Color and Credit: Race, Regulation, and the Quality of Financial Services*

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Abstract

The incidence of mis-selling, fraud, and poor customer service by retail banks is significantly higher in markets with lower income and educational attainment. Further, areas with a higher share of minority population experience significantly worse outcomes even after controlling for factors such as income, education, and house price changes. Regulations aimed at improving access to credit to such areas are partly responsible for these findings. Specifically, low-to-moderate-income (LMI) areas targeted by the Community Reinvestment Act have significantly worse outcomes, and this effect is larger for LMI areas with a high-minority population share. The results highlight an unintended adverse consequence of such *quantity*-focused regulations on the *quality* of credit to poor and minority customers.

Keywords: discrimination, product quality, financial sophistication, consumer protection, regulation

JEL Classification: G21, G28, L13, L14

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1 Introduction

Policymakers have been concerned about the unequal and unfair treatment of minority and poor customers by large financial institutions for many decades. Facets of differential treatment include excessive denial of credit, poor customer service, outright fraud, and mis-selling of financial products to name a few. Motivated by these concerns, policy-makers have enacted several consumer protection regulations to address discrimination and, in particular, promote equal access to credit for those living in poor and minority neighborhoods.[1] The Department of Justice (DoJ) often enforces provisions of these legislations to protect minority consumers against discriminatory lending practices.[2] More generally, allegations of large-scale fraud in the mortgage market during the 2000s and anecdotal evidence of fraudulent banking practices by Wells Fargo during the early 2010s have made consumer protection concerns even more salient in recent years (e.g., Griffin and Maturana, 2016; Gurun, Matvos, and Seru, 2016).

A number of papers such as the famous Boston-Fed study on loan denials to minorities by Munnell, Tootell, Browne, and McEneaney (1996) have looked at either the quantity or pricing of financial services provided to minority and poor customers. However, little is known about another key dimension of unequal and unfair treatment, namely, the *quality* of financial products and services received by these consumers. Our paper takes a first step in this direction by examining the incidence of fraud, mis-selling, and poor customer service – our measure of *quality* – in the consumer credit market. Piskorski, Seru, and Witkin (2015) and Griffin and Maturana (2016) document compelling evidence of fraud and mis-selling by

[1]Some prominent examples include the Fair Housing Act, the Equal Credit Opportunity Act, and the Community Reinvestment Act.

[2]The DoJ website provides a number of examples of exploitation in the mortgage market that we focus on in this paper. Based on their recent case, DoJ states that "On January 20, 2017, the court entered a consent order in United States v. JPMorgan Chase Bank (S.D.N.Y.). The complaint, which was filed on January 18, 2017 by the United States Attorney's Office, alleged that the defendant violated the Fair Housing Act and the Equal Credit Opportunity Act when African American and Hispanic borrowers paid higher rates and fees for wholesale mortgage loans than similarly situated white borrowers. The consent order provides monetary relief of $53 million, including a civil penalty of $55,000." `https://www.justice.gov/crt/recent-accomplishments-housing-and-civil-enforcement-section`

banks to their investors in the securitization markets. Our work, on the other hand, focuses on banks' customers in the retail markets who directly bear the costs of aggressive behavior.

We obtain a measure of the quality of financial services from a newly-available dataset from the Consumer Financial Protection Bureau (CFPB). In 2010, the Dodd-Frank Act established the CFPB as a watchdog of the financial services industry. Dissatisfied customers can send their complaints against financial institutions to the CFPB using the bureau's online system, email, postal mail, fax, phone, or through a referral from other agencies. By the very nature of this process, these are not typically minor complaints that are easily resolved between the customer and the financial institution. Rather, they range from a customer's allegation of serious failing in customer service to claims of egregious exploitative behavior by the financial institution. The incidence of consumer complaints against financial institutions for mortgage-related products in the CFPB dataset is our measure of the quality of financial services.[3] For many consumers, acquiring and choosing a home mortgage product involves difficult choices between various complex products. These transactions leave many potential borrowers at a substantial information disadvantage compared to sophisticated financial institutions (Campbell, 2006). Prominent examples of the nature of complaints include allegations of hidden or excessive fees, unilateral changes in contract terms after the purchase, aggressive debt collection tactics, and unsatisfactory resolution of mortgage servicing issues. Our data are from 2012-2016 and include about 170,000 mortgage-related complaints from 16,309 unique zip codes. All of our key empirical exercises are based on geographical variations across zip codes.

