Minority Specialized Lenders

Erica Jiang, Gregor Matvos, Amit Seru, and Lulu Wang*

This Version: March 23, 2026

Abstract

We study the equilibrium consequences of differences in mortgage shopping behavior between majority and minority borrowers. Race predicts lender choice far more than differences in income. We identify minority-specialized lenders, who disproportionately lend to minority borrowers and originate one-fifth of minority mortgages. These smaller lenders charge high mortgage rates, employ more minority employees, and have higher market shares in minority neighborhoods. Minority borrowers are also less likely to withdraw mortgage applications from these lenders. These facts suggest that the high prices at minority-specialized lenders partially reflect market power and valuable minority-specialized services rather than discrimination. To quantify the effect of minority-specialized service provision in equilibrium, we estimate a model in which minority-specialized lenders compete with mainstream lenders, and majority and minority borrowers differ in loan demand as well as the types of lenders they consider. Our novel identification strategy uses withdrawn mortgage applications to disentangle borrowers' consideration sets and preferences. The estimated model rationalizes specialized lenders' higher prices as a combination of both higher costs of serving minorities and higher markups. The model also matches differences in consideration set size across groups as well as actual cost data lenders. Minority-specialized lending attracts minorities primarily by lowering search frictions. Minority borrowers benefit from a broader diffusion of minority-specialized lending, and these gains are large relative to potential gains from eliminating residual racial discrimination in interest rates. Our model suggests fair lending laws can disincentivize mainstream lenders' investments in minority specialization, creating a tension between reducing discrimination and encouraging competition for minority borrowers.

*Jiang is at the University of Southern California. Matvos is at Northwestern University and the National Bureau of Economic Research (NBER), Seru is at the Stanford Graduate School of Business (GSB), the Hoover Institution, the Stanford Institute for Economic Policy Research (SIEPR), and NBER. Wang is at Northwestern University. We thank Jason Allen, Vivek Bhattacharya, Greg Buchak, Shan Ge, Arpit Gupta, Zhiguo He, Kilian Huber, Gaston Illanes, Sasha Indarte, Lu Liu, Timothy McQuade, Christopher Palmer, Tarun Ramadorai, Claudia Robles-Garcia, and other seminar participants at the SITE 2022 Financial Regulation meetings for excellent comments and discussions. We also thank Francesco Spizzuoco and Yiyang Han for outstanding research assistance.

I Introduction

Casual observation suggests that some lenders specialize in lending to minority borrowers. For example, the storefront of Metro City Bank in Atlanta displays its name in Mandarin and Korean but not in English (Figure 1). On its website, Metro City Bank also argues that it is differentiated from other lenders: "We believe that it is essential for a bank to speak the language of its customers," (Metro, 2022).

Figure 1: A Branch of Metro City Bank in Atlanta, GA



We begin the paper by showing that Metro City Bank is not an exception. We identify minority-specialized lenders in the universe of all mortgage lenders and show they are responsible for originating about one-fifth of minority mortgages. We also show that lenders differ far more in the racial composition of their borrowers than in income. We then document how minority-specialized lenders differ from mainstream lenders on dimensions of interest rates and fees, the racial composition of loan officers, as well as consumer responses such as withdrawing mortgage applications. These facts jointly suggest that minority borrowers demand specialized services from mortgage lenders and are more likely to consider these specialized lenders when searching for mortgages. Intuitively, minorities may require different services from white borrowers, for example, if they have lower English proficiency or need a specific understanding of their circumstances. Minorities may also consider different lenders. This could occur if they obtain

information from different channels or are subject to different advertising.

More broadly, we use the lens of minority-specialized lenders to investigate the gap in mortgage outcomes between white and minority borrowers. This lens shifts the focus to the provision of high-quality services to minority borrowers. This differentiates our approach from the existing literature and regulation, which have mostly focused on differences in credit access and prices (interest rates and fees) paid by different racial groups (Bartlett et al., 2022; Bhutta and Hizmo, 2021; Bhutta et al., 2022; Willen and Zhang, 2022; Frame et al., 2024; Giacoletti et al., 2021).[1]

In the second part of the paper, we build and estimate a structural model in which minority borrowers' preferences for specialized services and their search behavior (consideration sets) differ from that of white borrowers, but the provision of specialized services is potentially costly. We build on the growing literature at the intersection of finance and industrial organization, which recognizes that consumer financial products are differentiated and subject to search frictions (Allen et al., 2014; Gurun et al., 2016; Hastings et al., 2017; Egan, 2019; Benetton et al., 2023). We differ from those models by explicitly incorporating different preferences for services faced by minorities and allowing for a more flexible approach to search differences than just differences in search costs. The model can replicate the facts that we document as well as out-of-sample predictions on cost and advertising. We use the estimated model to understand better the incentives for providing minority-specialized services. The model highlights the regulatory tension between the provision of non-discriminatory pricing arising from fair lending regulation, the provision of costly minority-specialized services, and market power. Non-discriminatory pricing decreases incentives for the provision of minority services, resulting in substantial welfare losses to minorities who value these services and increased costs due to market power arising from limited competition in the minority service market.

We first introduce a measure of minority specialization from loan data based on approaches to measure polarized speech in Gentzkow et al. (2019). Roughly, a lender in a market is specialized in a minority group if it over-weights lending to that group relative to its share of total borrowers in that MSA by more than a factor of two.[2] Intuitively, if Asian borrowers comprise 6% of all loans in a market, then a lender is Asian-specialized

[1]Fair-lending laws include laws such as the Equal Credit Opportunity Act (ECOA), the Fair Housing Act (FHA), and the Civil Rights Act of 1968. Many agencies have the authority to evaluate or enforce compliance with laws and regulations: the Consumer Financial Protection Bureau (CFPB), the Department of Justice (DOJ), the Federal Deposit Insurance Corporation (FDIC), the Federal Trade Commission (FTC), the Federal Reserve Board (FRB), the Department of Housing and Urban Development (HUD), the Office of the Comptroller of the Currency (OCC) as well as various state regulators.

[2]MSA is the primary geographic unit of analysis when fair lending regulations are applied.

if Asian borrowers comprise 12% or more of its lending. Our classification accounts for differences in borrower and loan characteristics on which minorities can differ from the rest of the population, i.e., it can differentiate specialization in income from specialization in a certain minority.[3] Using our classification, we find that approximately one-quarter of minority mortgages are originated by minority-specialized lenders. One way to calibrate the importance of race in lender choice is the following. Whereas around one-quarter of minority mortgages are originated by minority-specialized lenders, only 3% of mortgages by high income borrowers are originated at income-specialized lenders.

While correlated, our measure is conceptually distinct from minority ownership. Our measure does not take a stance on whether it is minority ownership, leadership, or employment that is responsible or even necessary for a lender to be minority specialized. It allows multi-market lenders to specialize in some markets but not in others. For example, we find that Citibank specializes its mortgage lending to Asian borrowers in some markets, such as San Jose, CA, even though it does not specialize in minority lending in the majority of markets. Figure 2 displays Citi's Mandarin storefront in San Jose. This differentiates Citibank from another large bank, Wells Fargo, which does not minority-specialize in any market. More broadly, our measure recognizes that the supply of minority specialization is a lender choice and, therefore, allows us to think about incentives to supply such services.

Before proceeding to the model, we document several facts that shed light on the economic role of minority-specialized lenders. First, minority-specialized lenders charge higher rates than other lenders. This is the case even when comparing borrowers of the same race in the same market at the same point in time and conditioning on a rich set of borrower characteristics. We find similar results for fees, even after we control for credit scores on a sample matched with data from originated mortgages at the Government Sponsored Enterprises (GSEs). The highest prices are charged by the lenders who almost exclusively lend to minority borrowers. This result is not consistent with the idea that specialization allows these lenders to serve minority borrowers more cheaply and pass on some of these cost savings.

Second, specialized lenders are relatively more likely to use a workforce from the minority that they specialize in. We use data from the NMLS Loan Officer Registry and find that minority lenders hire a disproportionate share of their loan officers from the minority in which they specialize. There are many possible reasons why lenders might

[3]We use a shrinkage estimator to account for measurement error, which arises when lenders make small numbers of loans to a specific group. We do not find many lenders who engage in white-specialized lending. One such example is Trident Mortgage Company in Philadelphia, which also had an enforcement action from CFPB on grounds of fair lending in that MSA, further validating our measure.

Figure 2: A Branch of Citibank in San Jose, CA



use a specialized workforce, ranging from speaking the language of the mortgage applicant to providing a better service because they understand the borrower's circumstances to simply providing trust. While it is difficult to rule in all possible channels through which specialization operates, we show that these lenders have a higher market share in areas with a higher proportion of households who speak languages other than English at home. For example, Hispanic specialized lenders have an especially high market share in areas with Hispanic households that do not speak English rather than Hispanic households that do.

These facts are consistent with two broad sets of explanations of why minorities might shop at expensive specialized lenders and pay higher prices. The first is that these lenders, while not cheap, provide services that are valued by minorities. An example would be help with an application in a different language or an understanding of preferences, which allows the lender to offer a more suitable product. Alternatively, specialized lenders do not provide any direct utility benefits to minority borrowers. They attract these borrowers because they are more recognizable in the community through their use of minority loan officers, minority-specific language on storefronts (e.g., Metro City bank), or word of mouth, which places them in the borrowers' "consideration set." In other words, under this alternative, minority specialization is used to steer minority borrowers to expensive lenders.

We use withdrawn mortgages to show that minority-specialized lenders provide minority-specialized services but that the provision of services is insufficient to explain the data alone. A withdrawn mortgage suggests two things. First, the borrower was aware of the lender since they applied for a mortgage—the lender was in the borrower's consideration set. Second, the lender was not chosen, so another lender provided a higher utility mortgage. Intuitively, lenders with many mortgage applications but high withdrawal rates can be identified as lenders that offer low utility but high consideration. We find that minority-specialized lenders have lower withdrawal rates among the borrowers they specialize in. Our most stringent specification uses within lender-market-time variation to show that, for example, Asian-specialized lenders reduce the withdrawal rates of Asian borrowers relative to white borrowers. However, the quantitative magnitude of the withdrawal rate differences is small relative to the large differences in market shares between specialized and non-specialized lenders. This suggests that quality is insufficient to explain why minority borrowers choose specialized lenders.

Building on these facts, we build and estimate a structural model in which minority borrowers' preferences for specialized services and their search behavior differ from that of white borrowers, but the provision of specialized services is potentially costly. The model builds on existing models of product differentiation and search in credit markets with two important departures on the demand side (Woodward and Hall, 2012; Allen et al., 2014; Benetton, 2021; Buchak et al., 2023; Agarwal et al., 2023). First, we model search using consideration sets rather than incorporating a specific search model (Goeree, 2008; Honka et al., 2017; Abaluck and Adams-Prassl, 2021).[4] This approach allows more flexibility in estimating the minority-specific formation of consideration sets: minorities do not only differ in search costs but, as our estimates reveal, more broadly in where they search.[5] Departing from full consideration models also allows our model to match the significant mark-ups in the very fragmented mortgage market. Mark-ups play a central role in considering the incidence of regulatory changes in fair lending laws. Intuitively, under perfect competition, redistribution across consumer groups is a very likely outcome. Second, minority borrowers' preferences for specialized services and their search behavior can flexibly differ from that of white borrowers and other minority groups. For example, minority borrowers can not only demand different services or differ in their

[4]Imperfect consideration is important in the US mortgage market. Despite the large number of lenders in each market, consumers typically search over a much smaller set. The largest 10 lenders in a metropolitan area (MSA) typically cover only half of the mortgages originated in that MSA. In contrast, borrowers in the National Survey of Mortgage Originators typically consider fewer than two lenders.

[5]The disadvantage is that search models are less prone to the Lucas critique in counterfactuals if one is willing to accept the specific assumptions on the nature of search.

price sensitivity but also in where they search.

On the supply side, minority-specialized lenders compete with mainstream lenders for both white and minority borrowers by setting prices in each market. The costs of lending can differ based on the race of the borrower. In the baseline model, these costs can be real, such as hiring specialized loan officers and spending more time per borrower if they need more help, or psychological —- i.e., racial animus in the style of Becker (1971). Despite differences in costs, the lenders have to charge the same price independent of race. In other words, lenders are subject to fair lending laws. Given our setup, it is not obvious that the higher prices of minority-specialized lending that we document must be the result of higher costs. They can also arise because of mark-ups charged by these lenders due to product differentiation or limited competition due to limited consideration. We estimate the model and separately identify the utility and consideration differences between borrowers by race. Existing approaches to identification in these classes of models exploit Slutsky violations as in (Abaluck and Adams-Prassl, 2021), survey data (Honka et al., 2017) or require direct variation in consideration sets that is orthogonal to utility (Agarwal and Somaini, 2022). We exploit mortgage withdrawals to separately identify utility and consideration sets using the logic outlined above. Broadly, while standard demand systems use market shares to estimate differences in utility across products, we jointly use market shares in originations (chosen products as in standard demand system estimation) as well as market shares withdrawn mortgages (considered but not chosen products) to separately identify utility and consideration. Our identification approach is not limited to mortgages but is applicable to products in which customers can choose not to take up products after the application stage, such as credit products and insurance.

The model replicates the fact that minorities pay higher rates than white borrowers in equilibrium, i.e., the racial gap. However, our model suggests that the gap arises as a function of three forces. First, we estimate that minority specialization is costly—we later verify this estimate using regulatory cost data. Second, minority-specialized lenders provide additional services, which have a high value for minority borrowers, on the order of 30 bps. Last, minority-specialized lenders are about three times as likely to be considered as non-specialized lenders. Given the high value of services and especially consideration received by specialized lenders gives rise to additional mark-ups that these lenders earn. We thus use the economic forces in the estimated model to decompose the forces that shape the equilibrium gap in mortgage outcomes between white and minority borrowers.

Our model also performs well in "out of sample" tests. We obtain both revenue and

cost data specifically for mortgage originations for a subset of lenders using shadow bank call reports from regulatory filings in Jiang et al. (2023). Both cost and revenue estimates from the model are highly correlated with actual revenue and cost of lending despite not having served as a basis for the estimation of our model. Moreover, our model prediction that lending to Hispanic borrowers carries larger costs is also borne out in the accounting data. These correlations allows us to conclude that at least some of the costs of providing loans to minorities are real costs of labor and not simply the result of racial animus. Our model also matches the level and cross-section of average choice set size across racial groups despite not using consideration data in the estimation. Last, we find that lenders who we estimate have a high measure of consideration spend more on advertising using Nielsen data. Conversely, we do not find a positive correlation between advertising spending and estimates of service quality.

Our estimates illustrate the importance of search (limited consideration) when studying differences in mortgage outcomes across racial groups. First, our estimates suggest that the mortgage market exhibits substantial markups despite high fragmentation—a market with ten lenders features 90 bps markups. Second, we find that minorities are very price elastic with respect to utility, much more than in full consideration models. In fact, Hispanic and Black borrowers are more price elastic than white borrowers. However, unlike Asian borrowers, their search behavior is not targeted toward lower-price lenders. Asian borrowers, on the other hand, direct their search towards lower-cost lenders.

We use the model to study several regulatory implications and show that regulatory implications can markedly differ when considered through the lens of our model. For example, fair lending laws can result in the under-provision of financial services targeted at minorities but also provide a substantial force against third-degree price discrimination, which would extract substantial surplus from Hispanic and Black borrowers.

Fair lending regulation protects Black and Hispanic borrowers from third-degree price discrimination, i.e., market power. In the absence of fair lending regulation, lenders would be able to charge different prices to minority borrowers. This could occur by lenders triangulating on race rather than explicitly using race to set prices (Bhutta et al., 2021). Our model suggests that such triangulation on Black and Hispanic borrowers would be very profitable because they do not direct their search to cheap lenders, making them de-facto price inelastic. Interest rates for Black and Hispanic borrowers would rise by 5 and 49 bps in such a counterfactual. Asian borrowers, on the other hand, direct their search substantially to cheaper lenders. To keep these de-facto price-elastic borrowers, lenders would want to lower the interest rates by 9 bps. Because of fair lending

laws, Black and Hispanic borrowers are pooled with white borrowers, who are fairly price elastic and for whom there is a substantial amount of competition, limiting the amount of rent extraction lenders can achieve at their expense. In other words, even absent racial animus in the spirit of (Becker, 1971), fair lending benefits Black and Hispanic borrowers.

The downside of fair-lending laws is that they discourage lenders from specializing. Given that minority lenders are successful in attracting minority borrowers and can charge higher prices, a natural question arises as to why large lenders do not offer more specialized services. Specifically, we see some mainstream lenders specialize in some markets (markets with large minority populations), but minority-specialized lenders earn substantial markups. Our counterfactual suggests that fair lending laws provide a weak incentive to specialize. In a counterfactual, we recompute the equilibrium, having all major lenders specialize in all minority lending. We find large increases in the consumer surplus of minority borrowers, suggesting large gains from more minority service provision. More specialization benefits minority borrowers both by increasing quality and by expanding minority borrowers' consideration sets. Larger consideration sets generate more competition and can be interpreted as alleviating search frictions for minority borrowers. We find almost no difference in the prices paid by minority borrowers—if anything, prices charged to Black and Hispanic borrowers decrease because of more competition. In other words, large lenders can only recoup the costs of investing in minority specialization through higher quantities but not higher prices. The intuition is the following: white borrowers are both numerous and price elastic. Under fair lending laws, lenders can only pass through the cost of specialization by increasing prices for all borrowers. But this implies losing a substantial share of white borrowers. Therefore, fair lending substantially mutes the cost of investing in services to minorities.

Relaxing fair lending laws, on the other hand, provides substantial incentives to invest in minority-specific services while still benefiting minority consumers. We study a counterfactual in which large lenders specialize in minority lending, and all lenders are allowed to charge race-specific prices. In practice, rather than conditioning by race, lenders could triangulate on minority borrowers using their characteristics, which is currently not allowed. We find that prices to Black and Hispanic borrowers substantially increase, but they would still be considerably better off than under the status quo situation. One interesting aspect is that Hispanic borrowers, for whom we observe the least specialization by mainstream lenders, experience the largest wedge in the benefits due to specialization and the benefits that could be captured by the lenders with flexible pricing.

Our model suggests that Asian and Black borrowers would benefit from more specialized services even at the cost of discriminatory prices, but that Hispanic borrowers benefit significantly from current fair-lending laws. Our model also rationalizes why relatively few mainstream lenders specialize under fair lending laws. If serving minorities is costly, but lenders are not allowed to charge minority borrowers higher prices, then many lenders will choose not to specialize. We do not aim to provide a definitive welfare evaluation of fair-lending laws. Rather, we argue that the weak incentive for lenders to compete for minority borrowers is but one contributing factor to the high prices minority borrowers pay. In the language of Holmstrom and Milgrom (1991), fair-lending laws provide high-powered incentives for lenders not to discriminate but low-powered incentives to specialize. We do not mean to deny the existence of lending and housing discrimination. Rather, our model implies that a natural legacy of discrimination is that mainstream lenders may be ineffective at competing for minority borrowers. We view our results as providing a rough calculation showing that the marginal benefits of more competition for minority borrowers are large and are of a similar order of magnitude as the well-studied costs of racial discrimination in pricing.

