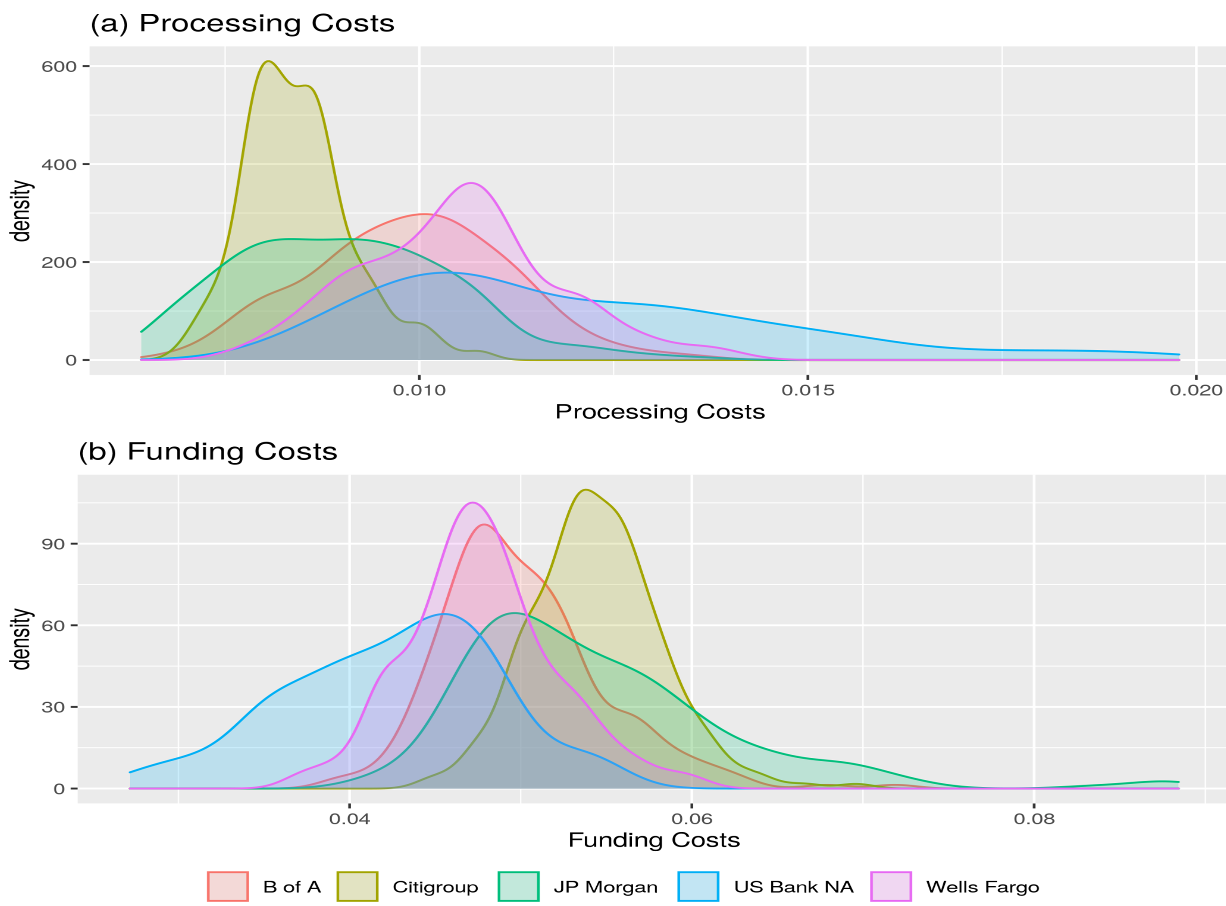
	OLS	2SLS	Interest Rate	Acc. Prob.
Interest Rate	-22.13	80.60		
	(15.43)	(133.1)		
Acc. Prob.	-1.117***	1.435***		
	(0.145)	(0.421)		
FICO	-0.00722***	-0.000740	-0.0000328***	-0.00172***
	(0.00219)	(0.00506)	(0.00000201)	(0.000201)
LTV	0.0313***	0.0372***	0.0000850***	-0.00527***
	(0.00573)	(0.0126)	(0.00000531)	(0.000531)
DTI	0.0545***	0.0641***	0.0000395***	-0.00806***
	(0.0108)	(0.0120)	(0.0000101)	(0.00101)
Noncurrent Loans			0.000188***	-0.0395***
			(0.0000268)	(0.00269)
Interest Expense			0.00139***	0.140***
			(0.000319)	(0.0319)
Branch Shr.			0.00141***	0.367***
			(0.000308)	(0.0308)
Constant	-0.270	-11.60	0.0598***	2.555***
	(2.020)	(8.650)	(0.00169)	(0.169)
Bank FE	x	x	x	x
MSA-Year FE	x	x	x	x
N	6052	6052	6052	6052
Interest Rate El.	1.080	-3.45		
Acc. Prob. El.	0.180	-0.62		

Notes: Standard errors in parentheses. Unit of observation is bank-MSA-year. The first two columns show OLS and 2SLS estimates respectively, and the third and fourth columns show the first stage regressions of the 2SLS regression. Positive coefficients on Interest Rate and Acc. Prob. (acceptance probability) represent moral hazard and adverse selection respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

score and LTV ratio of a borrower. Heterogeneity in the composition of borrowers across markets could explain heterogeneity in funding costs. For processing costs, the heterogeneity across markets could be driven by heterogeneity in the cost of property appraisals or the productivity of loan officers in processing applications.

Table 4 shows estimates of the parameters for the bank cost shifters where I control for bank and MSA-year fixed effects. Both cost shifters increase the funding cost as expected but the only the Noncurrent Loans cost shifter is statistically significant. This could be driven by the collinearity in the two funding cost shifters.

Figure 3: Heterogeneity in Processing and Funding Costs in 2010



Notes: Panel (a) and (b) show the distributions of processing costs ($c_{b,t}$) and funding costs ($mc_{b,t}$) per bank respectively. It illustrates the heterogeneity in processing and funding costs across banks and also across markets for any given bank. Processing and funding costs are expressed in terms of interest rates.

Table 4: Funding Costs Increase in Bank Cost Shifters

	$-mc$
Noncurrent Loans	-0.00314***
	(0.000145)
Interest Expense	-0.00223
	(0.00170)
Constant	-0.0253***
	(0.00143)
Bank FE	x
MSA-Year FE	x
N	6052

Notes: Standard errors in parentheses. Unit of observation is bank-MSA-year. The dependent variable is the negative of the funding cost $-mc_{b,t} = \pi_{b,t} - i_{b,t} \cdot (1 - d_{b,t})$. The bank cost shifters from UBPR data are noncurrent loans and leases as a percentage of gross loans and leases and interest expense as a percent of average assets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6 Counterfactuals

In this section I discuss three counterfactuals. First, I illustrate different implications that processing and funding costs have on how banks trade-off interest rates and acceptance probabilities. Second, I study how banks pass through lower funding costs through interest rates and acceptance probabilities and how factors such as market power and processing costs affect the heterogeneity in pass through. Third, I study the role that adverse selection and moral hazard play on pass through in the credit rationing margin.

To address the strong possibility of the existence of multiple equilibria in my model, for all counterfactuals I always set the starting values of interest rates and acceptance probabilities equal to the observed values in the data. This is done to prevent equilibria-switching to drive my counterfactual results where changing the starting values of a counterfactual simulation could lead to a different equilibrium purely due to multiple equilibria, rather than due to any changes in the primitives of the model. [30]

[30]More details on how I simulate counterfactuals can be found in Appendix D.