We find that there are substantially more complaints in zip codes with lower average income, lower educational attainment, and higher minority shares of the population. While each of these characteristics is associated with more complaints in multivariate regressions,

[3] The database also has complaints about other financial products (e.g., checking accounts and student loans). We focus on mortgage products because this is the category with most complaints in the dataset, and this is the product category that is economically large, involving many millions of homeowners and many trillions of dollars. Moreover, a home mortgage is often the single largest financial transaction for many households.

the effect of high-minority status is two-to-three times larger than the effect of low income or low education. We include fixed effects at the three-digit zip code levels in these regressions, indicating that our results are unlikely to be driven by differences in local economic conditions or other region-specific variation. Thus, the minority effect that we document cannot be simply explained away by differences in the areas income, educational attainment, or broad economic conditions. A one-standard-deviation increase in the minority share of the population leads to a 16% increase in complaints; the corresponding effects for area income and education are 2% and 6%, respectively. We also show that the relationship between the minority share of population and complaints is not only increasing, but it is also convex with the strongest effects in areas with greater than 80% minority population.

We conduct a number of additional tests to establish the statistical and economic importance of our results. Since all of our main tests control for *three-digit zip code* fixed effects, our results cannot be explained by differences in economic conditions at this level. One still may be concerned about differences in economic conditions at the five-digit zip code level within a three-digit zip code, particularly potential differences in house price appreciation. The concern is that consumers complain more when they experience a decline in their home value and are more likely to be underwater on their loan. If minority zip codes had disproportionately larger price declines and the complaints are driven only by these price drops, then our results could be spurious. We directly address this concern by also including in the regression model (a) the zip-code-level house price changes in the past five years and (b) the zip-code-level foreclosure rate during the sample period. Zip codes with larger declines in house prices and higher foreclosure rates do indeed have more complaints, but these factors appear to be orthogonal to our main effect as the relationship between minority population share and complaints do not change in any meaningful ways with the inclusion of these variables.

Another concern with our analysis may be geographical heterogeneity in the costs and benefits of complaining within the three-digit zip code. If consumers in high-minority zip codes have a relatively lower cost of complaining or perceive a higher marginal benefit of complaining, higher complaint frequency will occur irrespective of banks' behavior. Note that these differences in net benefits would have to go beyond what can be explained by differences in local income and educational attainment. To separate out the baseline "complainer" effect from our analysis, we include in the regression model the number of complaints in a given zip code to a different government agency: the Federal Communications Commissions (FCC). Our results remain similar. To further address the "complainer" effect, in a robustness analysis we limit our attention to only those complaints that were resolved with the bank providing relief to the customer (e.g., refund of fees or penalties): such complaints are unlikely to be frivolous or without any merit. Our results remain robust. We also show that our results are not driven by some specific types of mortgage products such as fixed-rate or adjustable-rate mortgages. Lastly, if a complaint is filed against a specialized mortgage servicer, the source of the discontent could be driven by the behavior of either the originating bank or the servicer. To make sure unscrupulous servicers are not driving the results, we drop companies whose primary business is loan servicing (e.g., Ocwen) from the tests and again find that the results are virtually unaffected.

What could be driving the robust relationship between minority-share of population and complaints about poor-quality products and services? In a frictionless world characterized by fully informed consumers and no distortions in the supply of banking services, there should be no systematic differences in the incidence of fraud, mis-selling, and poor customer service across areas based on racial composition. However, retail financial markets are filled with information frictions: consumers are often at a significant information disadvantage compared to large banks, they often face large search costs, and there is limited scope for learning from past experiences since mortgage decisions are relatively infrequent. Lower income and educational attainment are related to more complaints, and this is consistent with such frictions. Why, however, should minority consumers face still worse outcomes even after controlling for these influences?

There are two possible channels that can explain our results. The first one is purely a credit-demand side (i.e., consumer-driven) explanation: minority customers are more likely to complain due to unobserved reasons beyond those directly examined in the analysis, and thus our findings have nothing to do with credit-supply-side (i.e., lender-driven) forces. Said differently, lenders are providing similar quality to all communities, but minority customers end up complaining more about fraud, mis-selling and poor service because of baseline heterogeneity that is unobserved by the econometrician.