Our paper contributes to the recent literature on price dispersion and choice frictions in the mortgage market (Gurun et al., 2016; Allen et al., 2014; Woodward and Hall, 2012; Alexandrov and Koulayev, 2018). In the mortgage market, borrowers pay substantially different interest rates, even among borrowers with similar characteristics, in the same location, and at the same point in time (Gurun et al., 2016; Allen et al., 2014; Bhutta et al., 2021). We show that the observed price dispersion is consistent with borrowers having imperfect consideration sets and heterogeneous preferences. On the technical side, we provide a novel method of recovering attention parameters when consumer attention is imperfectly observed. The existing literature can be divided into approaches that only observe final choices (Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022) and those that require rich data on what lenders consumers consider (Honka et al., 2017; Cuesta and Sepulveda, 2021). We develop an intermediate approach. While the Home Mortgage Disclosure Act (HMDA) data does not contain borrower-level data on consideration, its contains data on withdrawn applications. A withdrawal at a lender provides information that a lender was in some borrower's consideration set but that it was not the best option. The advantage of our approach relative to the papers that only observe final choices is that we do not need as much variation in (potentially excluded) shifters of utility and attention. The main disadvantage is that we need to make stronger assumptions about how withdrawn applications are generated.

Racial disparities in credit access have received considerable attention since the sem-

inal work of Munnell et al. (1996). Existing literature has been mostly focusing on quantity and prices in characterizing the disparities and discussed factors like taste-based discrimination in contributing to the disparaties.[6] We investigate the gap in mortgage outcomes between white and minority borrowers through the lens of minority-specialized lenders. This lens shifts the focus to the provision of high-quality services to minority borrowers. This differentiates our approach from the existing literature and regulation, which have mostly focused on differences in credit access and prices (interest rates and fees) paid by different racial groups (Bartlett et al., 2022; Bhutta and Hizmo, 2021; Bhutta et al., 2022; Willen and Zhang, 2022; Frame et al., 2024; Giacoletti et al., 2021). Our paper illustrates that accounting for borrowers' imperfect consideration and heterogeneous preferences are critical for understanding the differential in credit outcomes between borrowers of different races. Fair lending laws may widen racial disparities in credit access by not considering how minority borrowers' shopping behavior differs from that of white borrowers.

Moreover, existing literature focuses on differential treatment conditional on formally applying. But lenders may unfairly discourage or informally reject minorities before a formal application is even submitted (e.g., Hanson et al. (2016)) or may provide minority applicants with poor service (Ross et al., 2008; Frame et al., 2024). We contribute to this literature by showing how an insufficient provision of minority-specialized services leads to disparities in credit access on margins that have not been empirically studied in this literature.

II Data

We combine ten different data sources to understand which lenders specialize in lending to minorities, how much they charge, and why they attract minority borrowers.

Home Mortgage Disclosure Act (HMDA) for loan applications. Our main data source for prices and market shares is the application-level data collected under the Home Mortgage Disclosure Act (HMDA) . We observe application outcomes, which allows us to identify, whether an application was approved by the lender and whether the borrower chose to take up the mortgage or to withdraw the mortgage application.[7] Since 2018,

[6] Evidence from correspondence experiments (Hanson et al., 2016) and audit studies (Ross et al., 2008) often supports a discrimination explanation for racial disparities in mortgage lending. However, some empirical studies also find that minority borrowers default more (Berkovec et al., 1998; Gerardi et al., 2023), which may be inconsistent with taste-based discrimination.

[7] Withdrawals include both applications withdrawn due to incomplete data, as well as borrowers who decline to originate a loan even after receiving a price quote.

HMDA has variables that are central to our analysis: interest rates, total loan costs, loan-to-value ratio (LTV), and the debt-to-income ratio (DTI). It also contains demographic information on borrowers, such as ethnicity, race, income, and gender, and information on loan applications, such as lender identity, loan purpose, loan size, and borrower location at census tract level. Our study therefore focuses on 2018–2021, and any metropolitan area in the top hundred origination volumes in any one year. Our sample is restricted to conventional, conforming, first-lien, mortgages originated for purchases of owner-occupied single-family homes with closed-end credit.

Fannie Mae and Freddie Mac Single-Family Loan Level Disclosure for credit scores. We merge the HMDA data with the Fannie Mae and Freddie Mac Single-Family Loan Level Disclosure data to obtain borrower credit scores. The merging procedure follows Buchak and Jørring (2021), who match the two datasets based on the purchaser, geography, and loan characteristics such as DTI, LTV, loan amount, and interest rate. Overall, we match around half of the initial HMDA observations.

Mortgage Call Reports for cost data. We obtain lender-level costs of loan origination from mortgage call reports. Pursuant to the S.A.F.E. Mortgage Licensing Act of 2008, non-bank mortgage originators that hold a state license or state registration to conduct mortgage origination are required to file a call report in each state in which they perform lending activities since 2011. In the call reports, lenders provide detailed information about their quarterly origination-related costs. We follow Jiang et al. (2023) to merge the call reports with lender loan origination records in HMDA to obtain costs per unit of loan volume of lenders analyzed in our main analysis.

NMLS Loan Officer Data for loan officer race. We obtain a novel administrative data set that contains all residential mortgage loan officers in the U.S. except for those whose license or registration became inactive before 2015. The S.A.F.E. Mortgage Licensing Act of 2008 requires every mortgage loan officer (MLO) to be registered in the Nationwide Mortgage Licensing System and Registry (NMLS). For each registered MLO, we obtain the name, registration history, work history, and branch or home location information. We then use loan officers' full names to infer their racial groups, following Frame et al. (2024).[8]

[8]Frame et al. (2024) start from the surname list provided by the 2010 U.S. Census that associates each surname with race and ethnicity probabilities and then refine our categorization using racial information of first names provided by Tzioumis (2018).

Other data. We collect lender names from the "**the Avery file**", in which each lender identifier is matched to banking information in the Federal Reserve Bank's National Information Center system for each filing year. We use the shadow bank classification scheme from (Buchak et al., 2023). At the census tract level, we collect demographic variables, such as linguistic ability, median household income, and number of minority households, from the Federal Financial Institutions Examination Council (FFIEC) **Census data**. We also build zip-code levels of default risk from the **Corelogic LLMA data**. To validate the model, we also use survey data from the 2018-2019 waves of the **National Survey of Mortgage Originators** and data on advertising occurrences from **Nielsen AdIntel**.

Table 1 presents the summary statistics of loan- and borrower-level information, by race. Black and Hispanic borrowers pay the highest prices, whereas white and Asian borrowers pay lower prices. We see similar racial patterns in fees. On average, FICO scores are higher for Asian and white borrowers, and lower for Black and Hispanic borrowers.

III Identifying Specialized Lenders

We use application data to identify specialized lenders who disproportionately lend to minority borrowers. After identifying these lenders, we present a set of reduced form facts, which suggest that these lenders offer a differentiated product that at least some minority borrowers value, and that these lenders also attract minority borrower by reducing their search frictions. These reduced-form facts motivate a model in which minority and White borrowers have different consideration sets and preferences.

III.A Measure Lender Racial Specialization

We define a racially specialized lender as a lender whose customer base over-represents one race. For example, in a market with 90 majority borrowers and 10 minority borrowers, a lender that serves 9 majority borrowers and 1 minority borrower is not racially specialized, but a lender that serves 5 majority borrowers and 5 minority borrowers is. This is because the former serves 10% of each borrower type, while the latter serves 5.6% of majority borrowers and 50% of minority borrowers. The measure of specialization of lender j for race r that reflects this idea is as follows

$$d_{r,j} = \log \frac{a_{r,j}}{a_{-r,j}} \tag{1}$$

Table 1: Summary Statistics

	HMDA			HMDA-GSE Matched		
	N	Mean	SD	N	Mean	SD
Rate spread						
Asian	953,591	0.17	0.68	260,968	0.20	0.37
Black	520,246	0.47	0.92	154,668	0.52	0.47
Hispanic	986,594	0.56	2.48	360,509	0.46	0.44
White	5,325,861	0.31	2.11	2,494,418	0.33	0.40
Fee share						
Asian	923,564	1.64	1.70	260,968	1.60	1.64
Black	501,044	2.10	1.75	154,668	1.97	2.90
Hispanic	956,680	2.18	3.27	360,509	1.98	1.83
White	5,230,675	1.79	2.50	2,494,418	1.71	1.27
FICO						
Asian	-	-	-	260,968	760.00	153.31
Black	-	-	-	154,668	740.00	148.49
Hispanic	-	-	-	360,509	745.00	129.00
White	-	-	-	2,494,418	757.00	143.75

Notes: The top panel presents summary statistics for the 2018-2021 HMDA sample. Our sample covers conventional, first-lien, conforming mortgages originated for purchases of owner-occupied single-family homes with closed-end credit. The bottom panel presents summary statistics for the merged HMDA-GSE sample from 2018 to 2021. We merge loan application data from HMDA to GSE origination data within an MSA based on loan amount, interest rate, leverage, and purchaser type.

where $a_{r,j}$ is the application share of lender j among members of racial group r, and $a_{-r,j}$ is defined analogously for consumers who are not of race r. In the example above, the less specialized lender has a measure of $\log \frac{0.1}{0.1} = 0$, while the more specialized lender has a measure of $\log \frac{0.5}{0.056} \approx 2.2$.

Using this measure, small lenders may be erroneously classified as specialized lenders as a result of finite sample measurement error. To overcome this, we adopt the shrinkage approach in (Gentzkow et al., 2019) to estimate the logistic regression using application records for each MSA-racial group:

$$P\left(r_i = 1\right) = \ell\Big(\beta_0 + \sum_{j=1}^{J} \beta_j X_{ij}, \epsilon_{ij}\Big), \tag{2}$$

in which $\ell\left(p\right) = \log \frac{p}{1-p}$ is the logistic link function, $P\left(r_i = 1\right)$ is the likelihood of mortgage applicant i being a given racial group r, X_{ij} is an indicator for whether applicant i works with lender j, and let it equal zero otherwise. Let $r_i = 1$ if applicant i is from a given racial group.

As we prove in Appendix B, the estimated β_j is equivalent to $d_{r,j}$ in equation 1. We impose a LASSO penalty on β_j, which shrinks noisy coefficients towards zero. Thus, very small lenders are not erroneously classified as specialized lenders from measurement error.[9]

III.B Measure Discussion

Variation in specialization within lenders. Our measure allows banks to minority specialize in some markets but not in markets. The first column of Table 2 shows that while many large banks specialize in Asian borrowers in some geographies, there is less specialization for Black borrowers and essentially no specialization for Hispanic borrowers. This table also shows that some banks specialize more than others. Whereas Bank of America and Citi over-represent either Black or Asian borrowers in around half of the markets they serve, Chase and Wells Fargo tend to lend proportional to the overall pool of applicants in their markets.

Large lenders tend to specialize when minority borrowers make up a large share of the market. Table 3 regresses the specialization measure of each of the large banks in each MSA on the demographic composition of loan applications in that MSA. We focus on specialization for Asian and Black borrowers because large lenders are most

[9] As we show in Appendix B, the naive market share ratio overstates specialization among small lenders due to the finite-sample bias of the market share ratio, but otherwise the relationship between the two measures is strong for all races.

Table 2: Variation in lender specialization across MSA's

Race	Average	Bank of America	Citi	Flagstar	US Bank	Chase	Wells Fargo
Asian	0.21	0.19	0.38	0.16	0.17	0.29	0.06
Black	0.09	0.32	0.21	0.02	0.01	0.00	0.00
Hispanic	0.02	0.04	0.07	0.02	0.02	0.00	0.00
White	0.01	0.00	0.00	0.02	0.03	0.00	0.00

Notes: The table shows the share of MSA's in which different large banks are specialized for each minority group.

Table 3: Variation in lender specialization across MSA's

	Asian	Black
Log applications	0.13***	0.02
	(0.03)	(0.03)
Asian share	1.40***	-0.50***
	(0.21)	(0.14)
Black share	-0.51	1.53**
	(0.38)	(0.48)
Hispanic share	-0.59***	-0.50***
	(0.13)	(0.12)
N	1172	1137

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table regresses the large bank's specialization measure for different races on the share of applications in each market from Asian, Black, or Hispanic borrowers. We focus on Asian and Black specialization because few large banks specialize in Hispanic borrowers.

likely to specialize for those groups. Lenders are more likely to specialize in Asian borrowers when there are more Asian borrowers in a market, and the same applies for Black borrowers. These facts suggest that lending specialization is something banks can adjust and is also a decision that's responsive to the profits at stake.

III.C Measure Validation and Robustness

We validate our measure of specialization in two ways. First, we find that the most recent three lenders against which the CFPB brought discrimination related enforcement actions– Trident, Provident, and Trustmark – all show up as White-specialized. Second, among the 17 minority-owned banks identified by the FDIC that can be matched to the lenders in our sample, 11 of them are classified as specialized lenders. We measure specialization at the MSA level. One concern is that specialization is driven by the decisions of lenders to lend in some neighborhoods but not others. Then an Asian-specialized lender like Metro City Bank appears specialized only because it lends more in Asian neighborhoods, and the Chase branches in the same neighborhood also attract Asian borrowers at the same frequency. To rule out this theory, we test if our lender-specialization measure can predict race even within finer geographic measures. However, most of the effect persists even after including tract fixed effects (Table D.1). We further show that the effect is not driven by distance in IV.F. Last, we can compute minority lender specialization, which controls for observables such as LTV, DTI, and loan size. Regressing the more sophisticated measure on out base measure gives a coefficient of 0.90. The striking importance of race motivates our analysis comparing minority borrowers' mortgage choices compared to white borrowers.

Benchmarking Importance of Race in Mortgage Choice Here we try to provide a back of the envelope for the importance of race in the choice of lender. Income frequently predicts which goods and services a consumer will purchase. For example, expensive cars are purchased on average by higher income consumers. We show that race predicts borrower choice of lender. We define an analogous notion of income-specialization, we find that only 3% of high-income borrowers originate their mortgages at an income-specialized lender, in contrast to the 25% of minority borrowers who use specialized lenders. Race also matters more than geography or risk characteristics in predicting lender choices (Appendix D).

IV Characteristics of Specialized Lenders

We next present a set of stylized facts on why minority borrowers choose specialized lenders. We show that specialized lenders are popular among minority borrowers

despite charging higher risk-adjusted prices. The higher prices reflect product differentiation, market power, and search frictions. These facts will motivate a model in which minority and white borrowers have different consideration sets and preferences.

IV.A Specialized Lenders Originate One-Quarter of Minority Mortgages

Minority-specialized lenders play an important role in minorities mortgage access. We define a racially specialized lender as a lender at which one race is more than two times overrepresented in its portfolio (i.e., $\exp\left(d_{r,j}\right) \geq 2$). As shown in Table 4, over a third of mortgage applications from Asian borrowers occur at Asian-specialized lenders, whereas around one-sixth of Black and Hispanic borrowers apply for mortgages from their own race-specialized lenders. In contrast, only 5% of mortgage applications from white borrowers occur at lenders that over-represent white borrowers.

Table 4: Distribution of Lender Racial Specialization at Mortgage Level

Group	Count	P50	P75	P99	Specialized Share
Aggregate	7,155,615	0.00	0.34	2.80	11.64
Asian	864,881	0.42	1.02	1.99	37.36
Black	503,544	0.00	0.38	0.99	16.15
Hispanic	916,591	0.04	0.48	1.16	18.04
White	4,870,599	0.00	0.24	0.52	5.41

Notes: This table presents the distribution of racial specialization measure assigned to individual mortgages. We compute lender level racial specialization measures based on the LASSO procedure described in Section III.A. We then assign lender specialization to individual mortgages in their portfolios. Column 1 indicates borrower racial groups, column 2 shows the number of mortgage applications from each racial group, columns 3-5 are the median, 75th, and 99th percentiles of lender racial specialization of mortgage applications in each racial group, and last column shows the percentage of total applications that are submitted to *specialized lenders* of the corresponding race. A specialized lender is defined as a lender at which one race is more than two times overrepresented in its portfolio (i.e., $d_{r,j} \geq 2$).

IV.B Specialized Lenders are Expensive

On average, minority borrowers, especially Black and Hispanic, pay higher mortgage rates than Whites. If these high rates are a consequences of taste-based discrimination (Becker 1957), one might expect minority specialized lenders (those who do not discriminate) to have high market shares among minorities, as we describe above. We would also expect them to charge lower rates. We next show that this is not the case. Table 5 compares risk-adjusted prices of specialized and non-specialized (hereafter "mainstream") lenders within an MSA. We residualize prices by regressing them on interactions between indicators for 20 bins of of property size, income, and loan size, as well as against

Table 5: Within market correlation between in group lenders and prices

	Rate spreads	Fee shares
Specialization score	0.128***	0.132***
	(0.011)	(0.012)
N	1340624	1340624
R2	0.1378	0.1175
MSA x Race x Year FE	X	X

+ p $<$ 0.1, * p $<$ 0.05, ** p $<$ 0.01, *** p $<$ 0.001

Notes: The table shows the results of the regressions of residualized rate-spreads and fee shares on lender specialization:

$$p_{irjmt} = \beta d_{rjm} + \delta_{rmt} + \epsilon_{irjmt}.$$

where p_{irjmt} is the residualized price measure on loan i obtained by borrower of race j from lender j in market m in year t, d_{rjm} is the specialization measure of lender j in MSA m for race r, and δ_{rmt} is market-race-year fixed effects. Fee shares are measured as a percentage of loan value. Both price measures are winsorized at the 1% level. Standard errors are clustered at the lender-race level.

indicators for loan to value, debt to income, maturity, whether the loan has an adjustable rate. In addition to risk adjustment, one might think that minority specialization differs in the degree to which their loans are brokered, changing the nature of price negotiation. We therefore also control for whether a loan was brokered.

This regression compares lenders of different specialization measures within an MSA. The regressions drop "negatively-specialized" lender-race combinations with $d < 0$ as these lenders are often specialized for other minorities. We measure price both with rate spreads and total loan fees as a percentage of the loan value. Loans originated by lenders with one unit higher in specialization have 13 bp higher rate spreads and 13 bp higher fees compared to other loans within an MSA. These magnitudes are more than double the 5 bps of within-lender price differences documented by Bartlett et al. (2022).

The price effects are strongest for Hispanic borrowers, and weakest for Asian borrowers. Table 6 compares rate spreads with specialization by race, whereas Appendix Table C.1 does the same comparison for fees.

Table 6: Race by race breakdown of the correlation between specialization and rate spreads

Residualized rate spreads				
	All	Asian	Black	Hispanic
Specialization score	0.128***	0.091***	-0.046**	0.229***
	(0.011)	(0.018)	(0.015)	(0.010)
N	1340624	508529	280821	551274
R2	0.1378	0.1002	0.0405	0.1711
MSA x Race x Year FE	X			
MSA x Year FE		X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results of regressing residualized rate-spreads on specialization for different minority groups.