6.1 Funding and Processing Costs

The first set of counterfactuals illustrates the different implications that funding and processing costs have on how banks trade-off interest rates and credit rationing. I pick a representative market in 2010 (Youngstown-Warren-Boardman OH-PA MSA)[31] and first exogenously shut down all heterogeneity across banks and calculate a new equilibrium as the baseline. Then, I compare how new equilibrium interest rates and acceptance probabilities move in response to adding back heterogeneity across banks in processing costs versus adding back heterogeneity in funding costs.

Figure 4 shows the results of the counterfactuals described above. In both panels (a) and (b) arrows indicate the movement from the baseline where there is no heterogeneity in any dimension across banks to the new equilibrium after bank heterogeneity is re-introduced. This is implemented by assigning all banks the average values of all exogenous variables. Panel (a) shows the movements in interest rates and acceptance probabilities when I add back processing cost heterogeneity to the baseline. In the baseline all banks charge 0.0527 interest rate and offer 0.323 acceptance probability. When processing cost heterogeneity is re-introduced, banks that experience an increase in processing costs compared to the baseline (Wells Fargo, JP Morgan) increase interest rates and acceptance probabilities. In contrast, banks that experience a decrease in processing costs compared to the baseline (Citigroup, US Bank NA) decrease interest rates and acceptance probabilities. Bank of America does not materially change its interest rates and acceptance probabilities because its actual processing cost is close the the value from the baseline.

Similarly, panel (b) shows the movements in interest rates and acceptance probabilities when I re-introduced funding cost heterogeneity across banks. It shows that for banks that see their funding cost increase from the baseline (Citigroup, US Bank NA), they increase interest rates and decrease acceptance probabilities. If banks see a decrease in the funding cost (Wells Fargo, US Bank NA, Bank of America), then they lower rates and increase acceptance probabilities. From this figure it can be seen that banks trade-off interest rates and acceptance probabilities differently for changes to different types of costs. This means that the welfare implications of a reduction in processing costs can be qualitatively different than a reduction in funding costs. When funding costs decrease, households unambiguously benefit because interest rates become lower and acceptance probability becomes higher. However, reductions in processing costs has ambiguous implications for households since

[31] I pick the MSA-year with demand, defaults and funding cost fixed effects close to their respective averages in 2010.

households benefit from lower interest rates but are harmed by lower probabilities of acceptance.

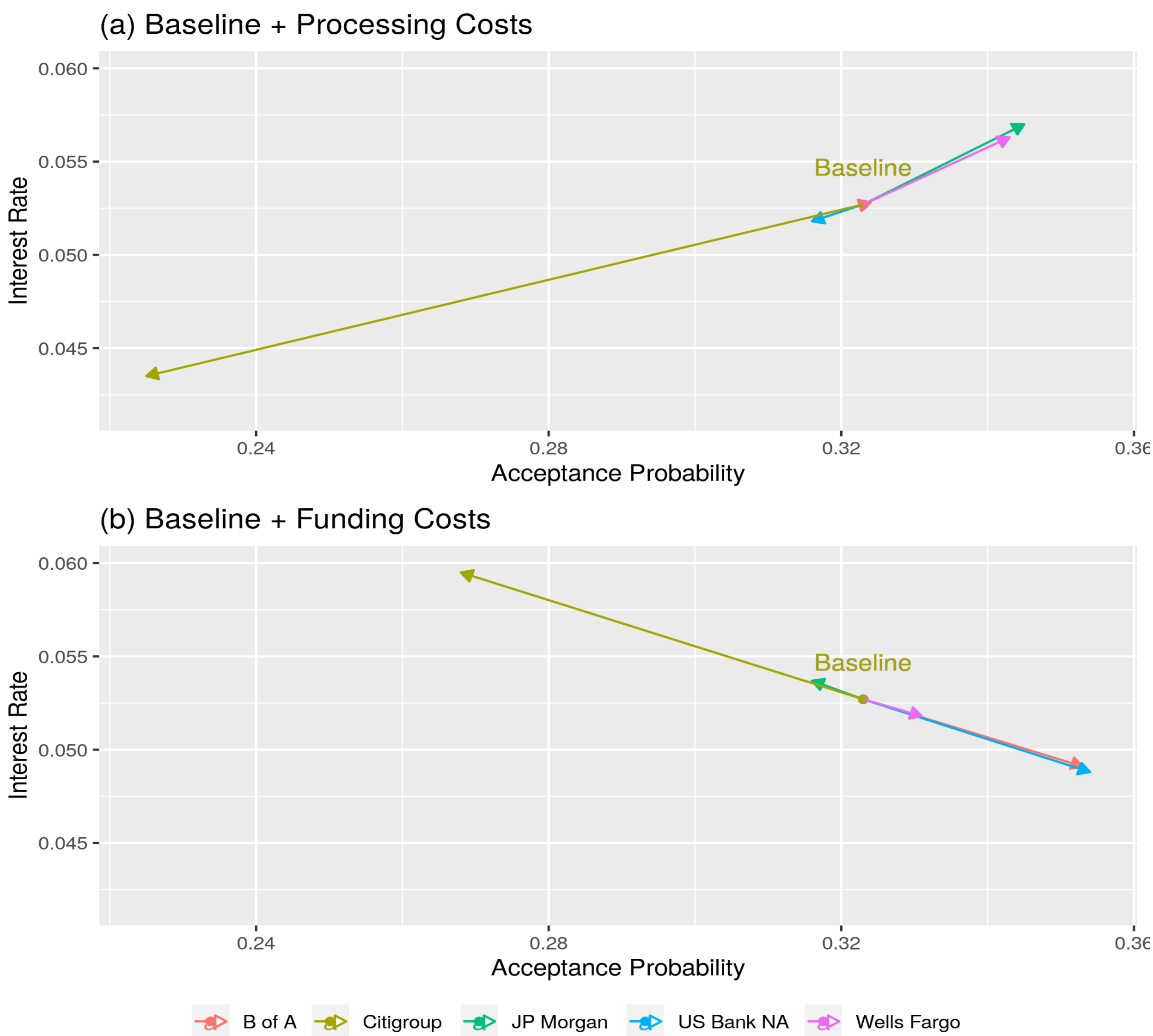
The intuition for this result is as follows. My estimates imply that acceptance probabilities are determined by the profit margin a bank makes on originated mortgages (as opposed to competition between banks for market share of applications), with a bigger profit margin implying higher acceptance probabilities. When funding costs decrease, banks lower interest rates to attract more applications at the expense of the now higher margin. Although the present value of a mortgage will decrease due to the direct effect of lowering monthly payments received from the borrower, the decrease in present value is somewhat mitigated by the indirect effect of lowering the default probability of the borrower due to the presence of moral hazard. Therefore, the present value of a mortgage will decrease less than the decrease in funding costs, resulting in a bigger profit margin. This is why interest rates will decrease and acceptance probabilities will increase when funding costs decrease. On the other hand, a processing cost decrease will also lead banks to decrease interest rates in order to attract more applications because now the cost incurred per application has decreased. However, since funding costs have not changed but banks lowered interest rates, the profit margin will be smaller than before the processing cost decrease which means banks will lower acceptance probabilities. This explains why funding and processing costs have different implications on how banks trade-off interest rates and credit rationing.

This result could shed new light on how regulation affects mortgage lending. For example, the Department of Housing and Urban Development recently announced that banks will be less vigorously prosecuted for originating fraudulent mortgages in violation of the False Claims Act. The goal is to increase mortgage lending by decreasing regulatory burden on banks. In the context of my model this could be thought of as a reduction in processing costs. My results show that not taking into account how acceptance probabilities decrease when processing costs decrease could lead to an over-prediction of the increase in lending from this regulatory change.