The other possible channel is related to the supply side of these services.[4] Specifically, it may be that lenders behave differently when they deal with poor or minority customers such as putting in less effort in explaining the costs and benefits of various products or even actively engaging in predatory lending aimed at these communities. For example, on May 15, 2017, the city of Philadelphia sued Wells Fargo for violations of the Fair Housing Act, alleging that since 2004 its employees were encouraged to push African-American and Hispanic borrowers toward riskier loans despite having credit scores that would warrant better loans for the borrowers.[5] Such behavior is consistent with findings in Gurun et al. (2016), who show that mortgage lenders were actively targeting minority consumers with misleading advertising to originate more high-priced mortgages. In congressional testimony, Ginny Hamilton of the Fair Housing Center of Greater Boston also provides some compelling anecdotal evidence in support of unequal treatment of minority consumers by banks (U.S. House of Representatives, 2007). Her organization performed "mystery shopper" tests in the mortgage market during 2005-2006 in Boston. They found that minority borrowers were treated systematically worse than white borrowers, even though the minority mortgage shoppers, by the design of the

[4] Some anecdotal evidence of the supply side driver of this behavior can be found in the recent allegations of aggressive sales tactics by the Wells Fargo Bank in which at least 2 to 3.5 million allegedly unauthorized accounts were opened from 2002-2017.

[5] City of Philadelphia v Wells Fargo & Co et al., U.S. District Court, Eastern District of Pennsylvania, No. 17-02203. Baltimore, Los Angeles, Memphis, Miami, and Oakland have filed similar lawsuits, though their ability to do so was legally in question. On May 1, 2017, the Supreme Court ruled that the city of Miami can sue Bank of America and Wells Fargo for "discriminatory conduct that led to a disproportionate number of foreclosures and vacancies in majority-minority neighborhoods, which diminished the city's property-tax revenue and increased the demand for police, fire, and other municipal services."

experiment, had better credit profiles. To further investigate the presence of a supply-side effect, we exploit an institutional feature of this market that allows us to examine differences in *quality* when there is regulatory pressure to increase the *quantity* of credit.

In light of concerns about discrimination in lending markets, a number of regulations have been enacted in the U.S. over the years to provide better access to credit to poor and minority consumers. These regulations make it illegal for lenders to discriminate against historically disadvantaged groups. Prominent examples of these regulations include the Fair Housing Act (FHA) of 1968, Equal Credit Opportunity Act (ECOA) of 1974, Home Mortgage Disclosure Act (HMDA) of 1975, and the Community Reinvestment Act (CRA) of 1977. The main focus of many of these laws is on ensuring access to credit products at fair lending rates. That is, these regulations focus on the *quantity* and *price* of credit. Subsequent empirical studies examining the impact of these regulations on consumers focus exclusively on these important and more-easily measured metrics and whether they are equal for poor and minority customers and neighborhoods (see Ladd, 1998, for a literature review). The potential effects of such regulations on product *quality* are ambiguous. Regulations may improve the quality of financial services received by poor and minority borrowers if lenders are concerned about close monitoring of quality by regulators. Alternatively, regulations that focus too much on ensuring the quantity of credit can provide incentives to dilute quality. In a multi-tasking framework, Holmstrom and Milgrom (1991) underscore the importance of a dilution in the quality of output when agents are rewarded for the quantity of output. In our setting, quantity-based goals may unintentionally encourage banks to, for example, engage in aggressive sales tactics or make loans to uninformed borrowers without proper disclosure as they seek to satisfy their regulatory quantity requirements.

We focus on CRA regulations because of an attractive empirical feature that allows us to identify the effect of regulation-driven supply-side shock on quality. The CRA designates certain census tracts as "underserved" if the median income of the area is less than 80% of the median income of the Metropolitan Statistical Area (MSA) to which it belongs. We refer these areas as *CRA target areas*. Banks that fail to lend enough to these target areas face repercussions including denial of M&A deals and branch opening applications, potential sanctions, and reputational harm. By the design of the regulation, these consequences provide pressure for lenders to increase lending to customers in these areas beyond what they normally would have. In terms of empirical design, the designation of an area as a CRA target area has the attractive feature that it depends on the area's *relative* income within an MSA, and not on its *absolute* level of income. Regional variation in MSA income provides several areas that are similar in terms many key characteristics including absolute income, but they have different CRA designation. We compare the number of complaints about fraud, mis-selling, and poor service across the CRA target areas (treatment group) and their observationally similar non-target areas (control group) and find substantially more complaints in target areas. Specifically, the CRA target areas have 32% more complaints relative to the control areas. Thus, holding fixed many demographic characteristics of the zip codes along with the recent change in home prices, CRA-targeted areas have relatively poorer quality. We interpret this finding as an unintended consequence of quantity-based regulation.[6]