This finding suggests that a standard Beckerian story of taste-based discrimination is an incomplete explanation of minority borrower shopping behavior in the mortgage market. While minority borrowers do sort to lenders who may be expected to discriminate less, the higher prices at these specialized lenders suggest that specialized lenders offer a differentiated product, or that they are more likely to be considered (searched and found) by minorities.

Not Driven by Risk Sorting. The positive correlation between racial specialization and mortgage prices does not seem to reflect the differential sorting of riskier borrowers into these specialized lenders.[10] Appendix Tables C.2 and C.3 show that LTV's and DTI's at specialized and mainstream lenders are not statistically or economically significantly different. Appendix E merges HMDA data with GSE origination data and shows that credit scores are highly predictive of within-lender pricing, but do not explain the differences in prices between specialized and non-specialized lenders.

These risk metrics may be less explanatory for minority borrowers (Blattner and Nelson, 2022). Thus, in Appendix V.B we use the GSE performance data to test whether loans originated by specialized lenders are more likely to become delinquent, conditional on observables. While loans originated by Black-specialized lenders are more

[10]There is a potential concern about risk sorting as Bayer et al. (2018) find that high-cost loans to minorities are largely explained by lender fixed effects which are highly correlated with ex-post foreclosure rates.

likely to become delinquent, those originated by Asian or Hispanic-specialized lenders do not have substantially higher delinquency rates. Given that the price effects that we find are the strongest for Hispanic borrowers and weakest for Black borrowers, we conclude that mismeasured risk does not explain our results.

IV.C Specialized Lenders are Located Farther Away

Our findings about quantity and price suggest that specialized lenders are popular among minority borrowers despite their higher risk-adjusted prices. This result could arise because specialized lenders locate in areas with large minority populations, and thus gain market power from proximity, e.g. because borrowers save on travel cost. In fact, specialized lenders tend to be located farther away from minority borrowers than mainstream lenders.

We collect data on branch addresses from the Summary of Deposits for banks and from the NMLS branch data for shadow banks. For each originated mortgage in the HMDA, we compute the distance between the census tract of the borrower and the lending institution's nearest branch. This allows us to assign branch distances to around 60% of originated mortgages in the HMDA. In Table 7, we examine whether specialized lenders are geographically closer than mainstream lenders:

$$g_{irlmz} = \beta d_{rlm} + X_{irlmz}\Gamma + \delta_{mz} + \epsilon_{irlmz} \tag{3}$$

For a mortgage i from a borrower of race r originated at lender l in census tract z in an MSA m, g_{ilmz}, is the distance between the census tract of the borrower and the nearest branch of the lender. d_{rlm} is lender l's specialization measure of race r in MSA m. X_{irlmz} include LTV and DTI of mortgage i, controlling for the difference in search across borrowers with different risk profiles (Agarwal et al., 2023). The inclusion of census tract fixed effects, δ_{mz}, allows us to compare two mortgage applications in the same census tract that are originated by lenders with different specialization measures. If the coefficient $\beta > 0$, then specialized lenders are, on average, farther away from the borrower than mainstream lenders.

Table 7 shows the regression results by borrower races. In general, specialized lenders tend to be located farther away for Asian and Hispanic borrowers, but modestly closer for Black borrowers. Minority borrowers' willingness to travel farther for specialized lenders highlights that specialized lenders' advantage does not primarily come from entering "banking deserts". To the extent that minority borrowers value specialized lenders, it is not primarily through geographic proximity. This result is intuitive if specialized lenders offer differentiate services to minorities or have more visibility among

those borrowers. Then minority borrowers are willing to travel farther than borrowers who services from mainstream lenders, which are more pervasive (i.e. tend to be located closer).

Table 7: Specialized lenders and distance

Log Distance			
	Asian	Black	Hispanic
Specialization	0.193***	-0.067***	0.062***
	(0.005)	(0.006)	(0.004)
N	467466	285994	544118
R2	0.38	0.37	0.34
MSA x Census Tract FE	X	X	X
Controls: LTV and DTI	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows loan-level regression results of regressing geographic distance between the borrower and the lender against the specialization status of the lender by borrower races. The underlying sample includes 60% of originated mortgages in HMDA 2018-2019 that we identify the nearest branches of the lending institutions.

IV.D Minority Loan Officers and Advertisement

If it is not driven by geographic proximity to minority borrowers, what makes racial-specialized lenders popular among minority borrowers despite offering higher risk-adjusted prices? Several specialized lenders claim to have missions to serve minority communities. The Hispanic specialized lender Panorama was founded with the mission to "increase family wealth through homeownership for first-time Hispanic homebuyers" (Panorama, 2022). Similarly, Metro City Bank was founded by a Korean immigrant entrepreneur, and its branches prominently feature Korean and Chinese language signs, as seen in Figure 1.Theory suggests two potential avenues to achieve these objectives: product differentiation that caters to minority borrowers or higher consideration by these borrowers. Below, we show two channels through which specialized lenders can achieve differentiation and visibility: specialized labor and advertising. Then we use a revealed preference argument from mortgage withdrawals to argue that differentiation in services is at least part of the explanation.

Minority Loan Officers. One way for a lender to provide minority specialized services is to hire loan officers from the same minority. Loan officers from minority backgrounds

Table 8: Lending and Labor Force Specialization at the MSA Level

	Asian	Asian	Hispanic	Hispanic
Specialization	0.060***	0.043***	0.071***	0.047***
	(0.013)	(0.005)	(0.020)	(0.008)
N	36839	36839	36853	36853
R2	0.10	0.32	0.17	0.43
MSA FE	X		X	
Zip Code FE		X		X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results of regressions of loan officer race on lender racial specialization measure. In the first (last) two columns, the outcome variable is an indicator for whether the loan officer race is Asian (Hispanic), and the explanatory variable is lender specialization in Asian (Hispanic) borrowers in the MSA that the loan officer is located.

can possess cultural insights and linguistic abilities that can streamline the mortgage application process for borrowers from their community (Liu, 2023). Alternatively, by participating in community activities and leveraging their networks, minority loan officers can also enhance a lender's visibility in the community, i.e advertise for the lender. In Table 8, we correlate lending institutions' loan officer racial composition with the racial specialization of their loan portfolios. We estimate the following logistic regressions to examine whether minority specialized lenders tend to have a higher likelihood of hiring loan officers from the same minority group:

$$L_{ljrmz} = \beta d_{jrm} + \delta_{mz} + \epsilon_{ljrmz} \tag{4}$$

L_{ljrmz} is an indicator for whether loan officer l at lender j located in zipcode z within MSA m is of race r. d_{jrm} is lender j's specialization for borrower race r in MSA m. The census tract fixed effects δ_{mz} absorb variation in geographic clustering of loan officers from different racial groups. We focus on Asian and Hispanic loan officers because we infer loan officer race from names, and conventional algorithms for identifying race have poor accuracy for Black names.

The positive β estimates across columns in Table 8 indicate that specialized lenders are more likely to have minority loan officers from the group in which they specialize. The magnitude of the coefficient only decreases by around 30 percent with the inclusion of zip-code fixed effects. These results suggest that the composition of the labor force is an active choice, and does not simply reflect hiring from workers who live in the minority neighborhoods.

Advertisement. One way to increase minority consumer awareness is to specialize advertising to minorities, as suggested by the Metro City Korean and Chinese language signs. We focus on Spanish language media because Nielsen AdIntel provides this data. We find that Hispanic-specialized lenders are much more likely to advertise in Spanish-language media. We compute the share of advertising counts and the share of advertising expenditure by each lender. Table 9 shows that a one-unit increase in specialization is associated with a ten percentage point increase in the share of advertising on Spanish-language venues. These results reveal two strategies minority-specialized lenders employ to achieve either product differentiation or additional visibility in minority communities. While these two approaches are the ones we can measure with our data, it's worth noting that minority-specialized lenders likely use a several other strategies to attract minority borrowers. We next use a revealed preference approach to measure product differentiation, allowing us to capture the effects of various unobserved strategies minority-specialized lenders may use.

Table 9: Hispanic specialization and advertising

	Counts		Expenditure	
	Radio	Spot TV	Radio	Spot TV
Hispanic Specialization	0.081*	0.069+	0.079*	0.085+
	(0.031)	(0.039)	(0.032)	(0.047)
N	613	652	608	493
R2	0.15	0.22	0.14	0.29
MSA FE	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results of regressing the lender-level share of advertising on Spanish-language venues on our measure of specialization for Hispanic borrowers.

IV.E Lower Withdrawal Rates at Specialized Lenders

Here, we use mortgage application withdrawals to argue that part of specialized lenders' advantage over mainstream lenders is through higher service quality. As we discuss above, there are broadly two reasons why specialized lenders have high market shares and high prices: either they offer high quality mortgage services to borrowers–high expected utility. For example, mortgage lenders may vary in their ability to help borrowers complete their applications (Frame et al., 2024), and this can be particularly important for borrowers who speak languages other than English (Liu, 2023). Or,

consistent with the evidence on advertising, they are more likely to attract mortgage borrowers–higher consideration– even if they offer the same expected utility product. We use withdrawals to rule in utility, but do not rule out consideration. Intuitively, a withdrawn mortgage application indicates that while a lender was in a borrower's consideration set, another lender ultimately provided a higher expected utility mortgage. Therefore if minority borrowers are less likely to withdraw their applications from from specialized lenders, that is an indication that specialized lenders offer a more attractive bundle of services and prices than mainstream lenders. We test if specialized lenders have fewer withdrawn applications by estimating the logistic regression

$$w_{ijrmt} = \beta_1 d_{jrm} + \beta_2 y_{ijrmt} + \delta_{rmt} + \epsilon_{ij} \tag{5}$$

where w_{ijrmt} is an indicator for a withdrawal. β_1 is the coefficient of interest, indicating if the lender is specialized to the race of the borrower. For example, if the borrower is Hispanic and the lender is Hispanic, then d_{jrm} is 1, and if the borrower is Asian for the same lender, then d_{jrm} is 0. We include race by MSA by year fixed effects, controlling for differences in application or withdrawal rates across borrowers of different races. We also control for lender by MSA by year fixed effects to account for possible differences in withdrawal rates across lenders, which can arise if specialized lenders offer different quality or have on average different visibility. We exploit variation from the fact that Asian specialized lenders are specialized only for Asian borrowers, and not for non-Asian borrowers. Column (2) of Table 10 shows that the reduction in withdrawals associated with specialized lenders, even in a within-lender design, with specialized lenders enjoying smaller withdrawal rates among minority borrowers.

Specialized lenders have smaller effects on rejections. The third column of Table 10 repeats the exercise but replaces the left-hand variable with an indicator for rejections. While specialized lenders reject borrowers less often, this effect is small. Column (4) shows that specialized lenders reject in-group borrowers less often relative to other borrowers, but it's nonetheless the case that rejection rates account for only a small share of why specialized lenders originate more loans to minority borrowers when compared to mainstream lenders.

Withdrawals may not reflect consumer preferences if they actually reflect shadow rejections, or if consumers who go to specialized lenders apply to fewer lenders on average . In Appendix F we show that neither possibility is likely. First, high income borrowers are *more* likely to withdraw their applications, whereas they are *less* likely to be rejected. Second, the tracts with larger minority populations feature higher market

Table 10: Lender specialization and withdrawal rates

	Withdrawals		Rejections	
	Across	Within	Across	Within
Specialization	-0.066***	-0.087***	-0.016	-0.071***
	(0.010)	(0.007)	(0.012)	(0.010)
N	3159008	3043273	3429958	3016493
Year x MSA x Race FE	X	X	X	X
Year x MSA x Lender FE		X		X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table tests whether specialized lenders have lower withdrawal and rejection rates. The first and third columns includes race-MSA-year fixed effects, and thus tests if specialized lenders have fewer withdrawals or rejections than mainstream lenders. The second and fourth columns uses within-lender variation, and shows that only in-group borrowers have lower withdrawal or rejection rates at the specialized lenders.

shares of specialized lenders yet *higher* application rates.

IV.F Heterogeneity in Borrower Preferences for Racial Specialization

We show that minority borrowers differ in how much they value lender specialization. In other words, while some minority borrowers can benefit from access to a minority loan officer, or simply value advertising in their community, other minority borrowers do not require such specialized services. We focus on two proxies of such heterogeneity among minority borrowers. The first is minority borrowers who live in neighborhoods with many minority residents. These borrowers may have a higher preference for homophily or may benefit more from the shared cultural undertaking. The second is minorities who speak a language other than English, and who may benefit, for example, from a loan officer who speaks that language.

Within each neighborhood (census tract), we the share of minority mortgages that originated by specialized lenders. From the FFIEC census files, we obtain tract-level median income, population shares of different racial groups, and education levels. We also use the census data to compute the share of the population that speaks either Spanish or an Asian language and include the language share as a control when studying Hispanic and Asian borrowers. We use census data to study which types of minority borrowers borrow from specialized lenders by estimating the following regression across tracts:

$$s_{rmz} = \beta n_{rmz} + \gamma Z_{mz} + \delta_m + \epsilon_{cm} \tag{6}$$

where s_{rmz} is the market share of lenders specialized for race r among borrowers of race

r in tract z, n_{rmz} is the population share of race r, and Z_{mz} contains other controls such as tract-level median income and MSA x Year x Race fixed effect. The coefficient β tests whether minority borrowers are more likely to borrow from lenders specialized for that minority in census tracts with more minority residents within a given MSA at a point in time, holding their race fixed. Column (1) of Table 11 uses data from all three minority groups and shows that minority borrowers in minority neighborhoods are much more likely to borrow from specialized lenders. Column (2) shows that this correlation with race holds even after controlling for education and income. Column (3) of Table 11 shows that in this sub-sample, language matters for the market share of specialized lenders in addition to the racial composition of a tract.

The main implication of this fact is that modeling lender competition for borrowers requires capturing this rich heterogeneity in preferences.Thus, even among minority borrowers, there is heterogeneity in how much they value the services provided by specialized lenders.

Table 11: Where specialized lenders have higher market shares

	Market Share			Withdrawal Rate
	Race	Demographics	Language	
Race share	0.24***	0.23***	0.19***	0.01
	(0.01)	(0.01)	(0.02)	(0.01)
Language share			0.14***	
			(0.02)	
Bachelors degree		-0.25***	-0.25***	
		(0.01)	(0.02)	
Log median income		0.04***	0.04***	
		(0.00)	(0.00)	
N	493579	493579	353900	172887
Adj. R2	0.41	0.42	0.40	0.02
Within R2	0.04	0.05	0.05	0.00
Race x MSA x Year FE	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results of regressing tract-level market shares of specialized lenders in originations for a given race against census demographic characteristics of the tract. Specialized lenders are more prominent in areas with more minority residents, and with more non-English language speakers. Specialized lenders do not have lower withdrawal rates relative to mainstream lenders in minority tracts. Regressions are weighted by the total originations in each tract. The withdrawal rate regression is run only on tracts with a positive number of specialized and non-specialized originations.

The data on withdrawals also suggests that most of this cross-tract variation in the

market share of specialized lenders arises due to differences in consideration sets, rather than differences in preferences. Although race is highly correlated with the market share of specialized lenders, Column (4) of Table 11 shows that race is not correlated with the relative withdrawal rates of specialized lenders compared to mainstream lenders. Thus quality differences are unlikely to be the primary drivers of differences in market shares of specialized lenders across tracts.

IV.G Summarizing the Reduced Form Facts

Specialized lenders attract minority borrowers despite higher risk-adjusted prices and more distant branch locations. The price and quantity facts suggest that a standard Beckerian story of taste-based discrimination in a homogeneous service market is an incomplete explanation of minority borrower shopping behavior in the mortgage market. While minority borrowers do sort to lenders who may be expected to discriminate less, the higher prices at these specialized lenders suggest that specialized lenders also offer a differentiated product . Specialized lenders may be able to attract minority borrowers despite high prices either by reducing search frictions for minority borrowers, or by improving service quality. Our model allows us to separate these channels and study the supply-side determinants of lender specialization.

V Model

Motivated by the evidence from the previous sections, we build and estimate a structural model of minority specialized lending. We model minority borrowers' demand for mortgages under imperfect consideration and lenders' pricing decisions under fair-lending enforcement. Our model allows us to recover minority borrowers' search behavior and preferences from publicly available mortgage application data while allowing for borrowers to conduct informal search before applying.

Motivated by the evidence from the previous sections, we build and estimate a structural model of minority specialized borrowing and lending. Our motivating results suggest that minority specialization encompasses two dimensions: delivering higher utility to minority borrowers and achieving greater visibility (consideration) among them. Separating these dimensions informs us about how lenders compete for minority borrowers. For example, limited consideration by borrowers results in substantial mark-ups in this otherwise fragmented market. We use the estimated preferences, consideration, as well as cost of lending to minorities to study the implications of fair lending laws. The model helps us understand why specialized lenders attract minority borrowers and why some lenders specialize but not others.

Our demand side builds on limited consideration models , adapting them on two dimensions to examine minority borrowing and lending. By modeling the application and withdrawal process, we leverage withdrawn applications as partial observations of consideration sets whose utility is lower than that of chosen products, enhancing our ability to separate consideration from utility. To study minority specialized borrowing, we allow differences in consideration set formation, acknowledging that search can differ along minority and racial status. Furthermore, we model racial differences in preferences, particularly regarding lender specialization.

The supply side of our model emphasizes two crucial aspects: multi-dimensional minority specialization and adherence to fair lending laws. Second, we impose fair lending laws prohibiting racial discrimination in pricing within a lender. This is the case even if lenders find it costlier to lend to minorities, either because minority lending requires specialized labor or effort, or because it is psychologically costlier in the spirit of taste-based discrimination of Becker (1957). We use data on actual costs of lending to minorities to verify model estimates and make some progress on determining to which extent these costs are real or psychological.

V.A Stages of the Game

There are four stages of the game pricing, consideration, application, and origination. *Pricing*: Lenders, post race-neutral prices for mortgages in an MSA. Intuitively, lenders are subject to fair-lending laws and do not discriminate on race in setting prices. *Consideration*: Consumers form consideration sets. These sets are larger than eventual mortgage applications, and capture borrowers informal search without applying. For example, a borrower may call many lenders to get approximate quotes for mortgage rates, but may only apply to some small number. Our model nests both a full-consideration model in which borrowers search over all lenders in a market before originating a mortgage. *Application*: consumers draw utility levels for each lender in the consideration set. They apply to a subset of lenders in their consideration set. *Origination*: Lenders can approve or reject applications. Borrowers choose which approved mortgage application to originate and which to withdraw.

Below we describe each stage of the consumer problem and conclude with the supply side. Because utility and consideration vary with MSA, tract, race, and years, we suppress those subscripts in the discussion of the consumer problem and re-introduce them when discussing supply.