6.2 Funding Cost Pass Through

The second set of counterfactuals study how banks pass through lower funding costs through interest rates and acceptance probabilities in order to simulate the effects of an expansionary monetary policy. For all observations in 2010, I lower funding costs by 10% and then look at

Figure 4: Interest Rates, Credit Rationing, and Funding and Processing Costs



Notes: Figure shows movements in equilibrium interest rates and acceptance probabilities as I add back heterogeneity across banks in processing and funding costs to a baseline where there is no heterogeneity across banks in any dimension. Panel (a) shows the results of adding back bank heterogeneity in processing costs to the baseline. Similarly, panel (b) shows the results from adding bank funding cost heterogeneity to the baseline.

equilibrium outcomes, in particular:[32] a) the magnitude of the pass through in acceptance probabilities, and b) the heterogeneity in pass through in interest rates and acceptance probabilities. In addition to calculating the equilibrium for each market where banks can endogenously adjust in interest rates and acceptance probabilities, I also run two parallel sets of counterfactuals where banks can only adjust in interest rates (holding acceptance probabilities fixed) and only adjust in acceptance probabilities (holding interest rates fixed). The purpose of these parallel counterfactuals is to compare and contrast equilibrium outcomes for a model where both interest rates and credit rationing are endogenous versus models that only allow for endogenous changes in one margin.

Figure 5 shows an illustration of pass through for a single market (same market explored in section 6.1). In panel (a), each colored arrow represents the equilibrium pass through where in the solid arrow banks can adjust through both interest rates and acceptance probabilities, in the dashed arrow banks can only adjust through interest rates holding acceptance probabilities fixed, and in the dotted arrow banks can only adjust in acceptance probabilities holding interest rates fixed. Panel (b) shows the same results for Bank of America only. Panel (b) shows that only allowing adjustments in interest rates over-predicts the interest rate pass through by 4 basis points. Holding the credit rationing margin fixed has ambiguous implications for household welfare predictions. On the one hand, it over-predicts the interest rate pass through which implies an over-prediction of the gains to households from the change in interest rates, but on the other hand it does not take into account the welfare gain for households in the increased acceptance probabilities.

Table 5 shows the average percentage change in equlbrium outcomes for the three parallel pass through counterfactuals. The first column shows average percentage change in equilibrium outcomes where banks can adjust in both interest rates and acceptance probabilities. From this column it can be seen that banks adjust significantly in both interest rates and acceptance probabilities when funding costs decrease. The second and third columns show results for the case where banks can only adjust in interest rates and acceptance probabilities respectively. Comparing the first two columns, the table shows that only allowing banks to adjust in interest rates over-predicts the interest rate pass through and, the gains to households, and the decrease in defaults due to the moral hazard in defaults w.r.t. interest rates. It also under-predicts the gains to banks. In terms of magnitudes, the over-prediction in the pass through is more important for under-predicting the average

[32] I estimate the variance of the idiosyncratic cost σ with the moment condition that interest rates decrease by 10% on average for a 10% decrease in funding costs using 2010 observations.

percentage gain to banks (approximately a percentage point) than gains to households (less than a percentage point). Finally, it shows that compared to the model where both interest rates and acceptance probabilities are endogenous, a model where banks can only adjust in interest rates under-predicts the increase in lending by approximately 5 percentage points.

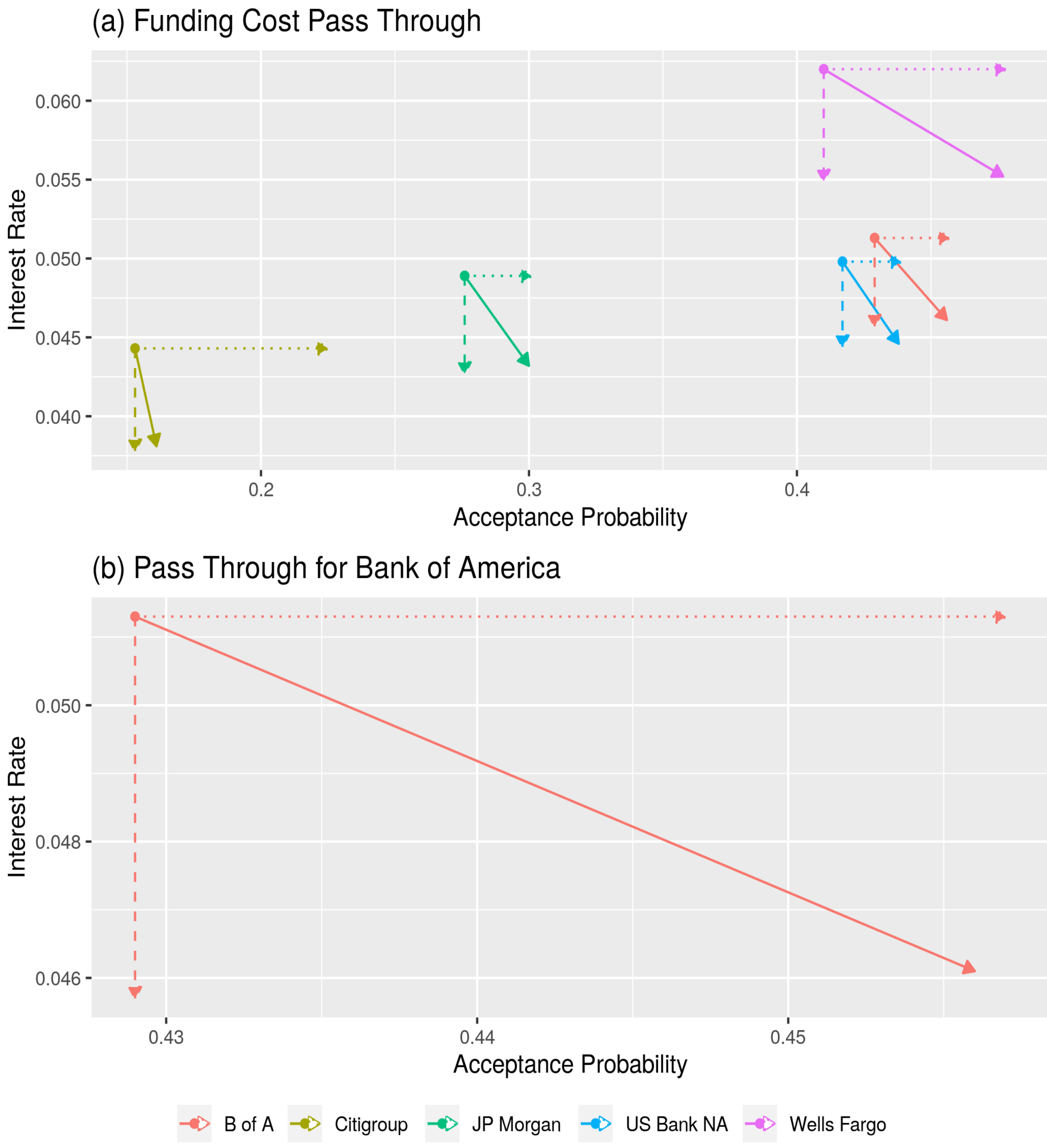
Comparing the first and third columns, only allowing banks to adjust in acceptance probabilities over-predicts the increase in acceptance probabilities, under-predicts to gains to households, and – most interestingly – significantly over-predicts the gains to banks. This seems to suggest that there is a prisoner's dilemma type of effect when funding costs decrease and banks can compete in interest rates as all banks would like to keep the interest rate fixed in response to lower funding costs, but each bank's best-response to other banks holding rates fixed is to undercut them, leading to a Pareto-inferior equilibrium where interest rates are lower in the new equilibrium. Finally, in the third column defaults increase due to adverse selection effects where bank increasing the proportion of mortgage applications leads to a riskier pool of accepted mortgages and defaults increase.[33]

Panel (a) of figure 6 shows the pass through in interest rates and acceptance probabilities for all observations in 2010 where each colored arrow represents the movement from observed data to the new pass through equilibrium for a bank-market observation. Interest rates decrease on average by 50 basis points and acceptance probabilities increase on average by 2.5 percentage points. The figure shows that there seems to be heterogeneity in the pass through of interest rates and acceptance probabilities. Panel (b) shows the average pass through in interest rates and acceptance probabilities per bank. There is clear heterogeneity across banks with US Bank NA showing the smallest pass through in both interest rates and acceptance probabilities and JP Morgan Chase showing some of the biggest pass through in both margins. On average Bank of America benefits the most in the pass through counterfactual.