We further develop the matched-sample test discussed above to tease out the supply-side channel behind our main result linking minority zip codes to quality by examining the difference in complaints across CRA target and control groups separately for below- and above-median minority share areas. The difference in complaints between target and control areas comes predominantly from zip codes with above-median minority population. Within neighborhoods with a below-median minority share of the population, complaints rate are higher by 5-10% (depending on the matching criteria) for the CRA target areas as compared to observationally similar control areas. This difference increases to 40-50% within neighborhoods with above-median minority population. The difference in these two differences is economically large and statistically significant. This differential effect suggests

[6]Our quantity-based interpretation is consistent with the findings of Agarwal, Benmelech, Bergman, and Seru (2012) who show that banks that are facing increased pressure to conform to CRA standards increase their lending volume by a considerable amount, as compared to similar banks that do not face such pressure.

that the unintended consequences of the regulation are particularly severe for minority areas. These results are hard to explain by a demand-side (i.e., customer driven) difference across neighborhoods since the target and control areas have very similar demographic characteristics such as income, education, population, and mortgage volume as well as recent house-price changes. Banks face pressure to increase the quantity of lending in every target area, but in high-minority areas, they effectively have two "boxes to check" for regulatory compliance – lending to poor and lending to minority customers. Our results remain similar for a wide range of matching techniques and criteria.

Our paper provides important inputs to policy debates on equality in the lending market and connects to several strands of literature including the consequences of bank regulation, the economics of household finance, and the role of consumer sophistication on financial outcomes. Our work relates to the often controversial literature on equality of consumer treatment in mortgage markets. This literature has traditionally focused on racial disparities in access to credit (e.g., Munnell et al., 1996; Ross and Yinger, 2002) and the cost of borrowing (e.g., Haughwout, Mayer, and Tracy, 2009; Bayer, Ferreira, and Ross, forthcoming). Another stream of work has focused on "predatory" behavior (Gurun et al., 2016; Di Maggio, Kermani, and Korgaonkar, 2016) and fraud (Griffin and Maturana, 2016; Mian and Sufi, 2017) in mortgage origination, but no work to our knowledge has examined the quality of financial products and services as reflected by consumers' experience. Our paper also contributes to the debate surrounding the effectiveness or unintended consequences of the Community Reinvestment Act (e.g., Bhutta, 2011; Agarwal et al., 2012) by providing evidence that CRA-targeted areas experienced a higher incidence of fraud, mis-selling, and general dissatisfaction with their mortgage products and services. At a broader level, our work suggests that regulators should consider, in addition to quantity and price, the effect of regulation on the quality of financial services received by underserved customers, particularly those in areas with a higher share of minority populations.

2 Theoretical Motivation and Research Design

The underlying theoretical motivation behind our work is rooted in three streams of literature: (a) informational frictions between borrowers and lenders, (b) the economics of discrimination, and (c) unintended consequences of quantity-based incentives. Lack of complete information about financial products is a key friction in consumer financial markets. In recent years there has been a lot of interest in developing theoretical models that focus on economic drivers of information obfuscation (see, e.g., Gabaix and Laibson, 2006; Carlin and Manso, 2011). These papers show that financial institutions can take advantage of uninformed customers in a variety of ways such as offering confusing products, selling bundled services, or by improper disclosure. Our first set of tests, relating the extent of complaints to levels of income and education, is designed to uncover the importance of these frictions in credit markets. We expect relatively poor and less educated neighborhoods to be financially less sophisticated and thus more likely to experience a higher incidence of fraud, mis-selling, and poor service.