A market is an MSA-year combination, so all potential borrowers in the Chicago MSA in 2020 comprise one market. We focus on MSA, because it is the primary geographic

unit of analysis when fair lending regulations are applied. Lenders are indexed by $j \in \mathcal{L} = \{0, \ldots, L\}$ where the outside option $j = 0$ is a competitive fringe post. They post one interest rate p_j across all races in a given MSA-year combinations. For example, Asian and white borrowers in the Chicago MSA face the same price from the same lender.

V.B Utility

Consumers are indexed by i. They differ in their race r and conditional on race, in characteristics d_i. The last term captures the idea that preferences within a certain race can differ based on observable borrower characteristics. For example, some minorities may speak a language other than English but others are native speakers, so they have different preferences for specialized services. For convenience, we suppress market subscripts and return to them when relevant in the estimation section. The utility from borrower i obtains from lender j, u_{ij} , depends on lender's pricing and the services that the lender provides:

$$u_{ij} = -\alpha_r p_j + \xi_j + \xi_{jr} + \gamma_r \times d_i + \epsilon_{ij} \tag{7}$$

A consumer's utility declines in the loan interest rate, where the extent of price sensitivity can differ across borrowers of different races, α_r^u. All consumers value lender convenience and services, ξ_j. For example, a lender with a high ξ_j has helpful loan officers, or a convenient online application tool, which appeal to borrowers of all ethnicities. Lenders also offer minority specific services ξ_{jr}. A lender with a high ξ_{jr} is racially specialized to race r. They may employ loan officers, who can better assist borrowers of that race, for example, by hiring from that community. As discussed above, there are differences between borrowers within race measured by d_i. γ_r measures the strength of differences in preferences for specialized services across these borrowers. Because we later normalize d_i to be between [-0.5,0.5], one can interpret ξ_{jr} as the average preference for specialized services by borrowers of race r, and γ_r as measuring the dispersion of these preferences within borrowers of the same race. Last, ϵ_{ij} captures idiosyncratic preferences for lenders across borrowers, and is distributed type 1 extreme value.

V.C Consideration

We model consideration with an alternative specific consideration (ASC) model (Goeree, 2008). Consideration captures broad, perhaps informal, search that customers undertake prior to applying for a mortgage, which we model below. The idea is that borrowers are better informed about mortgages than the relatively small number of

mortgage application suggests. [11] Within a market, each lender is included independently in a consumer's choice set with probability ϕ_j. As $\phi \to 1$, our model reduces to the usual full-consideration model. Borrowers always consider the outside option, so $\phi_0 = 1$. The probability that a consumer considers inside lenders $C \subset \mathcal{L}$ is given by

$$P(C) = \prod_{j \in C} \phi_j \times \prod_{j \notin C} (1 - \phi_j) \tag{8}$$

Consideration probabilities themselves can depend on price, which allows us to capture the effect of price changes on search behavior in a reduced-form way. We parameterize this as

$$\ell(\phi_j) = -\alpha_r^c p_j + \xi_j^c + \xi_{jr}^c + \gamma_r^c \times d_i \tag{9}$$

where $\ell(p) = \log \frac{p}{1-p}$. The parametrization of the consideration probabilities follows that of preferences, illustrating that we do not exclude or restrict preferences and utilities to be a priory driven by different forces.

V.D Application, Origination, and Withdrawal

After forming choice sets, consumers apply to the highest utility lenders in their choice set. For computational tractability, we assume that a share θ of consumers applies to the lenders with the top-two highest utilities, whereas the remaining $1 - \theta$ applies to only their top choice. [12] The parameter θ captures the heterogeneity in application cost across otherwise equally informed consumers. The share who apply to two lenders θ does not affect lender competition, which occurs at the consideration choice level. Instead, it influences how to use application data to distinguish consideration and utility.

Each lender rejects each application with a probability χ_j. For tractability, we choose to keep the rejection margin stylized because our analysis in Section IV.E suggests specialized lenders do not have substantially lower rejection rates. Among approved mortgages, the borrower originates the one with the highest utility and withdraws others, if any, which were also approved.

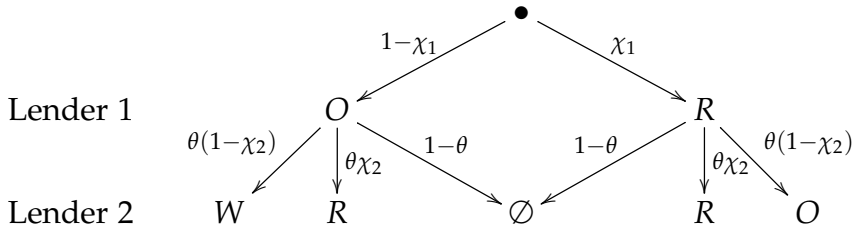
Figure 3 illustrates the possibilities for applications, and we walk through the specific cases below.

Aggregating across consideration sets allows us to construct lender market shares. We depart from the existing literature and construct two sets of market shares: the share

[11] Agarwal et al (2024) more extensive mortgage search in borrowers credit reports than is reflected in mortgage applications

[12] We model two applications because NSMO data suggests the average applicant applies to around 1.5 lenders. The exact number of applications can be increased without conceptually changing the estimation.

Figure 3: The outcomes of the application process. The row labeled "Lender 1" denotes what happens to the application to the highest-utility lender, and the row labeled "Lender 2" denotes what happens to the application to the second highest-utility lender. The rejection rates for lenders 1 and 2 are χ_1, χ_2. The share of consumers who apply to two lenders is θ. The symbols $O, W, R, \emptyset$ denote originations, withdrawals, rejections, and the lack of a second application.



of originated mortgages, and the share of withdrawn mortgages. These two shares allow us to separately identify consideration and utility, as we explain later. The market share of originated mortgages is the standard market share (choice probability) one constructs in demand estimation: it reflects consumers highest utility choice given the set of considered and approved mortgages. The withdrawn market share is new: it reflects mortgages that were in borrowers consideration set, but which the borrower decided not to take up because other, higher utility mortageges were also in their consideration set.

A consumer originates a mortgage at an inside lender j provided j was in their consideration set C . Conditional on the consideration set, it was the highest utility option and j did not reject the application, or j was the second choice, and the first choice was rejected. The origination probability at lender j conditional on choice set C is then:

$$\sigma_j(C) = I\{j \in C\} \times \left\{ \underbrace{\frac{\exp(\delta_j)}{\sum_{l \in C} \exp(\delta_l)} \times (1-\chi_j)}_{j \text{ is } 1^{\text{st}} \text{ choice, not rejected}} \right.$$

$$\left. + \theta \times \sum_{k \in C \setminus \{j\}} \underbrace{\frac{\exp(\delta_k)}{\sum_{l \in C} \exp(\delta_l)} \frac{\exp(\delta_j)}{\sum_{m \in C \setminus \{k\}} \exp(\delta_m)} \times \chi_k (1-\chi_j)}_{j \text{ is } 2^{\text{nd}} \text{ choice, } 1^{\text{st}} \text{ was rejected, } j \text{ was not}} \right\}$$

where $\delta_{ij} = -\alpha^r p_j + \xi_j + \xi_{jr}(1 + \gamma_r \times d_i)$.

The origination share s_j of a lender is the expected origination share, where the

expectation is taken over all possible consideration sets.

$$s_j = \sum_{C \in 2^{\mathcal{L}}} P(C)\, \sigma_j(C) \tag{10}$$

Intuitively, the origination market share is high for lenders if they are considered a lot and, conditional on being considered, offer high utility products.

We next construct withdrawal market shares. Conditional on considering lender j, a consumer withdraws a mortgage application if she applied to two lenders, and lender j did not offer the highest utility among approved choices. The conditional and unconditional withdrawal probabilities $\omega_j(C), w_j$ are:

$$\begin{aligned} \omega_j(C) &= I\{j \in C\} \times \theta \times \sum_{k \in C \setminus \{j\}} \frac{\exp(\delta_k)}{\sum_{l \in C} \exp(\delta_l)} \frac{\exp(\delta_j)}{\sum_{m \in C \setminus \{k\}} \exp(\delta_m)} \times (1 - \chi_k)(1 - \chi_j) \\ w_j &= \sum_{C \in 2^{\mathcal{L}}} P(C)\, \omega_j(C) \end{aligned} \tag{11}$$

Intuitively, lenders have high withdrawn market shares if they are frequently considered but offer low utility relative to other considered lenders.

For completeness, we also write out the market shares of lenders in rejections. Rejections occur with probability χ_j as long as lender j receives an application, regardless of whether lender j was a borrower's first or second choice. The conditional and unconditional probabilities of rejection $\rho_j(C), r_j$ are:

$$\begin{aligned} \rho_j(C) &= I\{j \in C\} \times \chi_j \times \left\{ \frac{\exp(\delta_j)}{\sum_{l \in C} \exp(\delta_l)} + \theta \times \sum_{k \in C \setminus \{j\}} \frac{\exp(\delta_k)}{\sum_{l \in C} \exp(\delta_l)} \frac{\exp(\delta_j)}{\sum_{m \in C \setminus \{k\}} \exp(\delta_m)} \right\} \\ r_j &= \sum_{C \in 2^{\mathcal{L}}} P(C)\, \rho_j(C) \end{aligned} \tag{12}$$

We assume that a borrower who is rejected by both of her top two inside lenders originates a mortgage at the outside option. This assumption means that every borrower originates a mortgage, as in Agarwal et al. (2023). Empirically, this lets us use the total number of originations in a market as the denominator with which to calculate probabilities.

V.E Supply

Consistent with fair-lending laws, lenders set uniform prices for borrowers of all races within an MSA-year. We suppress the MSA index m, but we let z index tracts and

M_{rz} equal the total dollar value of originated mortgages to borrowers of race r in tract z. Lender j posts a price p_j to solve

$$\underset{p_j}{\text{argmax}} \sum_{rz} M_{rz} s_{jrz}\left(p_j\right)\left(p_j - c_{rj}\right) \tag{13}$$

Costs depend on both the race and the lender. These costs can capture both physical costs and racial animus in the spirit of taste-based discrimination of Becker (1957). For example, if minority borrowers have less easily documented income, the process of completing an application may be more costly.. Alternatively, loan officers have varying degrees of racial animus towards minorities that can give rist to cost differences, as we micro-found in Appendix A. We thus assume that costs for lender j to serve race r in an MSA reflect both a lender-specific component c_j and a component that is common to all lenders for borrowers of race r.

$$c_{rj} = c_r + c_j \tag{14}$$

Despite potential racial animus, fair lending laws bind: lenders are unable to price discriminate between borrowers of different races, and therefore prices satisfy a pooled first-order condition. Taking derivatives of the definition of profits in equation 13 yields:

$$p_j + \frac{\sum_{r,z} M_{rz} s_{rzj}}{\sum_{r,z} M_{rz} \frac{\partial s_{rzj}}{\partial p_j}} = \sum_r c_r \frac{\sum_z M_{rz} \frac{\partial s_{rzj}}{\partial p_j}}{\sum_{r,z} M_{rz} \frac{\partial s_{rzj}}{\partial p_j}} + c_{mj} \tag{15}$$

Intuitively, the left-hand side is a pooled marginal cost, whereas the right-hand side is a weighted average of the costs for serving different races. The weights on the costs reflect both the number of borrowers of each race (M_{rz}) and the demand elasticities of borrowers of each race $\frac{\partial s}{\partial p}$.

V.F Discussion of Key Modeling Assumptions

Imperfect Consideration and Competition In the model, borrowers do not consider all lenders in the market before applying. One interpretation of imperfect consideration is a flexible way to capture borrower's likelihoods of searching at different lenders. Imperfect consideration is important for modeling the US mortgage market because of its highly fragmented market structure. The top 10 lenders in an MSA on average originate only half of the mortgages, and smaller lenders quickly drop off in size. At the same time, it is well understood that the mortgage market is imperfectly competitive. These facts can only be rationalized in a model where borrowers do not consider all of the lenders in the market.

We interpret the consideration probabilities ϕ as combining both pure awareness and search (Morozov, 2023). In a richer model, consumers may be aware of many lenders, search for prices and approvals over a subset of those lenders, and ultimately apply to a further subset. We abstract away from the microfoundations of such a model and instead model the choice set directly. We allow for consideration probabilities to depend on prices, which captures the idea that consumers are more likely to search items that will offer them high utility. Consumers may be more willing to search a lender if the lender-specific search cost is low, and this would generate variation in ϕ_j. Our specification flexibly captures these possibilities.

The assumption that borrowers apply to at most two lenders is a simplifying assumption to map the model to the data. The extent to which lenders compete with each other depends on the consideration probabilities ϕ, not the share θ of borrowers who apply to multiple lenders. By modeling the mortgage market as a posted price market, borrowers know the characteristics of lenders even without applying. Thus, as consideration probabilities $\phi \to 1$, the model is equivalent to a standard full-consideration discrete-choice model even if all borrowers apply to only one lender. The assumption of at most two applications is consistent with survey data from the NSMO and helps us to map consideration probabilities ϕ and mean utilities δ to withdrawal probabilities.

Uniform Pricing Our assumption that lenders charge the same price for different races is consistent with both empirical evidence and fair-lending laws. A large literature documents only $2-5$ bp differences in within-lender pricing conditional on creditworthiness (Bartlett et al., 2022; Bhutta et al., 2021; Willen and Zhang, 2022). Fair lending laws prevent lenders from implementing discriminatory prices by charging higher prices at subsidiaries or at branches in minority neighborhoods (FFIEC, 2009). Business practices that result in discriminatory prices without discriminatory intent are not allowed. The wholesale mortgage lender, Provident, was investigated for fair-lending violations because it gave independent brokers wide latitude in setting broker fees. Brokers working with Black and Hispanic borrowers would charge higher broker fees, and the CFPB prosecuted this as a fair-lending violation (CFPB, 2015). In the wake of the financial crisis, Wells Fargo settled a large fair-lending case that alleged it steered Black and Hispanic borrowers towards subprime adjustable rate mortgages instead of prime mortgages. While Wells Fargo did various forms of outreach to minority neighborhoods, such as connecting with Black church leaders in various communities, the DoJ nonetheless prosecuted the large price differences as violations of fair-lending laws (DOJ, 2012).

Lender Costs We assume that lender costs for different borrowers can be decomposed additively into a portion c_j that is specific to the lender but applies to loans made by that lender for all races, and a race-specific term c_r that is common to all lenders in a market. Some assumptions are necessary because the usual approach to identifying race-specific costs from optimal pricing conditions fails when lenders charge uniform prices to borrowers of different races. In Section VI.D we validate our cost measures with accounting data, thus giving support to our simplifying assumption.

VI Estimation

We estimate our model by matching observed data on originations, withdrawals, and rejections across races and across tracts. Our estimation recovers the consideration sets, preferences, and lenders' marginal costs for borrowers of different races. We validate our estimated model with external data on advertising, costs, and consideration. The estimated model allows us to study why specialized lenders are successful in attracting minority borrowers and why most specialized lenders are small.

VI.A Sample Construction

We construct market share and price data that lets us study how lenders compete for borrowers of different racial groups. We define the universe of lenders for a combination of MSA, year, and race as any lender in the top 10 lenders of any racial group for that MSA/year. For each MSA/year/race combination, we limit ourselves to the top 20 lenders. This construction allows us to study the largest lenders for each racial group while also capturing how lenders' market shares may differ across racial groups. Appendix Table C.8 shows the number of lenders in the average market, broken down into different institution types . The average market has around 15 inside lenders with a total market share of 50 percent.

We compute the lender's price in each market with the weighted average of its average prices across races, where the weights are the dollar value of originations for each race. Price captures both rate spreads and total fees divided by 7, the average duration of a mortgage. The correlation between the race-specific averages and the uniform price is 93%. We impose uniform pricing within lenders to both reflect existing fair lending laws and to help us focus on how equilibrium interactions between lenders affect borrowers of different racial groups.

We capture heterogeneity across tracts by matching the covariance of market shares across tracts with different minority populations. We sort all tracts by the census population share of that race. We then aggregate these tracts into 5 "synthetic tracts" with ap-

proximately the same number of originated mortgages in each group. By correlating the model-generated market shares of specialized and non-specialized lenders with the actual market shares across these "synthetic tracts,", we can then estimate how consumers' search behaviors and preferences vary across sub-geographies within an MSA.

VI.B Separating Utility and Consideration Probabilities

The main objective of the demand model is to estimate two (latent) dimensions of minority specialization for each lender: how much utility they provide to borrowers of each race, and their visibility (consideration) among these borrowers. In our model, these two dimensions are captured by ξ_j and ξ_j^c. As we highlight below, estimating race specific price sensitivity of utility (α^r)and consideration (α_r^c) also yields interesting insights into racial differences in mortgage outcomes.

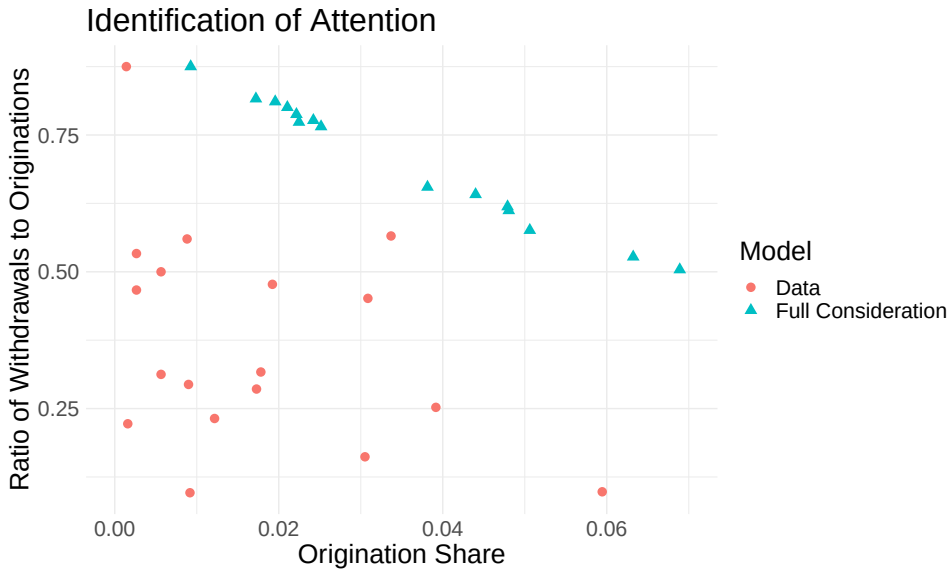
We estimate a flexible model of demand with rich heterogeneity in borrower preferences and consideration sets across races and tracts using lender market shares in origination, withdrawls, and rejections Appendix H contains the details. Our approach joinly uses originated and withdrawn applications to separate consideration and utility.

Intuitively, if we observe a lender with a high origination share but also high withdrawal rates when lending to borrowers of a given race, then this must be a lender with high consideration ϕ and low quality δ with respect to that race. This lender is frequently in consideration sets but is often only the second-highest option. In contrast to Abaluck and Adams-Prassl (2021), we do not use Slutsky asymmetry. We also do not need to make strong assumptions about excluded shifters of consideration and utility, as in Agarwal and Somaini (2022). Instead, we can in principle separate consideration versus utility from one cross-section of origination and withdrawal data.