Figure 7 looks more closely at the heterogeneity in pass through in 2010. Panels (a) and (b) show how processing costs and bank branch share (as a measure of bank market power) affect interest rate and acceptance probability pass throughs respectively. Each dot is a bank-MSA in 2010, and bright green dots indicate the largest pass throughs (largest decreases in interest rates and largest increases in acceptance probabilities). Panel (a) shows that interest rate pass through is larger in bank-MSA where banks have less market power and have lower processing costs. Things are more ambiguous for acceptance probability pass

[33]It is important to note that in my model consumer surplus does not include the cost of defaults to households and therefore gives an incomplete view of changes in household welfare. This is a common limitation in structural models of competition in credit markets.

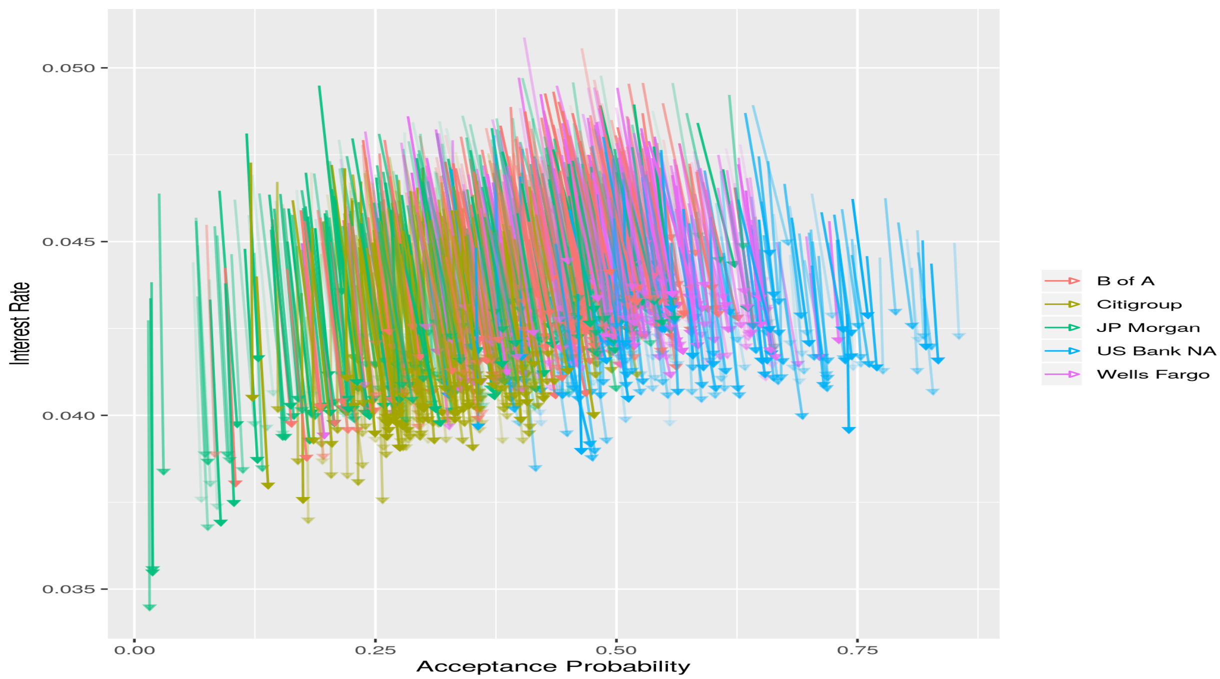
Figure 5: Funding Cost Pass Through in a Given Market



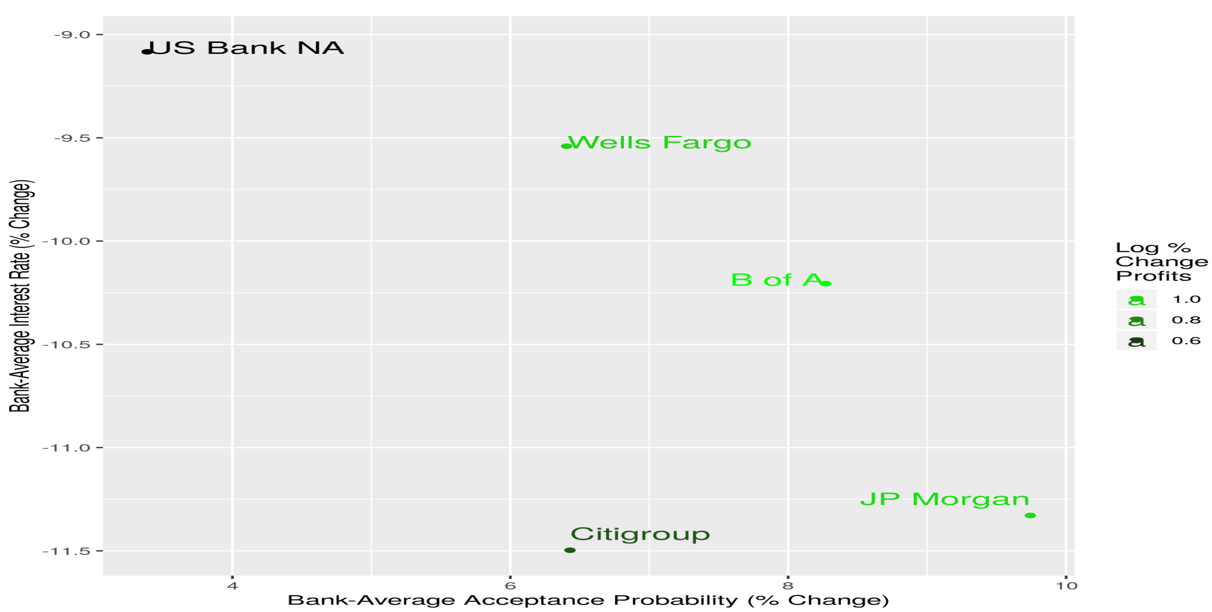
Notes: Figure shows the pass through in interest rates and acceptance probabilities for a 10% cut in funding cost. The solid line shows the case where banks can adjust to the new equilibrium through both interest rates and acceptance probabilities, the dashed line shows the case where banks can only adjust through interest rates, and the dotted line shows the case where banks can only adjust through acceptance probabilities. Panel (a) shows pass through for a single market and panel (b) shows pass through for a single bank.

Figure 6: Pass Through in Interest Rates and Acceptance Probabilities in 2010

(a) Pass Through in All Bank-Markets



(b) Average Pass Through per Bank



Notes: Panel (a) shows the pass through in interest rates and acceptance probabilities for a 10% cut in funding cost for all bank-MSA observations in 2010. Panel (b) shows average pass through per bank in 2010 with the color representing the log of the average percentage change in profits.