The second strand of literature that we connect to goes back to the seminal works on the economics of discrimination by Becker (1957), Phelps (1972) and Arrow (1973). There can be at least two potential reasons behind providing poor-quality treatment to minorities, over and above the effects that can be attributed to differences in observed income and education. The first one is a result of "taste-based" bias against minorities (Becker, 1957), and the other a result of "statistical" discrimination (Phelps, 1972; Arrow, 1973). Taste-based discrimination arises from racial prejudice even at the expense of profits. For example, a loan officer may not provide adequate information to minority borrowers or may not assist them in navigating through a costly search for correct mortgage products, regardless of profit motivations. Similarly, a loan officer may not expend enough time and resources in resolving genuine difficulties faced by minority borrowers after the loan has been made, even if it is not consistent with the bank's profit-maximizing behavior. As a result, minority consumers may end up with poor-quality treatment as compared to other consumers. Statistical discrimination, on the other hand, is motivated by profit concerns. For example, suppose a loan officer uses race as a proxy for unobservable (or simply costly to observe) borrower characteristics such as the profitability of future income from the client. If she thinks that minority customers are less likely to provide higher profits to the bank in the long run, she may be tempted to sell predatory or otherwise unsuitable lending products in the short run to maximize what can be extracted from the present transaction. Whether the motivation is taste-based or profit-based, both are harmful to minority consumers and, because they are driven by differences in race, illegal. We do not tease out the relative importance of these two particular channels in the paper; our goal is to establish clear empirical evidence of differential, worse results for minority communities.

Finally, our paper is related to the multi-tasking model of Holmstrom and Milgrom (1991). Policymakers have enacted a number of regulations over the years to ensure equal treatment of minority borrowers in the lending market. These regulations almost always end up focusing on the quantity dimension by encouraging banks to lend more to minority borrowers. We view this feature of the market in the context of classical multi-tasking models such as Holmstrom and Milgrom (1991). Specifically, the model predicts that when an agent is rewarded predominantly on quantity of products, quality might suffer. In our setting, quantity-based goals may end up encouraging banks to engage in strategies such as aggressive sales tactics or improper disclosure to minority borrowers. In other words, the quality of service received by minority borrowers may be worse when banks are evaluated based on quality of lending.

We begin our examination by relating various demographic characteristics to complaints using standard linear regression techniques. After establishing a strong relationship between poor, lowly-educated, and minority borrowers and their quality of financial services, we focus our analysis on teasing out the effect of supply-side forces in shaping these outcomes. We do so by analyzing the effect of a regulation-induced shock to increase the supply of credit to poor and minority communities.

2.1 Regulation-induced shock to lending incentives

The Community Reinvestment Act (CRA) was passed in 1977 with the goal of eliminating discrimination against lending activities in low- and moderate-income (LMI) areas to ensure that institutions meet the credit needs of the entire community. While there have been several adjustments to the details of the policy since the initial passage of the law, the primary focus on meeting the credit needs of "under-served" communities has remained unchanged. Regulators periodically evaluate lenders' performance in serving these areas and use these evaluations in approval decisions regarding lenders' applications for branch opening, mergers and acquisition activities, or entering new lines of business. These factors, along with the potential reputational harm, provide strong incentives for the lender to perform well on CRA exams. Thus, the designation of an area as LMI serves as a shock to lenders' incentives to increase the supply of lending to these "underserved" areas.

LMI status is determined at the census-tract level by a simple rule. Tracts with a median family income less than 80% of the MSA-level median income are designated as LMI. Thus the LMI designation is based on the *relative* income of an area, relative to the MSA in which it resides. We exploit variation in median MSA income across the country to compare outcomes for areas that are similar on observable characteristics including income, but differ in regulatory designation and thus the pressure for lenders to supply credit to the area. As an example, consider two MSAs in Texas in 2010: Dallas-Plano-Irving ("Dallas") and San Antonio-New Braunfels ("San Antonio"). The Dallas MSA median income is $68,900, which means tracts with median family income below $55,120 are designated LMI. In San Antonio, the MSA median income is $57,800, so tracts with median family income below $46,240 are LMI. As shown in Figure 1, the shaded area represents an absolute income range where neighborhoods in Dallas are designated as LMI, while neighborhoods with identical income in San Antonio are not LMI designated. Most simply, our empirical design assumes that shaded areas in Dallas and San Antonio (those with income between $46,240 and $55,120) are similar on unobserved demand-side dimensions such as their marginal propensity to complain. Under this assumption, we attribute differences in complaints across the two areas to the CRA regulatory designation that motivates banks to increase credit supply.