We illustrate the above intuition more systematically by comparing predictions from our model to those of a full consideration model. We simulate our model under full consideration, holding estimated parameters fixed. Under full consideration, lenders with high market shares should have low withdrawal rates. Because the only source of variation across lenders in a full-consideration model is quality (for a given price and borrower composition), lenders with higher average quality are less likely to be the second choice of a borrower. In the data however, the correlation between origination and withdrawal shares is low. We illustrate this in two ways.

Figure 4 uses data for Asian borrowers in the Atlanta MSA in 2018. The red dots represent different lenders. The horizontal axis is the lender's origination share, and the vertical axis is the ratio of withdrawn applications to originated applications. The red dots illustrate the data, and the blue triangles illustrate the predicted relationship

Figure 4: Illustration of how imperfect consideration is identified



Notes: The chart illustrates how withdrawal shares are highly correlated with origination shares under full consideration but are not highly correlated in the data. The red dots plot the relationship between the ratio of withdrawals to originations against origination shares for Asian borrowers in the 2018 Atlanta MSA. The blue triangles illustrate the relationship in a counterfactual world in which utilities are held constant, but consumers have full consideration.

when we hold fixed the estimated values of utility but allow consumers to have full consideration. A model of full consideration yields a counterfactually strong relationship between withdrawal ratios and origination shares.

More formally, we regress withdrawal rates on origination shares while allowing for MSA-race-year specific slopes and intercepts. In the full consideration model the R^2 is 0.98, confirming the intuition that lender quality drives both origination and withdrawals. In the data, on the other hand, this regression, despite the large number of fixed effects, yields an unadjusted R^2 of only 0.26. The low empirical R^2 compared to the high full-consideration R^2 illustrates that the weak relationship between withdrawal ratios and origination shares helps to identify consideration.

To identify price-sensitivity of preferences and consideration sets, we instrument for prices. As we discuss in Section VI.D , we use demand estimates to infer costs and mark-ups, which we then compare to accounting data. The high correlation gives us more confidence that our price sensitivity is reasonably well estimated. We instrument for price using two different approaches. We instrument for price using two different approaches. First, we use the average price charged by that lender to borrowers of all races in other MSAs that do not share a state with the focal MSA using lender fixed

effects. The fixed effects mean that price elasticities α are identified by within-lender variation in prices over time. The advantage of this approach is that we can use the variation in our entrie sample. The second approach.

In Appendix G, we use changes in the GSE's loan-level pricing adjustment (LLPA) matrix as an instrument for price and find similar demand elasticities. The LLPA matrix changed in 2023, and these changes affected different lenders differently depending on their mix of borrowers. The advantage of this approach is that it is arguably more plausibly exogenous, but only has power for the subset of lenders who focus on the most affected borrowers.

We find that Asian, white, and Black borrowers are similarly price-elastic, whereas Hispanic borrowers are the least price-elastic. Table 16 shows the results of these regressions. The first column shows a simple regression of the log origination share of a lender on the price and whether a lender is specialized. Here, we see that consumers seem to obtain fewer mortgages from high-cost lenders. The second and third columns decompose why consumers are less likely to borrow from high-cost lenders. Most of the effect comes from lower utility, while Asian, white, and Black borrowers appear also less likely to consider high-priced lenders. The fourth column shows that relatively little of this relationship comes from higher or lower rejections at high-priced lenders. We find that a one-basis point increase in interest rates at a lender lowers Asian, Black, white, and Hispanic borrowers' demand by 1.3%, 0.9%, 1%, and 0.7%, respectively. Hispanic borrowers' lower demand elasticity is an important force in the model for why Hispanic borrowers face higher markups.

VI.C Estimates of Supply Parameters

We estimate race-specific marginal costs using demand estimates and lenders' first order conditions. If lenders could charge race-specific prices, then we could use race-specific first-order conditions to recover lenderrace-specific costs. However, fair-lending laws mean that lenders must charge a pooled price for borrowers of different races. Thus we estimate the marginal cost using (15) from the pooled marginal cost and equilibrium weights. We include include institution-by-year fixed effects to accont for across-lender difference in average cost.

We estimate that minorities are approximately 20 basis points (bps) more expensive to serve than white borrowers. Table 13 shows the result of the cost regression. Our preferred specification drops the large banks as they may be more likely to enter endogenously in response to the opportunity to serve minority borrowers. Asian and Black borrowers are around 10 bps more costly to serve, whereas the additional cost for

Table 12: Estimating price elasticities

	Log Shares	Utility	Consideration	Rejection
Asian x Price	-1.343***	-1.339***	-0.974**	0.000
	(0.386)	(0.341)	(0.357)	(0.020)
White x Price	-1.119***	-0.956***	-0.772***	-0.001
	(0.226)	(0.237)	(0.222)	(0.016)
Black x Price	-1.052**	-1.216**	-0.635*	0.041
	(0.358)	(0.445)	(0.305)	(0.031)
Hispanic x Price	-0.799**	-1.197**	-0.392	0.000
	(0.302)	(0.426)	(0.276)	(0.026)
N	84034	84034	84034	84034
MSA x Tract x Year x Race FE	X	X	X	X
Lender x MSA x Tract x Race FE	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results of instrumental variable regressions of log market shares, our utility measure, and our consideration measure on price and lender specialization. Price is instrumented for by the average price of the same lender in other MSA's that do not share a state with the focal MSA. The prices, instruments, and measures are winsorized at the 1% level. Standard errors are clustered at the lender-year level.

Table 13: Estimates of incremental costs of serving different minorities

	All Lenders	Drop Big Banks
Asian	0.158**	0.169**
	(0.050)	(0.053)
Hispanic	0.523***	0.544***
	(0.062)	(0.062)
Black	-0.091	0.028
	(0.064)	(0.065)
N	6615	5665
MSA x Year FE	X	X
Institution Type x Year FE	X	X

Notes: Estimates of marginal costs for different minorities come from regressing lender level marginal costs on elasticity adjusted shares of lending to different minority groups.

Hispanic borrowers is even higher at around 50 bps.

The marginal cost estimates reflect the combination of how price elasticities and the relationship between specialization and prices differ across races. Black borrowers' marginal costs are not that different from white borrowers because the prices at Black-specialized lenders are not much higher than the prices at mainstream lenders. The model recovers higher marginal costs for Asian borrowers because lenders with a large share of Asian borrowers charge higher prices despite Asian borrowers' high price elasticity. The model recovers an even higher cost for Hispanic borrowers because Hispanic charge much higher prices, and this cannot be entirely accounted for by Hispanic borrowers' lower price elasticity.

VI.D Model Fit

We evaluate the fit of our model on several dimensions.

Margins and Costs Our model implied markups and costs are highly correlated with accounting estimates supplied in lenders' regulatory filings. Because the data used to infer these costs come from our demand estimation, especially the price IVs, we view this exercise also as a partial test of our IVs. We obtain costs from the shadow bank call reports which mortgage originators file with state regulators (Jiang et al., 2023). Revenueare the sum of total origination non-interest income and secondary market gains from mortgage sales. Origination income includes origination fees.[13] Costs are the sum of origination-related compensation, professional fees, and other operating expenses. This measure of costs excludes costs from servicing, as well as important fixed costs such as occupancy expenses or an allocation of corporate expenses.

Our model matches both the level of markups and cross-sectional variation in revenues and costs. On a sample of shadow banks for which we have regulatory data, our model recovers a markup of 97 bps, whereas the accounting data yields a markup of 130 bps.

Model-implied marginal costs correlate almost one-for-one with per dollar accounting costs (Table 14, Column 2) Similarily, we find that model implied price is correlated around one-for-one with per-dollar revenues (Column 1). While our measures of margins are noisy, the third column shows that our model-implied and accounting measures of margins are also correlated in the cross-section of lenders. The fourth column shows that a significant part of the variation in costs is explained by the fact that lenders who

[13]Because shadow banks operate on an originate-to-distribute model, net interest income is not a meaningful source of revenue relative to the gains from mortgage sales.

Table 14: Comparison of measured prices against measured revenues, and measured costs and model-implied costs

	Revenue	Costs	Margins	Accounting Costs
Model	1.011**	0.781*	0.899	
	(0.383)	(0.307)	(0.672)	
Asian				-0.768
				(0.663)
Black				-0.044
				(0.599)
Hispanic				1.003**
				(0.310)
N	178	178	178	178
Year FE	X	X	X	X

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

Notes: Model cost is the lender's marginal cost implied by the demand model. Marginal costs for each lender are computed as an origination dollar-weighted sum across markets. Price is the fee-inclusive rate spread as measured by HMDA. Per-dollar revenue and costs are measured from the shadow bank call reports in Jiang et al. (2023). Race shares are measured as a share of dollars originated to each race.

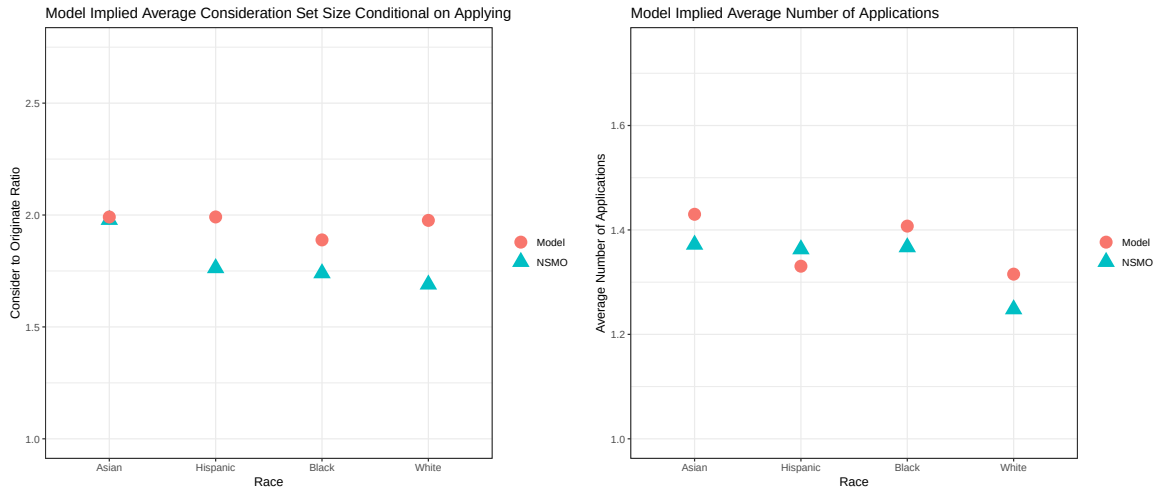
do more lending to Hispanic borrowers have higher costs. This suggests that our higher estimated marginal costs for Hispanic borrowers reflects real resource costs, rather than the psychological costs that may arise from taste-based discrimination.

These markup numbers also illustrate the value of modeling imperfect consideration. Even though there are on average 15 lenders in each market, we can still recover large markups because the average consideration set is small. In contrast, past studies have had to impose the assumption that the typical borrower considers borrowers in a narrow geographic area, such as their census tract (Buchak et al., 2023).

Consideration Data Our model matches the average size of consideration sets and applications from NSMO (2018-2019) survey evidence , even though we do not use survey data in the estimation. We calculate the average consideration set size $\overline{C}$ and average application size $\overline{A}$ from the estimated model as one plus the average number of inside lenders considered / applied for (since an outside lender is always considered). If a lender rejects an applicant, the lender is not counted in the consideration and application set:

$$\overline{C} = \sum_j \phi_j \left(1 - \chi_j\right) \qquad \overline{A} = (1+\theta) \times \frac{\sum_j \phi_j \left(1 - \chi_j\right)}{\sum_j \phi_j}$$

Figure 5: Comparing model implied consideration set and application set sizes with survey data



Notes: The size of an average consideration set in the model adjusts for the average rejection rate at each lender. The application set is the average number of applications per borrower, with fewer rejections. The empirical data is from the NSMO 2018-2019 waves.

Figure 5 shows that the model matches the fact that the typical borrower considers around two lenders matching the survey data. The fit is surprisingly good given that the model uses only observed applications and withdrawals to identify consideration. The right graph shows that the model correctly matches that borrowers apply to an average 1.4 lenders.

Advertising Our estimated lender level visibility (ξ_j^c) is positively correlated with advertising in the data, whereas the measure of quality (ξ_j) is not correlated. We compare the estimated parameters of lender visibility in a specific market (consideration) against TV television advertising expenditures, conditional on positive advertising expenditures in the Nielsen dataset. We include lender and MSA fixed effects, and testing if consumers are more aware of lenders in the MSA's where the lender is spending relatively more on advertising when compared to the lender's average expenditure. shows the results of these regressions. There is a positive relationship between consideration and advertising, but little relationship between utility and advertising. This matches the findings of Honka et al. (2017) who find that advertising in the banking industry primarily shifts consumer awareness, not utility.

Table 15: Advertising and Measures of Utility and Consideration

	Consideration	Utility
Log Spot TV Spending	0.044**	0.007
	(0.015)	(0.015)
N	1640	1640
MSA x Year x Race FE	X	X
Year x Race x Lender FE	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: These regressions compare estimated consideration and utility fixed effects with log TV advertising spending by lender. Regressions include parameters for all races and are clustered at the level of advertising, i.e. at the lender X MSA X year level

VII Results

After estimating our model, we can compare the choice sets and preferences of minority and White borrowers. We also use our model to simulate what happens to lender profits under different patterns of specialization, which sheds light on lenders' incentives to specialize. Our demand model shows that minority borrowers choose different lenders primarily because of different consideration sets, and our supply model shows that fair lending laws discourage mainstream lenders from targeting Hispanic borrowers. While our model cannot speak to the overall desirability of fair-lending laws, it nonetheless highlights how fair-lending laws can have adverse effects on the supply of minority specialized services and advertising.

VII.A Decomposing Demand for Specialized Lenders

Minority borrowers are more likely to choose specialized lenders when compared to borrowers of other races primarily because they are more likely to consider such lenders. We evaluate the effects of specialization on the demand parameters by projecting the recovered race-lender-market-tract fixed effects on specialization, market-fixed effects, and lender-MSA-tract fixed effects. We thus run the regressions:

$$\eta_{rjmz} = \sum_r \gamma_r d_{rjm} + \nu_{rmzt} + \nu_{jmzt} + \epsilon_{rjmzt} \tag{16}$$

where ν_{rmzt} are race-market-tract-year fixed effects and ν_{jmzt} are lender-MSA-tract-year fixed effects. Thus variation in this regression comes from comparing minority versus white borrowers at specialized lenders, with the difference between minority and white borrowers at mainstream lenders serving as the control group. If $\gamma_r > 0$, then borrowers

Table 16: Effects of specialization

	Utility	Consideration	Rejection
Asian x Specialized	0.419***	1.097***	-0.009***
	(0.049)	(0.038)	(0.002)
Hispanic x Specialized	0.205***	1.187***	-0.010**
	(0.061)	(0.052)	(0.003)
Black x Specialized	0.546***	1.055***	-0.001
	(0.096)	(0.057)	(0.005)
N	85059	85059	85059
MSA x Tract x Year x Race FE	X	X	X
Lender x MSA x Tract x Year FE	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results of projecting the estimated lender fixed effects on lender observables. Standard errors are clustered at the lender-MSA-race level.

of race r are more likely to consider or derive higher utility from specialized lenders when compared to borrowers of other races at those lenders. Table 16 shows the results of the regression. Because choice probabilities depend on the logistic of these utility and consideration measures, we transform these coefficients into marginal probabilities at the sample averages for utility and consideration. Because unconditional consideration probabilities are low, the parameter estimates imply that minority borrowers are near $3 \approx \exp(1.1)$ times as likely to consider a specialized lender when compared to borrowers of other races. In contrast, the utility effect is more modest and increases choice probabilities conditional on consideration by a much smaller 4%. Because rejection rates across races are less than 10%, the lower measured rejection rates only account for 1% greater market shares.

Consideration also explains why minority borrowers in minority neighborhoods are more likely to choose specialized lenders compared to minority borrowers in neighborhoods with a smaller minority population. Table 17 regresses the tract-level measures of utility, consideration, and rejection rates on lender specialization, the minority share of the tract, and the interaction. The minority share of the tract has been linearly scaled so that the coefficient represents the gap between the tracts with the highest and lowest population share of that minority. The key coefficient of interest is the interaction, which explains why specialized lenders are more common in areas with higher minority shares. The interaction is only large for consideration, which indicates that differences in consideration probabilities drive the relative market shares. This is consistent with the reduced-form results in Table 11, where we found that specialized lenders did not have

Table 17: Estimated parameters for specialized lenders across tracts

	Utility	Consideration	Rejection
Specialized	0.343***	0.470***	0.004+
	(0.034)	(0.021)	(0.002)
Normalized minority share	0.022	-0.018	0.019***
	(0.056)	(0.017)	(0.002)
Specialized x normalized minority share	0.094	0.746***	-0.019***
	(0.075)	(0.039)	(0.003)
N	52924	52924	52924
R2	0.24	0.21	0.14
MSA x Year x Race FE	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the results of projecting the estimated lender parameters on whether a lender is specialized, the minority population share of the tract relative to the median in the MSA, and the interaction. Consideration is the logit of the consideration probability, and Reject is the estimated arithmetic rejection rate for that lender.

substantially lower withdrawal rates in minority neighborhoods. Similar relative withdrawal rates mean that minority borrowers derive similar utility from specialized versus mainstream lenders. Thus the high market share of specialized lenders in minority census tracts must be explained by different consideration sets.

One concern with the regression in equation 16 is that the specialization measure on the right is constructed from market shares, and so there is a mechanical relationship between the specialization measure and the left-hand side variables which are themselves recovered from market shares. One version of this concern is that our results may be driven by small sample bias in our measurement of specialization. We can account for this by using predictive regressions as in equation 2 to build a "leave-one-out" measure of specialization in year t that uses only data from other years. We can use the leave-one-out measure to instrument for the main specialization measure. This IV approach negates any mechanical correlation between measured specialization and market shares in any given year. We do this in Appendix Table C.9 and find quantitatively similar results. While the leave-one-out measure does address any concerns with small sample bias, it is separately true that specialized lenders must show up as having higher utility or consideration in order to over-represent a minority group. However, ex-ante it is not clear how much of the effect is through utility or consideration.

VII.B Supply-Side Drivers of Specialization

While our demand estimates demonstrate that minority borrowers value the differentiated advertising of specialized lenders, they do not directly speak to why certain lenders choose to specialize compared to others. For example, why do Citibank and Bank of America overrepresent Black and Asian borrowers in many MSA's, but do not have as strong of representation among Hispanic borrowers? We find that one potential reason for this is that fair-lending laws discourage large lenders from attracting minority borrowers. Our supply estimates suggest that minority borrowers are more expensive to serve. Fair-lending laws prevent within-lender price dispersion, but allow for large price differences between lenders. Mainstream lenders, who must charge low prices to avoid fair lending scrutiny, then advertise less intensely for minority borrowers when compared to the specialized lenders who charge high prices.