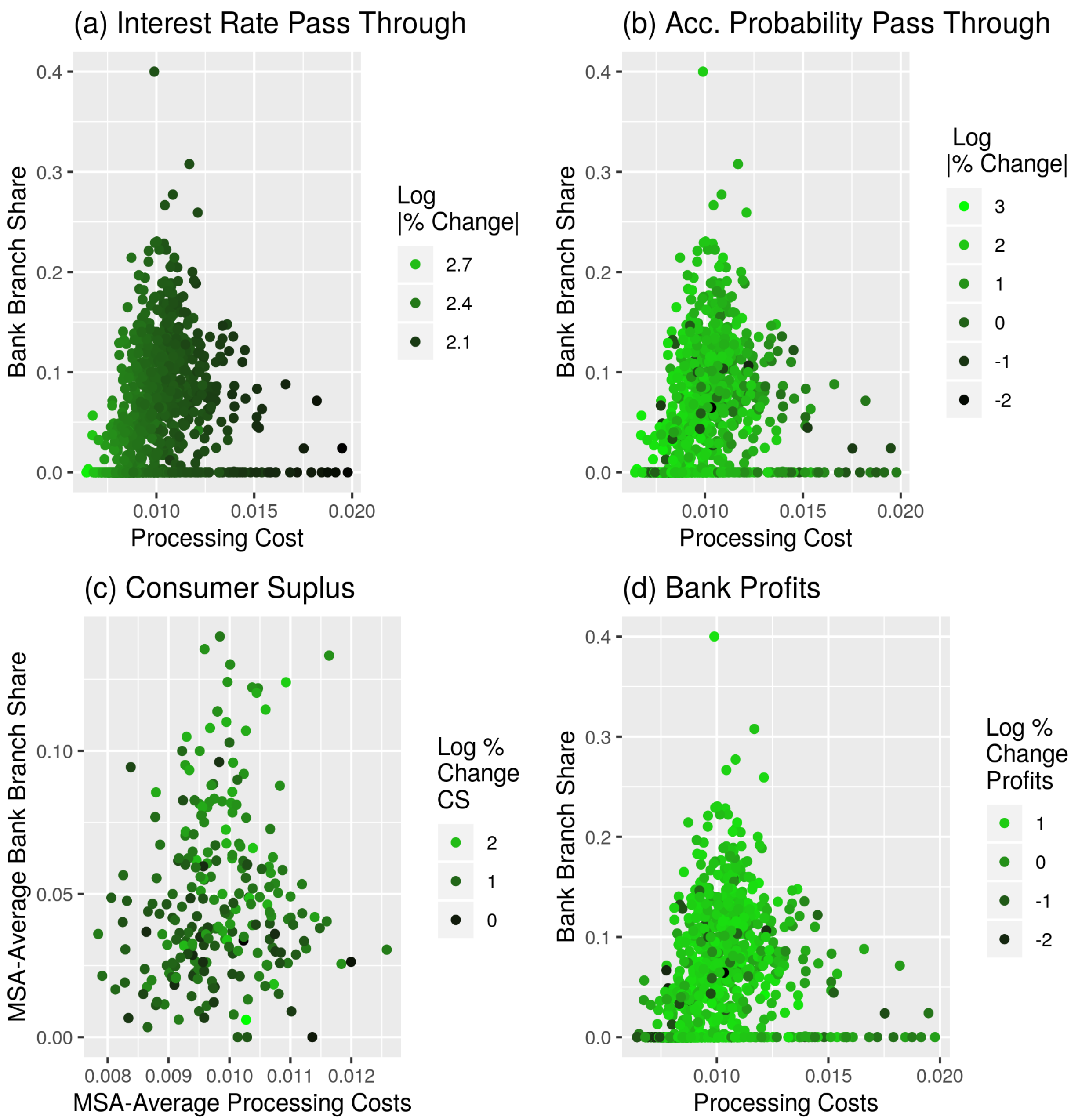
Table 5: Average Percentage Change in Equilibrium Outcomes with Pass Through

	i and a (%)	i only (%)	a only (%)
Interest Rates	-10.407	-11.328	0.000
Acc. Prob.	7.073	0.000	25.559
Consumer Surplus	3.608	3.963	0.269
Profits	2.461	1.467	16.508
Defaults	-28.864	-33.563	13.129
Applications	108.774	118.923	6.097
Mortgages	124.011	118.923	33.455

Notes: Table shows average percentage change in interest rates, acceptance probabilities, consumer surplus, profits, defaults, applications, and mortgages for counterfactuals where I decrease funding costs by 10% for all banks. The first column shows results for the case where banks can adjust through both interest rates and acceptance probabilities to reach the new equilibrium. The second and third columns show results for the cases where banks are only allowed to adjust in interest rates (holding acceptance probabilities fixed) and acceptance probabilities (holding interest rates fixed) respectively.

through in panel (b), although in general the brightest green dots are where there is lower processing costs. Panels (c) and (d) plot the gain to households and banks respectively on processing costs and bank branch share. There is heterogeneity in how much households and banks gain across MSAs and the pattern is not straightforward. Tables 6 and 7 compares how exogenous characteristics differ across quartiles of interest rate and acceptance probability pass through respectively. Table 6 shows that in bank-MSAs where there is higher interest rate pass through, the bank branch share is higher and processing costs are lower whereas the funding costs are higher. Average FICO, LTV, and DTI does not seem to vary across different quartiles of percentage pass through in interest rates. Mirroring results from table 6, table 7 shows that bank branch share and processing costs are lower in bank-MSAs with higher increases in acceptance probabilities, and funding costs are higher. Overall, it seems that processing costs are an important source of heterogeneity in interest rate pass through, with variation in processing costs explaining 78% of the variation in interest rate pass through across banks and markets.

Figure 7: Pass Through, Consumer Surplus, and Bank Profits in 2010



Notes: Panels (a) and (b) plot pass through in the interest rates and acceptance probabilities respectively on processing costs and bank branch share, where each dot represents a bank-MSA and bright green color indicates larger pass through in terms of the absolute value of the percentage change. Panel (c) plots the percentage change in consumer surplus on processing costs and bank branch share where each dot is an MSA. Panel (d) plots the percentage change in bank profits where each dot is a bank-MSA.

Table 6: Averages of Demand, Defaults, and Supply Variables for Quartiles of Interest Rate Pass Through

% Change in i $(-)$ Variables	$(6.142, 9.404]$	$(9.404, 10.216]$	$(10.216, 11.271]$	$(11.271, 19.521]$
Bank Branch Share	0.081753	0.076805	0.033329	0.007377
Processing Cost	0.012207	0.010203	0.009044	0.007905
Funding Cost	0.038348	0.043332	0.046673	0.052651
FICO	764.832644	764.595769	762.573313	763.322327
LTV	68.415884	68.246536	66.870548	66.181095
DTI	31.256928	31.586690	31.148484	30.823536

Notes: Table shows averages of bank branch share, processing costs, funding costs, and average FICO, DTI, and LTV for each quartile of (negative) percentage pass through in interest rates.