LMI designation is at the census-tract level. Since our data and analyses are at the zip code level, we first define zip codes as LMI if the majority of its population resides in LMI census tracts. We also call these *CRA-target*, *LMI*, or *treatment* zip codes, which are receiving the CRA-induced incentive shock. Using propensity score matching, we find a set of control zip codes that are very similar to the treatment groups in terms of not only income, but also population, outstanding mortgages, education, and house price change in recent past. We conduct a series of matched sample analyses that differ in terms of the precise matching criteria used, for example, matching based on continuous values of these variables versus matching based on coarse bins. For expositional simplicity, we defer their detailed discussions to when we present the results. After estimating the propensity score, we use a kernel-based weighting matching technique to construct a set of control zip codes for each treatment zip code in the sample. We estimate the average treatment effect on the treated (ATET) zip codes based on the difference in outcome variables across these two areas. The key identifying assumption behind this approach is that conditional on a host of demographic variables such as income, education, house price change, population, and volume of outstanding mortgages, CRA designation is close to randomly assigned. Thus, the supply-side incentives to lend is orthogonal to any omitted variables of concern that comes from demand side (i.e., consumer-driven) such as unobserved borrower characteristics across different areas.

Note that our treatment and control groups, by construction, are relatively poor areas of the country. Thus, the difference in outcomes between treatment and control group provides us with the effect of the quantity-focused regulation on quality in poor areas. We extend this analysis further by conditioning our analysis on the racial composition of the LMI areas. Specifically, we break all zip codes into two groups: below- and above-median minority areas. Within each subset, we separately estimate the ATET of the regulation. This analysis allows us to examine whether there is heterogeneity in the effect of supply shock for areas with low- versus high-minority composition. Thus, the test allows us to tease out the effect of supply-side forces on the quality of services received by high-minority areas as compared to low-minority areas.

3 Data and Sample

The Consumer Financial Protection Bureau (CFPB) was created as an independent consumer watchdog agency under the umbrella of the Dodd-Frank Act in 2010. The Bureau officially began its operations in 2011 with a mandate to "protect consumers from unfair, deceptive, or abusive practices and take action against companies that break the law." The CFPB has instituted a system for consumer complaints where consumers can lodge their grievances against financial institutions using a simple online system on the CFPB website.[7] The CFPB then forwards these complaints to the respective institutions for explanation or resolution of the complaints. It is reasonable to expect that these complaints are not minor irritants that can get easily resolved at the branch level. By reaching out to a government agency for assistance, consumers often come for help for serious issues involving the quality of products and services they receive. Appendix A provides an example complaint for illustration.

Individuals first choose the financial product or service about which there is a problem (e.g., mortgage, payday loan, bank account). The individual provides more details about the product and about the events that led them to file a complaint and their desired resolution.

[7] There are a variety of ways that individuals can reach out to the CFPB for help including web, email, fax, and postal mail, but the primary means is through a website interface.

They also list the company with which they have a problem along with account information or additional relevant documentation. Finally, the individual provides personal contact information (including their zip code) to ensure that they can be contacted regarding the company's response and resolution.

The database began in July 2011 with the coverage of credit card complaints first and mortgage-related complaints later in December 2011. It has since been expanded to cover other products such as payday loans, checking accounts and student loans. Our sample covers complaints made in 2012-2016. During this period, there are over 680,000 complaints in the database, with over 210,000 complaints about mortgages. We focus on mortgage-related complaints for a couple of reasons. First, it is economically less meaningful to compare quality across different products such as mortgages and credit card. Second, mortgage-related misconduct in the financial market has captured the center stage of many policy decisions and academic papers in recent years. Third, we need a reasonable "scaling" variable to compare the incidence of complaints across zip codes. Ideally, we want to evaluate the number of complaints regarding a product category while controlling for the number of transactions/interactions between banks and consumers in that category in the given area. It is difficult to find such a variable for transactions such as credit card complaints. We can, however, find such an appropriate variable for mortgages: number of tax filers with mortgage interest reported in their IRS tax filings in the zip code. Lastly, a home mortgage is one of the most significant financial products in the U.S. economy, involving trillions of dollars in outstanding loans and many millions of consumers across the country. The mortgage is often the single most significant and complex transaction that many households ever engage with.

The remainder of data comes from multiple sources. Demographics data are from the 2010 Census files. Data on average income at the zip code-level and the number of tax filers with mortgage interest in the zip code come from the 2012 IRS SOI database. Data on education is from the Census Bureau's American Community Survey 2012 5-year estimates. We measure education as the share of the adult population in the zip code with at least a bachelor's degree. Data on five-digit zip code median house price changes are from the Federal Housing Finance Agency. This data source covers the majority of zip codes in the sample. For those that have missing data, we impute a value based on the county where the majority of the housing units reside. Data on zip code level foreclosure rate are from Zillow.