VII.C Repealing Fair Lending

To quantify the effects of fair-lending requirements for uniform prices across races within lenders, we first simulate what happens when fair lending laws are repealed. We modify the lender conduct assumption to allow for race-specific prices. Equation 13 then changes to race-specific maximization problems described by

$$\underset{p_{rj}}{\operatorname{argmax}}\, s_{rj}\left(p_{rj}\right)\left(p_{rj}-c_{rj}\right) \tag{17}$$

This counterfactual shows how fair-lending laws protect Black and Hispanic borrowers at the cost of increasing prices for white and Asian borrowers. While prices rise on average by 13 bps from repeal, this hides substantial heterogeneity across races. Table 18 breaks down the results by race, and shows that while Asian and white borrowers see their prices fall by 9, 6 bps, Black and Hispanic borrowers see their prices rise by 5 and 49 bps. Uniform pricing insulates Black and Hispanic borrowers from their higher marginal costs and greater lender market power. In contrast, uniform pricing hurts relatively price-sensitive Asian and white borrowers by preventing lenders from competing to attract them. In equilibrium, repealing fair lending raises the surplus of Asian and white borrowers by 12 and 6 bps, respectively, whereas Black and Hispanic borrowers see their surplus fall by 4, 40 bps.

The idea that lenders would cut prices for white borrowers due to their higher price elasticities is consistent with the CFPB's supervisory highlights cautioning against this practice as a fair-lending violation. According to the CFPB, a lender that offered pricing exceptions to white borrowers in response to competitive offers from other institu-

Table 18: Counterfactual Results for Consumers by Race

		Counterfactual		
Race	Change In	Repeal	Specialize	Both
Asian	Shares (pp)	4	6	10
	Price (bp)	-9	-1	-11
	Surplus (bp)	12	16	31
Black	Shares (pp)	-1	6	5
	Price (bp)	5	-2	3
	Surplus (bp)	-4	17	14
Hispanic	Shares (pp)	-10	7	-3
	Price (bp)	49	-3	43
	Surplus (bp)	-40	17	-24
White	Shares (pp)	2	0	2
	Price (bp)	-6	0	-6
	Surplus (bp)	6	0	6

Notes: Repeal is a counterfactual in which all lenders can charge race-specific prices. More specialization changes minority borrowers' consideration and utility from large banks as if these lenders were in-group lenders. "Both" combines the two policies.

Table 19: Average changes in profit and prices when comparing the equilibrium with higher marginal costs, race-specific prices, but broader lender specialization against the baseline equilibrium

		Price (bps)			Profit (%)		
Race	Lender Type	Repeal	Specialize	Both	Repeal	Specialize	Both
Asian	New Specialized	-8	7	-3	-4	103	92
	Old Specialized	-4	-1	-6	-3	-5	-9
	Other	-12	-1	-15	-2	-7	-10
Black	New Specialized	11	8	18	4	116	127
	Old Specialized	9	-1	6	4	-7	-3
	Other	4	-1	1	3	-8	-5
Hispanic	New Specialized	58	10	64	68	168	347
	Old Specialized	39	-3	35	41	-6	33
	Other	65	-2	61	63	-8	52
White	New Specialized	-6	6	-6	-3	-3	-3
	Other	-6	-1	-6	-2	0	-2

Notes: Repeal is a counterfactual in which all lenders can charge race-specific prices. More specialization changes minority borrowers' consideration and utility from large banks and non-bank lenders as if these lenders were in-group lenders. Both combines the two policies.

tions violated fair-lending laws because the lender gave fewer exceptions to Black and Hispanic borrowers (CFPB, 2021).

VII.D More Specialization

To estimate the gains from more lender specialization, we evaluate how equilibrium prices and quantities change when large banks become specialized lenders for all minorities. We interpret this counterfactual as having these lenders introduce the same kinds of advertisements, loan officer hiring practices, and underwriting standards that make existing specialized lenders so successful at lending to minorities. We implement this counterfactual by increasing the baseline utility and consideration parameters for all large banks by the estimated coefficients in Table 16.

Specialization has the largest effects on increasing consideration probabilities. This dramatic increase in consideration probabilities forces lenders to cut prices and allows minority borrowers to have a greater chance of finding a lender that offers high utility. Thus across minority groups, surplus rises by 17 bps on average. Table 19 shows that these effects do not vary significantly across races.

Introducing new specialized lenders forces other lenders to compete harder for minority borrowers. Table 19 shows that while the newly specialized lenders roughly doubles, the resulting increase in competition lowers profits at existing specialized lenders. Prices at existing specialized lenders also have to fall in order to stay competitive. Thus, the model predicts that the increase in specialized lending creates benefits from reducing market power. This counterfactual also illustrates that minorities can benefit from changes to the market structure of the mortgage market that actually result in a reduced role for minority-owned lenders.

VII.E Combining Repeal with More Specialization

Our third counterfactual interacts the effects of repealing fair lending laws with increasing lender specialization. This helps to illustrate two points about how fair-lending laws and lender competition interact. First, more lender competition through more specialization can mitigate the harms of discrimination. When lenders compete intensely to attract minority borrowers, the harms of discriminatory pricing are reduced. Second, fair-lending laws can discourage large lenders from investing in attracting minority borrowers. Intuitively, if minorities are costlier to serve, then fair-lending laws prevent large lenders from charging prices commensurate with costs. Ultimately, it then falls on smaller lenders who exclusively serve one minority group to lend to minorities.

Specialization, when combined with a repeal of fair-lending laws, results in more modest price increases for Black and Hispanic borrowers when compared to a repeal of

fair-lending laws by itself. The last column of table 18 shows the results of combining the two changes. Whereas repealing fair-lending laws results in 5 and 49 bps average price increases for Black and Hispanic borrowers, this moderates to only 3 and 43 bps when the repeal is accompanied by an increase in lender specialization. This price decline is even more impressive given that the increase in specialization increases average product quality in this market, which would typically be associated with higher prices. After accounting for the effects of higher quality, surplus rises by 14 and -24 bps for Black and Hispanic borrowers, respectively.

VII.F Uniform Pricing, Lender Profits, and Investment Incentives

The model highlights that fair-lending laws may be one reason why large banks specialize in lending to Black and Asian borrowers but not to Hispanic borrowers. By comparing lender profits from Asian and Black borrowers under the repeal of fair-lending laws combined with specialization versus specialization alone, we see that the marginal effect of repealing fair lending laws only has a small effect on profit. This picture differs for Hispanic borrowers. Whereas specialization on its own increases the profits of the large banks and non-bank lenders by from serving Hispanic borrowers by 168%, this increases to 347% if they are also allowed to freely set prices. Table 3 shows that large banks are more likely to become specialized when the market opportunity for serving the minority group is large. Taken together, these facts suggest that large banks would also provide more Hispanic specialized services if they could afford to cover the higher costs of serving Hispanic borrowers.

One way to understand the potential harms of fair lending laws is to interpret them as imposing a ceiling on price differences between borrowers of different races, despite borrowers having different costs. This extends the argument in Cuesta and Sepulveda (2021) to the cases where price differences between races are capped. An important difference is that while the harms of price ceilings in other consumer credit settings may show up in rejections, banks have strong reasons to limit their rejections of minority borrowers in order to comply with fair-lending laws. Instead, large banks optimally choose not to advertise or provide specialized services to certain segments of the market that have higher costs. Thus the harms of uniform pricing show up in underinvestment rather than rejections or higher prices.

A Beckerian interpretation of our results is that price regulations such as fair-lending laws may hurt minorities even if some lenders have a taste for discrimination. Our results show that when lenders have market power, preventing discriminatory prices can help Black and Hispanic borrowers in the short run. However, if lenders can adjust

their marketing and service provision in the long run, then fair lending laws discourage investment in attracting minority borrowers. Allowing repugnant profits from discriminatory pricing may still improve minority borrower welfare to the extent the profits encourage more lender specialization.

VII.G Interpreting Extensive Margin Discrimination in the Context of our Model

Our counterfactuals have a different interpretation if one believes large mainstream banks are discriminating against minority borrowers on the extensive margin in the baseline equilibrium. For example, perhaps the reason minority borrowers go to specialized lenders is because they know that the mainstream lenders do not lend to minorities. Minority borrowers pay high prices at specialized lenders not because these lenders are higher quality, but rather because minority borrowers do not have access to the cheaper, mainstream lenders. Because we only use data on borrower choices, we cannot separately identify if mainstream lenders are discriminating and specialized lenders are not, or if mainstream lenders are not discriminating and specialized lenders are taking additional actions to attract minorities. If mainstream banks are discriminating against minorities, our counterfactuals can be thought of as quantifying the welfare gains of ending this kind of extensive margin discrimination at mainstream lenders.

VIII Conclusion

In this paper we study the equilibrium consequences of differences between minority and majority borrowers' shopping behavior for the potential welfare effects of fair-lending laws. We document that minorities benefit from the presence of specialized lenders who are effective at attracting minority borrowers despite charging higher prices than mainstream lenders. We use a model to show that the benefits these specialized lenders are large, so that the gains from more lenders being able to serve minority borrowers in the same way are large relative to the costs of discriminatory pricing. In fact, fair lending laws may discourage mainstream lenders from investing in attracting minority borrowers. Our story goes beyond the standard Beckerian story with homogenous products to incorporate product differentiation, but ultimately arrives at a Beckerian conclusion. Even if lenders harbor taste-based discrimination, fair-lending laws may not help minorities.

A full welfare analysis of fair-lending laws is beyond the scope of this paper. Rather, we see our results as a first step towards understanding the equilibrium consequences of fair-lending laws. An interesting extension would be to study the equilibrium allocation of loan officers to lenders. Our model suggests that the highest skilled minority loan

officers should be hired by the specialized lenders who can charge high prices. Because minority borrowers are less profitable to a mainstream bank, the bank cannot pay the minority loan officers high wages. To the extent that minority loan officers reduce information frictions for minority borrowers (Frame et al., 2024), fair-lending laws may make large banks less effective at lending to minority borrowers in equilibrium. We hope to address such questions in future work.

References

Abaluck, Jason and Abi Adams-Prassl, "What Do Consumers Consider Before They Choose? Identification from Asymmetric Demand Responses," *The Quarterly Journal of Economics*, June 2021, *136* (3), 1611–1663.

Agarwal, Nikhil and Paulo Somaini, "Demand Analysis under Latent Choice Constraints," *Demand Analysis under Latent Choice Constraints*, April 2022, *NBER Working Paper.*

Agarwal, Sumit, John Grigsby, Ali Hortaçsu, Gregor Matvos, Amit Seru, and Vincent Yao, "Searching for Approval," *Econometrica*, 2023, *Forthcoming.*

Alexandrov, Alexei and Sergei Koulayev, "No Shopping in the U.S. Mortgage Market: Direct and Strategic Effects of Providing Information," May 2018.

Allen, Jason, Robert Clark, and Jean-François Houde, "The Effect of Mergers in Search Markets: Evidence from the Canadian Mortgage Industry," *American Economic Review*, October 2014, *104* (10), 3365–3396.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace, "Consumer-Lending Discrimination in the FinTech Era," *Journal of Financial Economics*, January 2022, *143* (1), 30–56.

Bayer, Patrick, Fernando Ferreira, and Stephen L. Ross, "What Drives Racial and Ethnic Differences in High-Cost Mortgages? The Role of High-Risk Lenders," *The Review of Financial Studies*, January 2018, *31* (1), 175–205.

Becker, Gary S., *The Economics of Discrimination* Economic Research Studies, Chicago, IL: University of Chicago Press, August 1971.

Benetton, Matteo, "Leverage Regulation and Market Structure: A Structural Model of the U.K. Mortgage Market," *The Journal of Finance*, 2021, *76* (6), 2997–3053.

_ , Alessandro Gavazza, and Paolo Surico, "Mortgage Pricing and Monetary Policy," *Working Paper*, September 2023.

Berkovec, James A., Glenn B. Canner, Stuart A. Gabriel, and Timothy H. Hannan, "Discrimination, Competition, and Loan Performance in FHA Mortgage Lending," *The Review of Economics and Statistics*, May 1998, *80* (2), 241–250.

Bhutta, Neil and Aurel Hizmo, "Do Minorities Pay More for Mortgages?," *The Review of Financial Studies*, February 2021, *34* (2), 763–789.

_ , Andreas Fuster, and Aurel Hizmo, "Paying Too Much? Borrower Sophistication and Overpayment in the US Mortgage Market," *Working Paper*, January 2021.

_ , Aurel Hizmo, and Daniel Ringo, "How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions," August 2022.

Blattner, Laura and Scott Nelson, "How Costly Is Noise? Data and Disparities in Consumer Credit," *Working Paper*, June 2022.

Buchak, Greg and Adam Jørring, "Do Mortgage Lenders Compete Locally? Implications for Credit Access," *SSRN Electronic Journal*, 2021.

_ , Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy," *Journal of Political Economy*, June 2023, *Forthcoming*.

CFPB, "United States of America and Consumer Financial Protection Bureau v. Provident Funding Associates, L.P.," May 2015.

_ , "Supervisory Highlights," Technical Report 25 December 2021.

Cuesta, José Ignacio and Alberto Sepulveda, "Price Regulation in Credit Markets: A Trade-Off between Consumer Protection and Credit Access," *SSRN Electronic Journal*, September 2021.

DOJ, "United States of America v. Wells Fargo Bank, NA," July 2012.

Egan, Mark, "Brokers versus Retail Investors: Conflicting Interests and Dominated Products," *The Journal of Finance*, June 2019, *74* (3), 1217–1260.

FFIEC, "Interagency Fair Lending Examination Procedures," August 2009.

Frame, W Scott, Ruidi Huang, Erik J Mayer, Adi Sunderam, Erica Xuewei Jiang, Yeonjoon Lee, Will Liu, and Ruidi Huang, "The Impact of Minority Representation at Mortgage Lenders," *Journal of Finance*, 2024, *Forthcoming*.

Gentzkow, Matthew, Jesse M. Shapiro, and Matt Taddy, "Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech," *Econometrica*, 2019, *87* (4), 1307–1340.

Gerardi, Kristopher, Paul S. Willen, and David Hao Zhang, "Mortgage Prepayment, Race, and Monetary Policy," *Journal of Financial Economics*, March 2023, *147* (3), 498–524.

Giacoletti, Marco, Rawley Z Heimer, and Edison G Yu, "Using High-Frequency Evaluations to Estimate Discrimination:," *Working Paper*, 2021.

Goeree, Michelle Sovinsky, "Limited Information and Advertising in the U.S. Personal Computer Industry," *Econometrica*, 2008, *76* (5), 1017–1074.

Gurun, Umit G., Gregor Matvos, and Amit Seru, "Advertising Expensive Mortgages," *The Journal of Finance*, 2016, *71* (5), 2371–2416.

Hanson, Andrew, Zackary Hawley, Hal Martin, and Bo Liu, "Discrimination in Mortgage Lending: Evidence from a Correspondence Experiment," *Journal of Urban Economics*, March 2016, *92*, 48–65.

Hastings, Justine, Ali Hortaçsu, and Chad Syverson, "Sales Force and Competition in Financial Product Markets: The Case of Mexico's Social Security Privatization," *Econometrica*, 2017, *85* (6), 1723–1761.

Holmstrom, Bengt and Paul Milgrom, "Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design," *Journal of Law, Economics, & Organization*, 1991, *7*, 24–52.

Honka, Elisabeth, Ali Hortaçsu, and Maria Ana Vitorino, "Advertising, Consumer Awareness, and Choice: Evidence from the U.S. Banking Industry," *The RAND Journal of Economics*, August 2017, *48* (3), 611–646.

Jiang, Erica, Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Banking without Deposits: Evidence from Shadow Bank Call Reports," *Working Paper*, September 2023.

Liu, Chao, "Language Frictions in Consumer Credit," *Working Paper*, November 2023.

Metro, "Senior Management," https://www.metrocitybank.bank/investor-relations/senior-management 2022.

Morozov, Ilya, "Measuring Benefits from New Products in Markets with Information Frictions," *Management Science*, March 2023, *Forthcoming*.

Munnell, Alicia H, Geoffrey M B Tootell, Lynn E Browne, and James Mc Eneaney, "Mortgage Lending in Boston: Interpreting HMDA Data," *American Economic Review*, 1996, p. 30.

Panorama, "The Team," https://www.panoramamortgagegroup.com/team 2022.

Ross, Stephen L., Margery Austin Turner, Erin Godfrey, and Robin R. Smith, "Mortgage Lending in Chicago and Los Angeles: A Paired Testing Study of the Pre-Application Process," *Journal of Urban Economics*, May 2008, *63* (3), 902–919.

Willen, Paul and David Zhang, "Testing for Discrimination in Menus," *Working Paper*, March 2022, p. 60.

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

A Microfoundation for Cost Decomposition

This section outlines a simple model of taste-based discrimination in line with Becker (1971) in which lenders who serve minority borrowers face higher marginal costs.

Within an MSA, suppose there are two markets $k = 0, 1$. Market 0 is purely white borrowers and so the minority share $m_0 = 0$, and market $k = 1$ has some share of minority borrowers m_1. Let the share of overall borrowers in market 1 be s, and normalize the total mass of borrowers to 1. Within each market, lenders compete in undifferentiated Nash-Bertrand.

The cost of originating a mortgage is the cost of hiring a loan officer to process the mortgage. Suppose in this simple case the mass of loan officers and borrowers are identical, so every loan officer is matched up to a borrower in equilibrium.

Loan officers are mobile across markets. For a loan officer i, her utility from working at a lender j in a market k as a function of the wage w_j and the minority share m_k in the market is:

$$u_{ijk} = -d + w_j - \theta_i m_k \tag{18}$$

Where d is the disutility of labor, and the variable $\theta_i \sim F$ captures the distribution of taste-based discrimination in the population of loan officers. Each loan officer has an outside option of zero, and let F admit a density.

An equilibrium is a wage level w_k in each market k and a set of loan prices p_k in each market such that lenders are maximizing profits, loan officers and consumers are optimizing, and loan supply equals loan demand in each market.

In equilibrium, there is a cutoff type $\underline{\theta}$ such that $F(\underline{\theta}) = s$, $w_k = d + m_k\underline{\theta}$, and $p_k = w_k$. All loan officers with $\theta_i \leq \underline{\theta}$ work in the minority market 1. Such a cutoff type exists because F has no atoms.

In the putative equilibrium, no loan officer with $\theta_i > \underline{\theta}$ would switch markets because the wage is not enough to compensate for the distaste of working with minority borrowers. Similarly, no loan officer with $\theta_i \leq \underline{\theta}$ would gain from switching to the market without minorities because the wage is too low relative to the disutility of working with minorities. Firm wage setting and pricing is then pinned down by the assumption of undifferentiated Nash-Bertrand competition for both consumers and workers.

The assumption that loan officers are mobile whereas consumers are fixed in markets captures the idea that lenders may target specific consumers (e.g. those in a neighborhood, those in one community), whereas lenders can hire more broadly.