Table 7: Averages of Demand, Defaults, and Supply Variables for Quartiles of Acceptance Probability Pass Through

% Change in a Variables	$(0.117, 4.677]$	$(4.677, 6.925]$	$(6.925, 9.314]$	$(9.314, 21.114]$
Bank Branch Share	0.051887	0.065872	0.059254	0.022304
Processing Cost	0.010954	0.010103	0.009682	0.008622
Funding Cost	0.041742	0.043854	0.045361	0.050044
FICO	766.643856	765.091407	763.245272	760.347764
LTV	67.181043	67.007546	67.504334	68.018938
DTI	30.744499	31.257379	31.404827	31.408668

Notes: Table shows averages of bank branch share, processing costs, funding costs, and average FICO, DTI, and LTV for each quartile of percentage pass through in acceptance probabilities.

6.3 Adverse Selection, Moral Hazard, and Pass Through

The final set of counterfactuals explore how adverse selection and moral hazard affect funding cost pass through. Because adverse selection and moral hazard are key frictions that can appear in any credit market, it is important to understand how they affect the pass through of expansionary monetary policy. Note that all my results discussed below only include observations from 2010.

I first examine the effects of adverse selection and moral hazard on mortgage lending. Table 8 shows the average percentage change in going from the observed data to equilibrium outcomes where adverse selection and/or moral hazard is shut down exogenously. My model predicts that interest rates and acceptance probabilities will increase in all of the scenarios above. For example, the first column shows that interest rates would increase on average by 1.082% (5 basis points) and acceptance probabilities would increase by 12.202% (4.8 percentage points). If I shut down moral hazard, the percentage change from observed to new interest rates would be 1.729% (8 basis points) and for acceptance probabilities it would be 22.626% (8.1 percentage points). Shutting down both adverse selection and moral hazard yields results very similar to the case where I only shut down moral hazard.

Two things should be noted. First, the directions in which interest rates and acceptance probabilities move as I remove adverse selection and moral hazard effects from the model are as expected. These frictions prevent banks limit banks' ability to charge higher rates for higher default risk, so removing these frictions leads to higher interest rates charged by banks, and higher acceptance probabilities due to the larger profit margins. Second, moral hazard is quantitatively the more important friction. Shutting down moral hazard from the model leads to larger increases in interest rates and acceptance probabilities than when I shut down adverse selection.

Now I move on to calculating the pass through of decreased funding costs as I shut down adverse selection and moral hazard respectively. Table 9 shows the results of these counterfactuals. The first column shows the results from the full model with both adverse selection and moral hazard. Each of the last three columns specify what part of the model was shut down. For each of these columns, I calculate the pass through of lower funding costs in the following way. First, I calculate the new equilibrium outcomes after shutting down one of the frictions mentioned above. Then, I calculate the new equilibrium under the same model conditions with funding costs decreased by 10%. Then I calculate the average percentage change in equilibrium outcomes from the former to the latter equilibria.

Table 9 reports the average percentage change in equilibrium outcomes going from before the funding cost decrease to after. I explore the same three scenarios reported in table 8: no adverse selection, no moral hazard, and no adverse selection nor moral hazard. In all three scenarios, the interest rate pass through is very similar to the counterfactual pass through for observed data reported in table 5 of -10.407%. What is interesting is that the pass through in acceptance probabilities is lower in all scenarios than as predicted for the full model with adverse selection and moral hazard. With no adverse selection, pass through in acceptance probabilities is 3.789% on average, whereas for the full model pass through in acceptance probabilities is predicted to be 7.073% on average. When I shut down moral hazard acceptance probability pass through is even lowered to 0.443%. These results imply that banks only pass through funding cost decreases in the credit rationing margin if there are frictions such as adverse selection or moral hazard in mortgage lending.

The intuition for the above result is that according to my estimates, acceptance probabilities are almost entirely driven by the profit margins on originated mortgages, and that the profit margins become larger after the funding cost decrease when there is adverse selection or moral hazard. I explain the intuition for the case where there is no moral hazard in more detail. Following a funding cost decrease, the marginal benefit of a bank reducing its interest rate comes from the increased market share that it will attract, at the expense of reducing profit margins and incurring higher processing costs from attracting more applications. When there is moral hazard, the expense of lowering profit margins by lowering interest rates is somewhat mitigated by households becoming less likely to default as interest rates decrease. This means that for any decrease in interest rates, the profit margins are larger in the case where there is moral hazard than where there is no moral hazard. In all the above scenarios banks find it optimal to reduce interest rates on average by approximately 10% for a 10% decrease in funding costs, so profit margins will be bigger where there is moral hazard than where there is no moral hazard. When there is moral hazard, banks find it optimal to decrease interest rates by approximately 10% and enjoy the large profit margins on originated mortgages by increasing the acceptance probability, rather than decreasing interest rates by less than 10% and keeping similar profit margins. Therefore banks increase the acceptance probability more for the case where there is moral hazard than when there is no moral hazard. These results imply that the extent of adverse selection and moral hazard in a credit market is important for policy makers in predicting the effects of expansionary monetary policy on pass through in the credit rationing margin.

Table 8: The Effects of Adverse Selection and Moral Hazard

	No AS (%)	No MH (%)	No MH/AS (%)
Interest Rates	1.082	1.729	1.745
Acc. Prob.	12.202	22.626	23.063
Consumer Surplus	-0.154	-0.210	-0.210
Profits	3.498	7.791	7.890
Defaults	-39.442	-97.221	-98.573
Applications	-4.192	-6.279	-6.283
Mortgages	7.473	14.689	15.084

Notes: Table shows the average percentage change in equilibrium outcomes when comparing the new equilibrium outcomes where I shut down key frictions in the model to the observed data. First, second, and third columns report the average percentage change in equilibrium outcomes from the observed data to counterfactuals where I shut down adverse selection, moral hazard, and both adverse selection and moral hazard respectively.

Table 9: Adverse Selection, Moral Hazard, and Funding Cost Pass Through

	Full Model (%)	No AS (%)	No MH (%)	No MH/AS (%)
Interest Rates	-10.407	-10.426	-10.493	-10.490
Acc. Prob.	7.073	3.789	0.443	0.416
Consumer Surplus	3.608	3.466	3.403	3.402
Profits	2.461	1.711	0.267	0.263
Defaults	-28.864	-31.952	0.281	0.000
Applications	108.774	109.374	109.982	109.949
Mortgages	124.011	117.741	110.937	110.845

Notes: Table shows the average percentage change in equilibrium outcomes after funding cost is decreased by 10%. The first column shows the results from the full model (same as the results in the first column of table 5). Second, third, and fourth columns show funding cost pass through where there is no adverse selection, no moral hazard, and neither adverse selection nor moral hazard respectively.

7 Conclusion

In this paper I study how banks optimally trade-off interest rates and credit rationing in U.S. mortgage lending, where credit rationing is defined as the probability of accepting a mortgage application. I develop a novel model of imperfect competition in mortgage lending with adverse selection and moral hazard where the model allows me to identify the cost of processing mortgage applications in addition to the cost of funding mortgages. These costs play an important role in explaining the relationship between interest rates and credit rationing, and the changes in these two types of costs have potentially different welfare implications. I estimate the model using U.S. data on mortgage applications, originations, interest rates, and defaults aggregated at the bank-MSA-year level.

I use the estimated model to run counterfactuals where funding costs decrease in order to understand how banks trade-off interest rates and credit rationing, and to show how this trade-off has important policy implications. First, I show that credit rationing is an important margin in the pass through of changes in funding costs. For a 10% decrease in funding costs, the average percentage change in interest rates and acceptance probabilities are -10.407% and 7.073% respectively. Second, there is substantial heterogeneity in the pass through of changes in funding costs in both interest rates and acceptance probabilities, which implies that some markets will receive significantly more benefit from say, expansionary monetary policy, than others. Processing costs play an important role in the heterogeneity in pass through since banks gain less from cutting interest rates to attract more applications where the cost of processing applications is higher. In particular, I find that variation in processing costs can explain 78% of the variation in interest rate pass through across banks and markets. Third, I quantify the role that adverse selection and moral hazard has on pass through in the credit rationing margin. I find that moral hazard is the more important friction for U.S. mortgage lending: with no moral hazard, the average percentage change in acceptance probabilities almost goes to zero. This implies that frictions such as adverse selection and moral hazard play a key role in how banks trade-off interest rates and acceptance probabilities, and how this trade-off is of central importance for policy questions.