Our final sample covers all mortgage-related complaints from 2012-2016 for which we have matched demographic data: about 170,000 complaints across 16,309 zip codes.[8] Table 1 provides summary statistics. Each observation represents a five-digit zip code in the sample. After winsorization at 1% tails, the mean (median) zip code has 10.33 (5.00) complaints from 1,973 (1,190) underlying mortgages. We have large cross-sectional variation in complaints, ranging from a minimum of one to a maximum of seventy-one complaints in a zip code with an interquartile range from two to thirteen. To remove the effect of skewness from the dependent variable, in our regressions we use a log transformation of this variable. However, our results remain similar with the number of raw complaints as a dependent variable as well.

Complaints come from various types of mortgage products ranging from conventional fixed-rate mortgages (FRM) to more complex hybrid products. About 29% of complaints are about FRM, 11% conventional ARM, 9% FHA, with the remaining portion from home equity loans or lines of credit, VA loans, reverse mortgages, second mortgages or other mortgages.

Complaints also vary in terms of their timing: some complaints arise because of problems encountered at the time of origination, whereas others stem from problems that occur at a later date. About 13% of complaints are related to problems at the origination of the loan. These include complaints surrounding the application process, credit decision, loan origination and the loan signing/closing. The majority, about 85%, of complaints arise after the origination involving problems in the course of loan servicing such escrow maintenance,

[8]Since 2015, complaints in the database are allowed to have a narrative included along with the basic complaint information. Appendix A provides an example complaint for illustration. When a narrative is included (about 30% of the time for 2015-2016 when the option is available), the five-digit zip code is replaced with a three-digit zip code to provide an extra layer of anonymity for the consumer. From the total of 212,669 mortgage-related complaints, 182,175 complaints remain that have the five-digit zip code identified. After matching to demographic data and winsorizing the zip-code-level complaint counts at the 1% level, 168,539 complaints form the basis of our analysis.

payment disputes, and foreclosure decisions. We are unable to classify the timing of about 2% of complaints because of incomplete information.

Finally, we consider the resolution of the complaint. The data categories for resolution are somewhat ambiguous for the purposes of our study. About 5% are closed explicitly *without* relief, so these are the complaints that are more likely to be about issues that are the fault of the borrower or are more frivolous in nature. About 10% are closed explicitly *with* relief and are thus the complaints that are likely to be about more egregious behavior (e.g., fraud) on the part of the financial institution. About 82% are coded by the CFPB as "closed with explanation" and are likely to be in between the two prior categories in severity. This category likely contains, among others, issues we have in mind about traditional mis-selling, where the borrower feels they have been led to a product that is unsuitable for them or different from what was promised to them. The remaining are coded by the CFPB as "closed" and have no further indication of the nature of the complaint closure.

On the measures of consumer demographics, the average zip code has a non-white population of 21%, again with a large cross-sectional variation. Median household income is about $51,000, and the median zip code has about 22% of its population with at least a graduate degree. These figures are representative of broad U.S. population. In terms of house price growth, we compute the five-year house price change in the given zip code starting in 2007 and ending in 2012, i.e., starting before the great recession and ending just before our complaints sample. The median zip code experienced a -15.5% change in house prices during this window.[9] We use this measures to control for the effect of losses in home value on the propensity to complain. We use different estimation windows to ensure that our results are not sensitive to the inclusion or exclusion of large drop in home value during the great recession.

[9]In untabulated tests, we also consider another measure based on a five-year change between 2010 and 2015, where the median zip code experienced a gain of 3.5%. We obtain similar results.

4 Results

4.1 Variation in quality across demographics

We estimate the following regression model to examine the relationship between demographic characteristics and the quality of financial services to consumers:

$$lnComplaints_{zip5} = \rho(IER_{zip5}) + \sum_{b=2}^{50} \left(Mort_{b,zip5} + Pop_{b,zip5}\right) + \zeta_{zip3} + \nu_{zip5} \tag{1}$$

The dependent variable is the log of the number of complaints in the five-digit zip code (zip5). IER_{zip5} is our demographic variable that takes a value based on income (I), educational attainment (E), or racial composition (R) of the neighborhood. All continuous variables are winsorized at 1% to minimize the effects of outliers and are standardized by subtracting their respective means from the raw variable and then dividing them by their standard deviations. Thus, all reported estimates represent the effect of one standard deviation (s.d.) change in explanatory variables on (approximately) the percentage change in the number of complaints. Hence, we can directly compare the coefficients across regression specifications to assess the economic magnitude of various explanatory variables. We compute clustered standard errors at the level of three-digit zip codes.