In equilibrium, a regression of marginal costs on minority shares recovers the equilibrium amount of taste-based discrimination that is priced.

B Proof of Logistic Regression Approximation

Let X be the lender and R be the race of the borrower. Let $\sim$ denote the complement. By Bayes' rule, the ratio of application shares captures

$$\begin{aligned}\log \frac{a_{rj}}{a_{-rj}} &= \log \frac{P(X|R)}{P(X|\sim R)} \\ &= \log \frac{P(R|X)}{P(\sim R|X)} + \log \frac{P(\sim R)}{P(R)}\end{aligned}$$

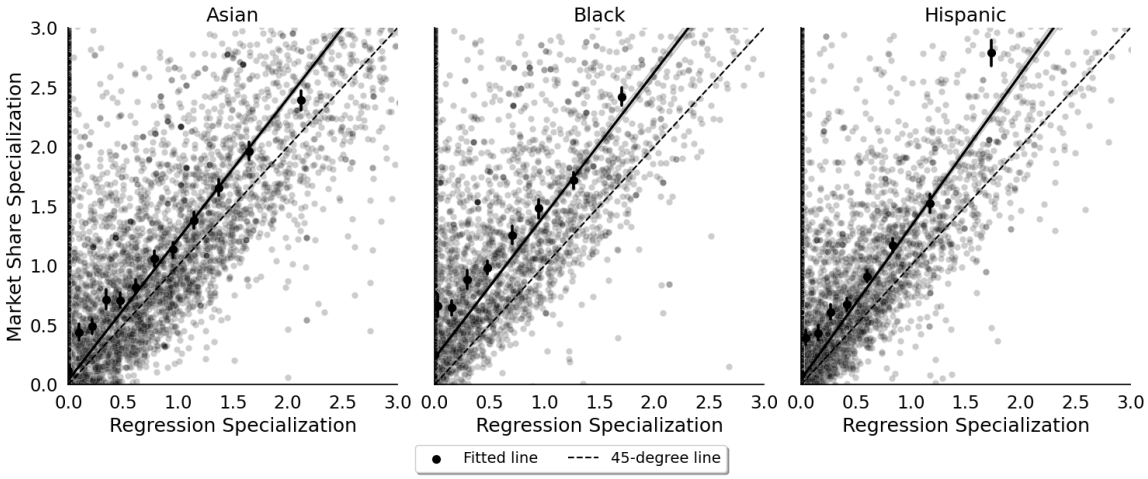
By the definition of a logistic regression, the regression coefficient recovers

$$\begin{aligned}\beta &= \log \frac{P(R|X)}{P(\sim R|X)} - \log \frac{P(R|\sim X)}{P(\sim R|\sim X)} \\ &\approx \log \frac{P(R|X)}{P(\sim R|X)} + \log \frac{P(\sim R)}{P(R)}\end{aligned}$$

where in the last step we use the fact that if lender X is small, $P(R|\sim X) \approx P(R)$.

Figure B.1 tests this relationship in the data by computing the plug-in market share ratio and comparing it against the regression coefficient. The naive market share ratio overstates specialization due to the finite-sample bias of the market share ratio, but otherwise the relationship between the two measures is strong for all races.

Figure B.1: Comparison of regression approach to measuring specialization and raw market share approach



C Additional Tables

Table C.1: Race by race breakdown of the correlation between specialization and fees

Residualized fee shares				
	All	Asian	Black	Hispanic
Specialization score	0.132***	0.073***	0.072**	0.238***
	(0.012)	(0.015)	(0.027)	(0.020)
N	1340624	508529	280821	551274
R2	0.1175	0.1069	0.0894	0.1215
MSA x Race x Year FE	X			
MSA x Year FE		X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.2: Borrower LTV at specialized and mainstream lenders

Race	Mainstream	Specialized	Diff	Pooled Std. Dev.	(Diff)/Pooled Std. Dev.
Asian	80.8	78.2	-2.5	14.3	-0.2
Black	89.5	92.8	3.3	11.3	0.3
Hispanic	86.7	88.5	1.8	13.1	0.1
White	82.2	80.4	-1.8	15.3	-0.1

Notes: The table compares average LTV at specialized and mainstream lenders.

Table C.3: Borrower DTI at specialized and mainstream lenders

Race	Mainstream	Specialized	Diff	Pooled Std. Dev.	(Diff)/Pooled Std. Dev.
Asian	36.3	36.5	0.2	11.6	0.0
Black	38.0	38.7	0.7	11.3	0.1
Hispanic	38.4	38.8	0.5	10.8	0.0
White	34.7	34.7	0.0	11.1	0.0

Notes: The table compares average DTI at specialized and mainstream lenders.

Table C.4: The interaction of specialization and institution type and rate spreads

Residualized rate spreads				
	All	Asian	Black	Hispanic
Specialization x Big bank	-0.061*	-0.005	-0.335***	0.004
	(0.025)	(0.023)	(0.026)	(0.062)
Specialization x Small bank	0.208***	0.209***	-0.020	0.297***
	(0.017)	(0.030)	(0.015)	(0.017)
Specialization x Non-fintech shadow bank	0.039***	-0.002	0.052***	0.158***
	(0.007)	(0.009)	(0.012)	(0.010)
Specialization x Fintech shadow bank	0.032***	0.027	0.105*	0.104***
	(0.010)	(0.017)	(0.044)	(0.016)
N	1625901	527646	294488	573464
R2	0.1763	0.1965	0.1570	0.2082
MSA x Race x Year FE	X			
MSA x Year FE		X	X	X
Institution Type FE	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.5: The interaction of specialization and institution type and fee shares

Residualized fee shares				
	All	Asian	Black	Hispanic
Specialization x Big bank	0.288***	0.142*	0.389**	0.464***
	(0.043)	(0.068)	(0.120)	(0.110)
Specialization x Small bank	0.178***	0.143***	-0.010	0.297***
	(0.018)	(0.025)	(0.046)	(0.029)
Specialization x Non-fintech shadow bank	0.035**	-0.016	0.136***	0.140***
	(0.011)	(0.010)	(0.035)	(0.030)
Specialization x Fintech shadow bank	0.011	0.002	0.074	0.016
	(0.015)	(0.016)	(0.131)	(0.065)
N	1579381	513852	283913	557162
R2	0.1356	0.1378	0.1258	0.1498
MSA x Race x Year FE	X			
MSA x Year FE		X	X	X
Institution Type FE	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.6: Rate spread regression with a categorical definition of specialization

Residualized rate spreads				
	All	Asian	Black	Hispanic
Specialization score greater than 2	0.357***	0.208***	-0.076	0.664***
	(0.037)	(0.050)	(0.053)	(0.054)
Specialization score between 1 and 2	0.033*	-0.078***	-0.112**	0.230***
	(0.013)	(0.014)	(0.037)	(0.022)
Specialization score between 0 and 1	-0.028***	-0.114***	-0.072***	0.045***
	(0.007)	(0.009)	(0.014)	(0.011)
Specialization score less than 0	-0.008	0.042***	-0.054***	-0.065***
	(0.008)	(0.009)	(0.012)	(0.012)
N	1625901	614842	345117	665942
R2	0.1092	0.1049	0.0424	0.1353
MSA x Race x Year FE	X			
MSA x Year FE		X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.7: Fee share regression with a categorical definition of specialization

Residualized fee shares				
	All	Asian	Black	Hispanic
Specialization score greater than 2	0.317***	0.086*	0.154	0.628***
	(0.039)	(0.043)	(0.118)	(0.079)
Specialization score between 1 and 2	0.073**	-0.109***	0.098+	0.257***
	(0.025)	(0.031)	(0.057)	(0.047)
Specialization score between 0 and 1	-0.025	-0.182***	0.003	0.061*
	(0.015)	(0.019)	(0.030)	(0.026)
Specialization score less than 0	-0.005	0.064***	-0.102**	-0.070*
	(0.016)	(0.017)	(0.031)	(0.029)
N	1579381	598972	333229	647180
R2	0.1031	0.1123	0.0879	0.1023
MSA x Race x Year FE	X			
MSA x Year FE		X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.8: Average number of lenders of each institution type per market

Institution Type	Average Count
Large Bank	2.4
Fintech Shadow Bank	2.2
Non-Fintech Shadow Bank	7.7
Small Bank	3.0
Total	15.4

Notes: This table shows the typical size of a market in our sample, broken down by institution type.

Table C.9: Leave-one-out estimates of the effect of specialization on utility, consideration, and rejection rates

	First Stage	Utility	Consideration	Rejection
Leave One Out	0.821***			
	(0.015)			
Asian x Specialized		0.449***	1.190***	-0.010***
		(0.052)	(0.041)	(0.003)
Hispanic x Specialized		0.237***	1.294***	-0.010**
		(0.067)	(0.058)	(0.003)
Black x Specialized		0.523***	1.179***	-0.001
		(0.096)	(0.061)	(0.005)
N	86234	85059	85059	85059
MSA x Tract x Year x Race FE	X	X	X	X
Lender x MSA x Tract x Year FE	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table replaces the lender-level specialization measure which is computed with data from all of the years with a leave-one-out measure in which the specialization in year t is calculated only using applications from other years $neqt$. The leave one out measure is then used as an instrument for the baseline measure. The different columns show how specialization affects utility, consideration, and rejection.

D Comparing Race Versus Other Characteristics

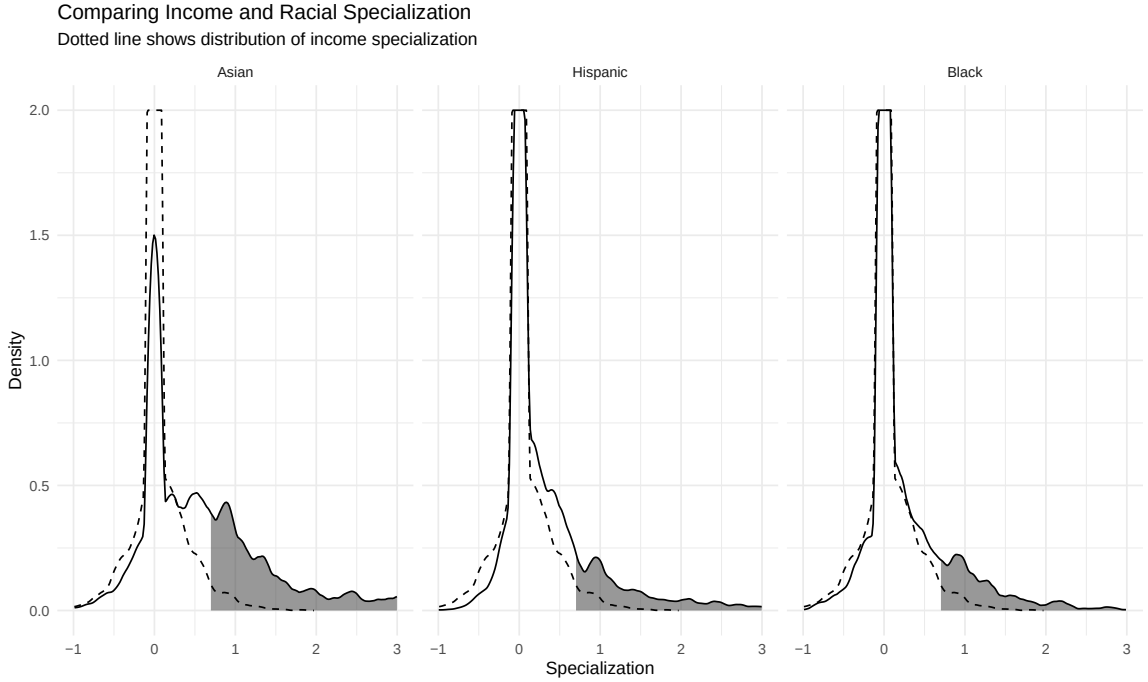
IV.A Income Specialization

We adapt our approach for measuring racial specialization to measure income specialization among lenders and find that almost no lenders specialize in serving high-income borrowers.

To adapt the approach, in each MSA we define the borrowers in the top-10 percent of income as "high-income". We choose 10 percent to match the typical size of a minority borrower group. We then repeat the exercise of the main text of using lender identities to predict whether a borrower is high-income. We can define a lender as income specialized if its LASSO coefficient exceeds $0.7 \approx \log 2$.

By this definition, only 3% of high-income borrowers originate their loan at a lender that specializes in high-income borrowers, whereas around 25% of minority borrowers originate their mortgages at a racially specialized lender. Figure D.1 overlays the mortgage-level distribution of income specialization among high-income borrowers against the distribution of racial specialization among minority borrowers. The tails in the racial specialization distributions are much thicker, illustrating how many more lenders racially specialize rather than specialize by borrower income.

Figure D.1: Comparing the distribution of income specialization with the distribution of racial specialization



IV.B Geography

We measure specialization at the MSA level. One concern is that specialization is driven by the decisions of lenders to lend in some neighborhoods but not others. Under this story, an Asian-specialized lender like Metro City Bank appears specialized only because it lends more in Asian neighborhoods, and the Chase branches in the same neighborhood also attract Asian borrowers at the same frequency.

To rule out this theory, we test if our lender-specialization measure can predict race even within finer geographic measures. However, most of the effect persists even after including tract fixed effects.

Add an index z for the census tract of the loan. We then regress the race of a borrower against the specialization measure with census tract fixed effects:

$$r_{ijmt} = \beta d_{jmt} + \delta_{mz} + \epsilon_{ijmt} \tag{19}$$

Table D.1 shows the results of this regression. For each race, we compare the results with and without census tract fixed effects. Adding census tract fixed effects reduces the coefficient by only around 30 percent across the races. If specialized lenders' advantage arose because they put more branches in minority neighborhoods, we would expect that the racial composition of their borrowers within those minority neighborhoods should match the composition of the borrowers at mainstream lenders within that neighborhood. However, we instead find that even within a census tract, specialized lenders are much more likely to serve minority borrowers.

Table D.1: Within census tract effects of lender specialization

	Asian	Asian	Black	Black	Hispanic	Hispanic
Specialization	0.162***	0.122***	0.135***	0.085***	0.178***	0.134***
	(0.004)	(0.001)	(0.009)	(0.001)	(0.006)	(0.001)
N	7002099	7000840	6948923	6947632	7011425	7010106
R2	0.15	0.26	0.06	0.21	0.15	0.23
MSA FE	X		X		X	
Census Tract FE		X		X		X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

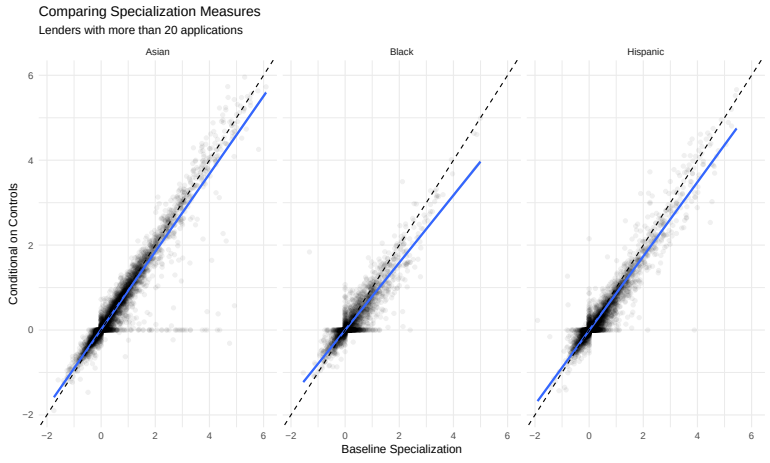
IV.C Other Observables: LTV, Loan Size, Income

Little of the observed specialization reflects specialization on the basis of loan to value, debt to income, or raw income. To study the role of these other observables, we can modify the regression framework in equation 2 to include observables Z_i on the right hand side of the regression. After we include observables, the coefficients on the lender dummies then indicate whether a certain lender's identity predicts race, even conditional on the loan observables. We can then re-run the regression and compare the estimated β_j coefficients with the ones reported in the main text.

We design our approach and comparison to account to prevent mechanical results arising from our L1 regularization scheme. First, when estimating the regressions we do not penalize the coefficients on the observables. This allows us to conservatively assess how much lender identity matters for predicting race. Second, in comparing the two measures, we drop lenders who make fewer than 20 or who are in MSA/race combinations with fewer than 100 total applications. We make these restrictions because the regularization methods we use can shrink coefficients to zero when there are not enough applications.

Figure D.2 compares the two measures of specialization. The average slope from regressing the adjusted measure of specialization against the measure from the main text is around 0.90. Thus the racial specialization we observe is not mainly driven by observable features of the mortgages.

Figure D.2: Comparing specialization conditional on observables versus the specialization measure from the main text



E Risk Adjustment

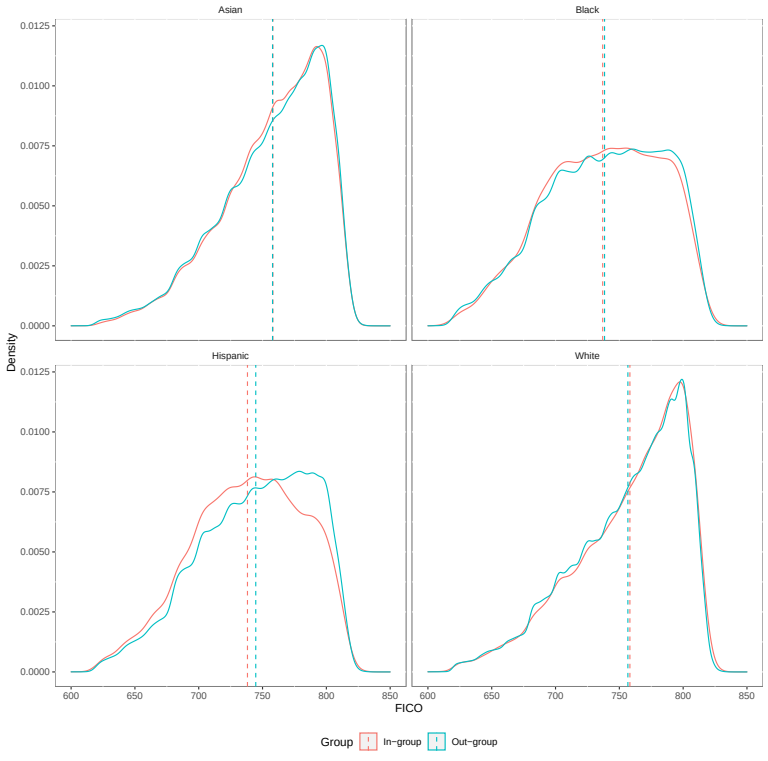
Even with richer controls for ex-ante and ex-post risk, the higher prices at specialized lenders are not explained by differences in borrower risk.

V.A FICO

Throughout the paper, we control for LTV and DTI to construct risk-adjusted prices. In this section, we show that our results on risk-adjusted price differences between specialized and non-specialized lenders are robust to adding credit scores as a control.