My paper can be extended in several different directions. More work can be done on explaining the variation in funding and processing costs across banks and markets. One potential key dimension is the extent to which a bank securitizes its mortgages to the GSEs and how this affects funding costs. Greater familiarity and access to the GSEs as a source of funds for originating mortgages could provide a competitive advantage for banks. Processing costs increase in years after the financial crisis, which is consistent with the increasing regulatory burden as Dodd-Frank Act comes into effect and the Consumer Financial Protection Bureau is established during this period. However, more can be done to understand the cross-sectional variation in processing costs, for example whether differences in regulations across markets such as recourse versus non-recourse are important. Finally, distinguishing between funding and processing costs could be a natural framework for studying competition between banks and Fintechs.

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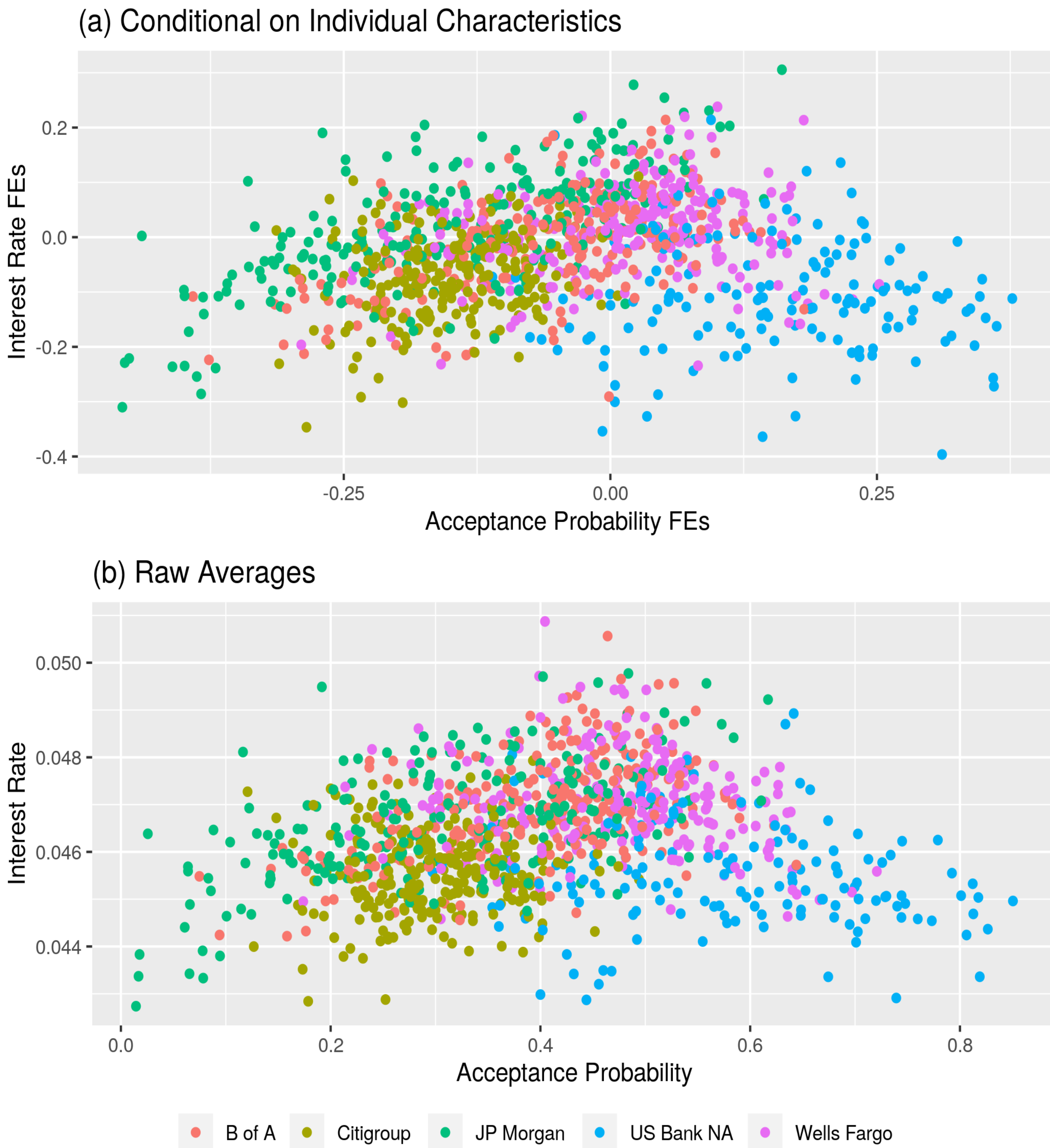
Appendix

A Controlling for Individual Characteristics

One concern with figure 1 is that differences in the composition of borrowers could be driving the cross-sectional variation in interest rates and acceptance probabilities. In order to test this concern, I look at the variation in interest rates and acceptance probabilities conditional on individual borrower characteristics. Using observations from 2010, I run loan-level regressions of interest rates or an indicator for whether the application was accepted as the dependent variable, and individual borrower characteristics and bank-MSA fixed effects as the explanatory variables. For the interest rate regression, the borrower characteristics used as explanatory variables are: loan size, FICO, DTI, LTV, purchase/refinance, whether the property is a single-family home, whether the property is owner-occuppied, the number of borrowers, and whether the borrowers are first time buyers. For the acceptance regression, the borrower characteristics used as explanatory variables are: applicant income, loan size, whether the borrower is white, purchase/refinance, whether the borrower is male, whether the property is owner-occupied, and whether the property is a single-family home. One caveat of the acceptance regression is that I cannot control for FICO, LTV, and DTI.

In figure 8 I compare the variation in interest rates and acceptance probabilities with and without controlling for individual borrower characteristics. This figure suggests that the cross-sectional variation in interest rates and acceptance probabilities are not driven by differences in the composition of borrowers. In panel (a) I plot the bank-MSA fixed effects from the two loan-level regressions described above. The y-axis is the bank-MSA fixed effect from the interest rate regression and the x-axis is the bank-MSA fixed effect from the regression where the dependent variable equals one if and only if the application was accepted. In panel (b) I re-plot the bank-MSA average interest rates and acceptance probabilities from figure 1 panel (a). It is clear that panel (a) resembles panel (b). In addition, correlation between bank-MSA average interest rates and the interest rate fixed effect is 0.867 and the correlation between bank-MSA acceptance probability and acceptance probability fixed effect is 0.985. Although keeping in mind the caveat that the loan-level acceptance regression cannot control for credit scores, the fact that the cross-sectional variation in interest rates controlling for credit scores does not change much suggests that differences in the composition of borrowers does not drive the cross-sectional variation in interest rates and acceptance probabilities.

Figure 8: Source of Cross-Sectional Variation in Interest Rates and Acceptance Probabilities



Notes: Figure compares variation in interest rates and acceptance probabilities with and without controlling for individual borrower characteristics. Panel (a) plots the variation in interest rates and acceptance probabilities conditional on individual borrower characteristics. Panel (b) plots the raw bank-MSA average interest rates and acceptance probabilities from figure 1 panel (a). It is clear that panel (a) resembles panel (b), implying that the cross-sectional variation in interest rates and acceptance probabilities are not driven by differences in borrower characteristics. Observations are from year 2010.

B Optimal Decision Rule ρ_b

Here I derive the optimal decision rule $\rho_{b,t}$ with all the parametric assumptions of the model. First, with idiosyncratic cost shocks $e_{b,t}$ distributed EVI, from Hotz and Miller (1993) we know that the observed acceptance probabilities $a_{b,t}$ satisfy:

$$\rho_{b,t}(\pi_{b,t}) + \sigma G'(a_{b,t}) = 0 \tag{25}$$

Where, $G'(a_{b,t}) \equiv ln(1 - a_{b,t}) - ln(a_{b,t})$. From equation (21), the first order condition w.r.t. $a_{b,t}$ can be written as:

$$\begin{aligned} FOC^a_{b,t} \equiv \pi_{b,t} \times \Big[\alpha_a \cdot (1 - q_{b,t}) \cdot a_{b,t} + 1\Big] + \alpha_a \cdot (1 - q_{b,t}) \cdot [a_{b,t} \cdot \sigma \cdot g(a_{b,t}) - c_{b,t}] \\ - \delta_a \cdot a_{b,t} \cdot i_{b,t} \cdot d_{b,t} \cdot (1 - d_{b,t}) + \sigma \cdot G'(a_{b,t}) = 0 \end{aligned} \tag{26}$$

Therefore, in order for equations (25) and (26) to be consistent, it must be that:

$$\begin{aligned} &\rho_{b,t}(\pi_{b,t}) = \rho^1_{b,t} \cdot \pi_{b,t} + \rho^2_{b,t} \\ &\rho^1_{b,t} \equiv \alpha_a \cdot (1 - q_{b,t}) \cdot a_{b,t} + 1 \\ &\rho^2_{b,t} \equiv \alpha_a \cdot (1 - q_{b,t}) \cdot [a_{b,t} \cdot \sigma \cdot g(a_{b,t}) - c_{b,t}] - \delta_a \cdot a_{b,t} \cdot i_{b,t} \cdot d_{b,t} \cdot (1 - d_{b,t}) \end{aligned} \tag{27}$$

Notice that if $\alpha_a = \delta_a = 0$, then $\rho^1_{b,t} = 1$ and $\rho^2_{b,t} = 0$, i.e., with households that do not have any preference over acceptance probabilities and no adverse selection, banks accept mortgage applications if and only if it is ex-post profitable ($\rho_{b,t} = 1, \forall \pi_{b,t} \Rightarrow y_b = 1 \Leftrightarrow \pi_{b,t} - e_{b,t} > 0$).

C Estimating Funding and Processing Costs

The first order conditions of optimality from equation (21) can be re-arranged to solve for $\pi_{b,t}$ and $c_{b,t}$ under the assumption that σ is known. First, rearrange $FOC^i_{b,t}$ from equation (21) and define:

$$\kappa^i_{b,t} \equiv a_{b,t} \cdot \sigma \cdot G(a_{b,t}) + \frac{a_{b,t} \cdot (1 - d_{b,t}) \cdot (1 - \delta_i \cdot d_{b,t} \cdot i_{b,t})}{\alpha_i \cdot (1 - q_{b,t})} = c_{b,t} - a_{b,t} \cdot \pi_{b,t} \tag{28}$$

Also rearrange $FOC^a_{b,t}$ from equation (21) and define:

$$\kappa^a_{b,t} \equiv a_{b,t} \cdot \sigma \cdot G(a_{b,t}) + \sigma \frac{G'(a_{b,t})}{\alpha_a \cdot (1-q_{b,t})} - \frac{\delta_a \cdot a_{b,t} \cdot i_{b,t} \cdot d_{b,t} \cdot (1-d_{b,t})}{\alpha_a \cdot (1-q_{b,t})} = c_{b,t} - \frac{\alpha_a \cdot (1-q_{b,t}) \cdot a + 1}{\alpha_a \cdot (1-q_{b,t})} \cdot \pi_{b,t} \tag{29}$$

Note that all objects on in $\kappa^i_{b,t}$ and $\kappa^a_{b,t}$ are known (with σ assumed to be known). Taking the difference between $\kappa^i_{b,t}$ and $\kappa^a_{b,t}$ and rearranging yields $\pi_{b,t}$:

$$\alpha_a \cdot (1-q_{b,t}) \cdot (\kappa^i_{b,t} - \kappa^a_{b,t}) = \pi_{b,t} \tag{30}$$

Next, substituting in and rearranging $\pi_{b,t}$ into $\kappa^a_{b,t}$ and rearranging yields:

$$\kappa^a_{b,t} + [\alpha_a \cdot (1-q_{b,t}) \cdot a_{b,t} + 1] \cdot (\kappa^i_{b,t} - \kappa^a_{b,t}) = c_{b,t} \tag{31}$$

Thus, conditional on knowing the value of σ the two first order conditions of optimality from equation (21) identify $\pi_{b,t}$ and $c_{b,t}$.

D Details on the Simulation of Counterfactuals

The algorithm for calculating a counterfactual equilibrium for a given market consists of an inner loop that finds the optimal interest rate and acceptance probability for each bank given the interest rates and acceptance probabilities of rival banks, and an outer loop that checks whether a proposed vector of interest rates and acceptance probabilities are in equilibrium.

Let $r \in \{0, 1, 2, ...\}$ represent an iteration of the outer loop. For a starting vector of interest rates $\mathbf{i}^r$ and acceptance probabilities $\mathbf{a}^r$, the inner loop finds the optimal interest rate $i_b^{r,*}$ and acceptance probability $a_b^{r,*}$ given interest rates ($\mathbf{i^r_{-b}}$) and acceptance probabilities ($\mathbf{a^r_{-b}}$) of rival banks. Then, with the resulting vectors of optimal interest rates $\mathbf{i}^{r,*}$ and $\mathbf{a}^{r,*}$ from the inner loop, the outer loop checks whether these are in equilibrium according to equation (14). If $\mathbf{i}^{r,*}$ and $\mathbf{a}^{r,*}$ is not in equilibrium, then I set $\mathbf{i}^{r+1} = \mathbf{i}^{r,*}$ and $\mathbf{a}^{r+1} = \mathbf{a}^{r,*}$ and feed these vectors into the inner loop again. This algorithm continues until an equilibrium is found, meaning the maximum of the difference between $\mathbf{i}^r$ and $\mathbf{i}^{r,*}$, and $\mathbf{a}^r$ and $\mathbf{a}^{r,*}$ is smaller than 0.00001. To address the fact that multiple equilibria is a strong possibility and that I do not want my results to be driven by equilibria switching across counterfactuals, the starting values $\mathbf{i}^0$ and $\mathbf{a}^0$ are always set to the observed interest rates and acceptance probabilities in the data.

The inner loop finds the optimal interest rate and acceptance probability for a bank given the interest rates and acceptance probabilities of rival banks. I use a hybrid algorithm where I first evaluate the bank profit function on a grid of interest rates and acceptance probabilities[34], and then for each of the 20 highest grid points in terms of profits I run a constrained optimization algorithm (implemented with Python SciPy Optimize package). I found that this hybrid algorithm yielded the best combination of speed and robustness. Counterfactual equilibria for different markets were calculated in parallel using MPI for Python in the SciNet high performance computing cluster.

[34] The grid for interest rates are [0.02, 0.07] with step values of 0.0001 and the grid for acceptance probabilities are [0.001, 0.999] with step values of 0.0001.