To explore the importance of credit scores in explaining cross-lender differences in prices, we first follow Buchak and Jørring (2021) to construct a merged sample of mortgages in both the HMDA data and the GSE mortgage data. As a first pass, Figure E.1 plots the distribution of credit scores at specialized versus non-specialized lenders by race. The credit score distributions, conditional on securitization, are similar across both types of lenders.

Figure E.1: The distribution of credit scores at specialized and non-specialized lenders



As a more formal test, we regress rate spreads on an interaction between specialization and institution type combined with controls for LTV and DTI. We then include

controls for the credit score (which we derive from the GSE data) to see if the differential sorting of borrowers with different credit scores across lenders explains cross-lender differences in prices. In running these regressions, we include the controls non-parametrically with 8 bins of LTV, 4 bins of DTI, and 7 bins of credit scores.

Table E.1 shows the result of this exercise. On the merged HMDA-GSE sample, by focusing on the columns with no FICO controls, we see that the relationship between specialization and prices is more moderate compared to the relationships in Table C.4 in the main text. This is consistent with the GSE sample being skewed towards larger lenders who exhibit a weaker relationship between specialization and high prices. However, when we compare the columns that include credit score controls with the columns that do not, we see that the inclusion of the credit score control has a minimal effect on the specialization coefficient. Credit scores matter for pricing, as evidenced by the much higher R^2 after including them. However, they do not explain differences in pricing between specialized and non-specialized lenders. Moreover, the general pattern that non-bank lenders and small banks have a stronger relationship between specialization and high prices is consistent with the tables from the main text that omit credit scores.

Table E.1: Incorporating credit scores into pricing regressions

	Rate Spread					
	Asian	Asian	Black	Black	Hispanic	Hispanic
Specialization	-0.159***	-0.150***	-0.281***	-0.267***	-0.221**	-0.215**
	(0.019)	(0.017)	(0.036)	(0.033)	(0.071)	(0.066)
Specialization x Fintech Shadow	0.092***	0.090***	0.337***	0.316***	0.276***	0.256***
	(0.020)	(0.018)	(0.050)	(0.043)	(0.075)	(0.069)
Specialization x Non-Fintech Shadow	0.125***	0.120***	0.368***	0.341***	0.393***	0.365***
	(0.020)	(0.018)	(0.038)	(0.034)	(0.072)	(0.067)
Specialization x Small Bank	0.118***	0.109***	0.274***	0.250***	0.247***	0.224***
	(0.023)	(0.021)	(0.038)	(0.034)	(0.073)	(0.067)
N	215802	215802	120695	120695	263976	263976
R2	0.2791	0.4060	0.2203	0.4370	0.2672	0.4338
MSA x Year FE	X	X	X	X	X	X
Institution Type FE	X	X	X	X	X	X
Controls: LTV and DTI	X	X	X	X	X	X
Controls: FICO		X		X		X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

V.B Defaults

Only Black-specialized lenders are more likely to originate loans that become delinquent, but Black-specialized lenders exhibit the weakest relationship between prices and specialization. Thus the strong relationship between specialization and prices for Asian and Hispanic-specialized lenders is unlikely to reflect unobserved default risk.

We study specialization and default by merging the GSE performance data with our HMDA-GSE origination data. We measure default as any period with more than 3 months of delinquency. We then regress default on specialization, with controls for observable measures of risk such as DTI, LTV, and credit scores as well as MSA-year and origination month fixed effects. Thus our regression compares loans with similar observable characteristics that were originated at the same point in time. Table E.2 shows the results. Loans by Asian and Hispanic-specialized lenders to Asian and Hispanic borrowers, respectively, are not statistically significantly more likely to default. In contrast, loans originated by Black-specialized lenders are much more likely to default than loans by mainstream lenders to Black borrowers.

Table E.2: Default and lender specialization

Default Indicator x 100			
	Asian	Black	Hispanic
Specialization	-0.103	0.747**	0.130
	(0.098)	(0.232)	(0.114)
N	186982	102949	225806
R2	0.0449	0.0581	0.0495
MSA x Year FE	X	X	X
Origination Year x Month FE	X	X	X
Controls: LTV, DTI, and FICO	X	X	X
Mean Default Rate (in percentage)	3.29	6.76	4.72

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

If pricing were entirely driven by risk, we would expect that the pricing gap between mainstream and Black-specialized lenders should be the largest, Hispanic-specialized lenders should have an intermediate price difference, and finally Asian-specialized lenders should have the lowest price differential. In contrast, Table 6 shows that Black-specialized lenders actually have the lowest difference, Hispanic-specialized lenders have the highest difference, and Asian-specialized lenders are in the middle.

F Validating Withdrawals as Reflecting Consumer Preferences

Withdrawals appear to reflect consumer preferences rather than shadow rejections. To validate our interpretation of withdrawals as a sign that the consumer has a better offer elsewhere by showing that withdrawals are associated with borrowers that look less risky based on income. We focus on income as the key observable because it is reported even for applications that are abandoned by the applicant, whereas other observables such as LTV or DTI are not. We test the correlation between income and withdrawals versus rejections with logistic regressions of the form

$$y_{ijrmt} = \beta_1 \text{Log Income}_i + \delta_{rmt} + \epsilon_{ij} \tag{20}$$

where y_{ijrmt} is an indicator of whether applicant i at lender j of race r in MSA m in year t withdraws the application or is rejected. We also run regressions with lender by MSA by year fixed effects to exploit comparisons of higher and lower income borrowers within a lender. Table F.1 shows the results of this regression. Withdrawals have higher incomes, whereas rejections have lower incomes. These relationships hold both within and across lenders. This supports the finding in Munnell et al. (1996) that withdrawals in the HMDA data do not appear to be shadow rejections.

Table F.1: Correlations of income with withdrawals and rejections

	Withdrawals		Rejections	
	Across	Within	Across	Within
Log income	0.087***	0.031***	-0.734***	-0.823***
	(0.010)	(0.009)	(0.011)	(0.009)
Log income / loan size	0.062***	0.031***	-0.187***	-0.294***
	(0.010)	(0.009)	(0.017)	(0.017)
N	3118882	3002693	3384962	2972499
Year x MSA x Race FE	X	X	X	X
Year x MSA x Lender FE		X		X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table reports the results of logistic regressions of withdrawal or rejection on income. The regressions exploiting across lender variation drop white borrowers to exploit only variation among minority borrowers. For the withdrawal regression, the base class is if the mortgage was originated. For the rejection regression, the base class is if the application was either withdrawn or resulted in a originated mortgage.

The vast majority of withdrawals (80 %) are cases when the applicant actively withdraws the application, whereas the remaining cases are evenly split between cases when the loan is approved, but not accepted and when the application is closed for incomplete information. By comparing Tables F.1 and F.2, we see that the negative relationship between income and rejections is not evident for any category of withdrawals.

Table F.2: Correlations of income with specific withdrawal categories

	Withdrawn by Applicant	Approved not Accepted	Incomplete Data
Log income	0.058***	-0.109***	-0.024
	(0.008)	(0.014)	(0.015)
Log income / loan size	0.001	0.195***	0.034*
	(0.009)	(0.017)	(0.017)
DV Mean	0.18	0.02	0.03
N	2901649	1941253	1747864
Year x MSA x Race FE	X	X	X
Year x MSA x Lender FE	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The table reports the results of logistic regressions of different types of withdrawal on income. In each regression, the base class is if the mortgage was originated.

The lack of withdrawals at specialized lenders also does not reflect lower application rates by borrowers who have a preference for specialized lenders. One concern is that minorities who borrower from specialized lenders are less financially sophisticated and are therefore less likely to apply to multiple lenders. This mechanically would result in these applicants withdrawing fewer applications even if these specialized lenders provide worse services. We test this hypothesis by exploiting the fact that minority borrowers who live in tracts with large minority populations are more likely to originate loans at specialized lenders. If the preference for specialized lenders is correlated with lower application rates, then we should expect to see fewer withdrawals in these tracts. However, Table F.3 shows that minority tracts have higher aggregate withdrawal rates. Thus the lower withdrawal rates seen at specialized lenders is strong evidence that specialized lenders provide high utility for minority borrowers because the borrowers who value specialized lenders are more likely to apply to multiple lenders.

Table F.3: Cross-tract correlations of withdrawal rates and minority population shares

	Withdrawal Rate		
	Asian	Black	Hispanic
Race share	0.03*	0.11***	0.04***
	(0.01)	(0.01)	(0.01)
N	164684	139679	189216
Adj. R2	0.08	0.04	0.03
Within R2	0.00	0.01	0.00
MSA x Year FE	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: We regress the ratio of withdrawals to originations against minority population shares across tracts. For all minority groups, tracts with a larger minority population have higher aggregate withdrawal rates, suggesting they apply to more lenders.

G LLPA Price Instrument

Lenders pay the guarantee fees (g-fee) on loans sold to the government-sponsored entities (GSE). The g-fees cover the GSE's cost of ensuring timely payment of principal and interest to investors, even in case of borrower defaults. The g-fees are risk-based fees, calculated according to the loan-level pricing adjustment (LLPA) matrix published by the GSEs. In 2023, the GSEs implemented a new LLPA matrix. As Figure G.1 illustrates, relative to the pre-2023 level, the g-fee increases for less risky borrowers with a higher credit score and a lower LTV while decreasing for riskier borrowers with a lower credit score or a higher LTV. At the individual level, these fee changes could have been quite large, on the order of basis points to more than one percentage point.

Figure G.1: Change of G-Fees

FICO \ LTV	30	60	70	75	80	85	90	95	100
780	0	0	-0.25	-0.25	-0.125	0.125	0	0	-0.625
760	0	0	-0.25	0	0.125	0.375	0.25	0.25	-0.5
740	0	0	-0.125	0.125	0.375	0.75	0.5	0.375	-0.25
720	0	0	0	0.25	0.5	0.75	0.5	0.375	-0.25
700	0	0	-0.125	-0.125	0.125	0.5	0.25	0.125	-0.625
680	0	0	0.125	-0.125	0	0.375	0.25	0.125	-0.375
660	0	0	-0.25	-0.875	-0.875	-0.625	-0.5	-0.625	-1
640	-0.5	-0.5	-0.125	-1.25	-0.75	-0.75	-0.75	-0.875	-1.25
620	-0.5	-0.5	0	-0.875	-0.25	-0.375	-0.625	-1	-1.75
600	-0.5	-0.5	0	-0.875	-0.25	-0.375	-0.625	-1	-2

We exploit this rule change to construct a Bartik instrument for mortgage prices. We find an individual lender's exposure to the rule change in a given MSA by interacting a lender's reliance on GSE-securitization with the average g-fee increase in an MSA given its borrower composition. In particular, the Bartik shock at lender-MSA level is defined as follows

$$\Delta gfee_{i,m} = sold_i^{1819} \times \underbrace{\left(\sum_c (gfee_{c,post} - gfee_{c,pre}) \times s_{c,m}^{1819}\right)}_{\Delta gfee_m} \tag{21}$$

$sold_i^{1819}$ is the average share of lender i's conventional conforming loans sold to the GSE during 2018-2019. $gfee_{c,post}$ and $gfee_{c,pre}$ are the g-fee charged on loans with LTV-borrower FICO bucket c before and after the rule change, respectively. $s_{c,m}^{1819}$ is the proportion of mortgage loans in MSA m falling into LTV-borrower FICO bucket c during

2018-2019. The second component, denoted by $\Delta gfee_m$, captures the change in the cost of lending in MSA m caused by the rule change. Intuitively, the borrower composition in an MSA determines the change in the cost of securizing mortgages provided to local borrowers after the LLPA shock, and the cost of origination for a lender is higher if it has a higher reliance on securitization ($sold_i^{1819}$).

Let $gfee_{i,m,t}^{1819} = sold_i^{1819} \times \left(\left(\sum_c gfee_{c,t} \times s_{c,m}^{1819}\right)\right.$ denote our cost shifter for lender i in MSA m in year t. We then estimate the following 2SLS using 2022-2023 HMDA data:

$$\begin{aligned}(1) Price_{i,m,t} &= \beta_1 gfee_{i,m,t}^{1819} + \mu_{i,m} + \nu_{i,t} + \eta_{m,t} + \epsilon_{i,m,t} \\ (2) log(s_{i,m,t}) &= \beta_2 \overline{Price}_{i,m,t} + \kappa_{i,m} + \phi_{i,t} + \zeta_{m,t} + \xi_{i,m,t}\end{aligned} \tag{22}$$

$s_{i,m,t}$ is lender i's market share in MSA m in year t, which is defined as a lender's 30-year fixed rate conventional conforming loan origination volume divided by MSA total volume.

To construct the estimation sample, we restrict to lender-MSA that has at least 0.1% market share in both 2022 and 2023. We exclude lenders originating too many refinance loans or too non-conventional loans, such as FHA. In particular, we find a lender's shares of home purchase loans and conventional loans out of its total origination in 2018-2019, respectively, and exclude lenders with home-purchase shares below 1st percentile and conventional loan share below 5th percentile among all lenders in the final analysis sample. In addition, we exclude MSAs with too little total loan origination volume in our 2022-2023 sample, about 5% MSAs.

Table G.1 presents the results. Columns 1 and 2 are the OLS results. Column 3 is the first stage. Columns 4 is the second stage. Column 5 is the reduced-form IV. The IV estimates suggest a semi-elasticity of -2.1, which is larger in magnitude than our model's baseline measure of -1.1 for White borrowers. However, the standard errors are large, and thus should be interpreted as generally supporting the model's estimate that consumers are sensitive to interest rates when choosing between lenders.

Table G.1: Bartik Instrument Using LLPA Change

	OLS		2SLS		
	log(s)	log(s)	Price	log(s)	log(s)
Price	-0.162***	-0.034*		-1.430*	
	(0.02)	(0.02)		(0.77)	
IV			1.465***		-2.095**
			(0.54)		(0.98)
MSA-Year FE	Yes	Yes	Yes	Yes	Yes
Lender-Year FE	Yes	Yes	Yes	Yes	Yes
Lender-MSA FE	No	Yes	Yes	Yes	Yes
Adjusted R2	0.300	0.852	0.627	-0.553	0.852
Observations	55650	42712	42712	42712	42712

H Estimation Details

We recover lender-level parameters for each combination of race, MSA, and year by matching MSA-level and cross-tract moments for each lender. Since all calculations are done within a market, we suppress race, MSA, and year subscripts in the following discussion.

Within each "synthetic tract" z, we can calculate the total number of originations $M_z = \sum_{j=0}^{L} O_{jz}$ where O_{jz} is the number of originations by lender j in tract z. For each lender j, we can construct the empirical tract-level origination share as

$$\hat{s}_{jz} = \frac{O_{jz}}{M_z} \tag{23}$$

We also construct the empirical withdrawal and rejection shares for lender j as

$$\hat{w}_{jz} = \frac{W_{jz}}{M_z} \tag{24}$$

$$\hat{r}_{jz} = \frac{R_{jz}}{M_z} \tag{25}$$

where W_j, R_j are the number of withdrawals and rejections at lender j.

Each synthetic tract is ranked according to the population share of the racial group. Order the tracts in the order of increasing population share $z = 1, \ldots, G$, and we can define the normalized tract rank $g_z = \frac{z - \frac{G+1}{2}}{G-1}$ as a linear transformation of these ranks so that $g_1 = -0.5$ and $g_G = 0.5$.

Each lender has a racial specialization of d_j, where $d_j = 1$ if the lender is specialized for the racial group and $d_j = 0$ otherwise.

Our model requires us to recover L mean utilities δ, L consideration probabilities ϕ, L rejection probabilities χ, one share θ of consumers who apply to multiple lenders, 4 slopes β of how average utility, consideration, rejection rates, and per-capita application counts vary across tracts, and 3 slopes γ of how utility, consideration, and rejection differ across specialized and mainstream lenders across tracts.

To recover the $3L + 1$ mean utilities, consideration, rejection, and the share of applicants who apply to multiple lenders, we match MSA-level origination, withdrawal, and

rejection probabilities for each lender

$$\begin{aligned}
\frac{1}{\sum_z M_z}\sum_z M_z \times \left(\hat{s}_{jz} - s_{jz}\left(\theta\right)\right) &= 0 \qquad && j = 1, \ldots, L \\
\frac{1}{\sum_z M_z}\sum_z M_z \times \left(\hat{w}_{jz} - w_{jz}\left(\theta\right)\right) &= 0 \qquad && j = \underline{0}, 1, \ldots, L \\
\frac{1}{\sum_z M_z}\sum_z M_z \times \left(\hat{r}_{jz} - r_{jz}\left(\theta\right)\right) &= 0 \qquad && j = 1, \ldots, L
\end{aligned}$$

To recover the 4 slopes across tracts, we target the covariance of the prediction errors across tracts by setting the following moments to zero

$$\begin{aligned}
\frac{1}{\sum_z M_z}\sum_z M_z \times g_z \times \sum_{j>1}\left(\hat{s}_{jz} - s_{jz}\left(\theta\right)\right) &= 0 \\
\frac{1}{\sum_z M_z}\sum_z M_z \times g_z \times \sum_{j>1}\left(\hat{w}_{jz} - w_{jz}\left(\theta\right)\right) &= 0 \\
\frac{1}{\sum_z M_z}\sum_z M_z \times g_z \times \sum_{j>1}\left(\hat{r}_{jz} - r_{jz}\left(\theta\right)\right) &= 0 \\
\frac{1}{\sum_z M_z}\sum_z M_z \times g_z \times \left(\hat{w}_{0z} - w_{0z}\left(\theta\right)\right) &= 0
\end{aligned}$$

Last, to recover the last 3 parameters on how mainstream and specialized lenders offer different utility, consideration, or rejection rates across tracts with different racial composition, we target the joint covariance of tract demographics, lender specialization, and the shares.

$$\begin{aligned}
\frac{1}{\sum_z M_z}\sum_z M_z \times g_z \times \sum_{j>1} d_j \times \left(\hat{s}_{jz} - s_{jz}\left(\theta\right)\right) &= 0 \\
\frac{1}{\sum_z M_z}\sum_z M_z \times g_z \times \sum_{j>1} d_j \times \left(\hat{w}_{jz} - w_{jz}\left(\theta\right)\right) &= 0 \\
\frac{1}{\sum_z M_z}\sum_z M_z \times g_z \times \sum_{j>1} d_j \times \left(\hat{r}_{jz} - r_{jz}\left(\theta\right)\right) &= 0
\end{aligned}$$

In practice, we modify the approach in a small way to reduce computational burdens. In principle, calculating a market share s_j requires iterating over 2^L potential choice sets. Since NSMO data suggest most borrowers only consider a small number of lenders, we re-normalize our probability measure over choice sets to only consider choice sets

with $k \leq 4$ options. This reduces an exponential number of choice sets to a polynomial number. Thus we replace the $P(C)$ with $\tilde{P}_k(C)$, where

$$\tilde{P}_k(C) = \begin{cases} 0 & |C| > k \\ \frac{P(C)}{\sum_{S,|S|\leq k} P(S)} & |C| \leq k \end{cases} \tag{26}$$

Given that the typical choice set features one inside lender, this approximation is quite accurate.