Since zip codes vary considerably in terms of their population and mortgage activities, we need to account for these differences across zip codes in our analysis. We do so in an extremely flexible way as follows. We categorize all zip codes into one of fifty buckets based on their relative rank in terms of the number of outstanding mortgages and population. Based on these ranks we create two vectors of fifty indicator variables $Mort_b$ and Pop_b with an element equal to one for the respective mortgage quantity and population buckets where the zip code resides. We include these flexible controls in all of the regression estimates, and this allows us to separate out the baseline effects of mortgage volume and population on complaint frequency. The choice of fifty is admittedly arbitrary, and our results remain similar if we use other sensible techniques to separate out these effects such as using ten or 100 buckets or a flexible polynomial approach.

We also include fixed effects for three-digit zip codes (ζ_{zip3}) to remove the effects of local macroeconomic conditions and state regulations from affecting our results. Thus, our model captures variation in outcomes across five-digit zip codes within a given three-digit zip code. Our 16,309 five-digit zip codes fall under 876 three-digit zip codes, providing us with enough variation within the three-digit zip codes to identify the effect of variation in demographic conditions after soaking away differences in economic and regulatory considerations.

Table 2 presents the estimates of the regression in equation (1). In column (1) we only include zip3 fixed effects in the model as explanatory variables and find R^2 of 47% for the model. Column (2) that also includes fixed effects for the fifty mortgage buckets shows a dramatic increase in model fit, with R^2 increasing to 80%. Column (3) - (5) present our main results. One standard deviation decrease in income is associated with about 10% more complaints, whereas the corresponding effect for lower education is comparable at 8%. The effect of non-white population, on the other hand, is considerably higher at about 17%.[10] Needless to say, these demographic variables are correlated. Column (6) separates out the relative importance of each of these three variables by including them all in the model. While all three variables remain statistically significant (though income is only marginally significant), the non-white population of the zip code clearly dominates income and education in terms of economic magnitudes. The effect of the *NonWhite* variable is almost three times as large as that of education, and eight times as large as that of income.

To further examine the difference in complaints along the minority dimension, we estimate

[10] More precisely, the coefficient of 0.17 indicates an increase in complaints of $e^{0.17} - 1 = 19\%$.

the following regression:

$$lnComplaints_{zip5} = \sum_{r=2}^{5} \psi_r NWgroup_{r,zip5} + \sum_{b=2}^{50} \left(Mort_{b,zip5} + Pop_{b,zip5} + Inc_{b,zip5} + CollEd_{b,zip5} \right) + \zeta_{zip3} + \nu_{zip5} \quad (2)$$

NWgroup represent indicator variables for minority population share in the zip code: 20-40%, 40-60%, 60-80%, and 80-100%. Zip codes with 0-20% form the omitted base category in the regression and $\psi_2 \ldots \psi_5$ represent the increase in the frequency of complaints for their respective groups. $Mort_b$, Pop_b, Inc_b, and $CollEd_b$ respectively represent vectors of fifty indicator variables with an element equal to one for the respective number of mortgages outstanding, population, income, and education where the zip code resides. Figure 2 presents these results graphically, all of which are statistically different from zero and each other. These estimates reinforce the earlier results and demonstrate that the results are even stronger in areas with highest minority concentrations, with areas above 80% of minority population having nearly double the complaints compared to those with below 20% minority population.

4.2 Alternative channels

We now provide evidence that our key results relating minority consumers to the number of complaints is not driven by baseline differences in the propensity to complain, house price declines, or the behavior of mortgage servicers. To ease comparisons across these tests, we restrict the sample to observations with complete information on all of these additional variables (9,234 zip codes).

4.2.1 Propensity to complain

An alternative explanation of our results linking high-minority neighborhoods to complaints could be that high-minority areas contain residents that are simply more likely to complain regardless of how they are treated or what products they are sold. If such variation is regional or related to relative income or education, then the baseline model already soaks away this heterogeneity with three-digit zip code fixed effects and direct controls for income and educational attainment. To further address this potential confounder, we use the number of complaints made by consumers to a different government agency that is unrelated to the mortgage business. We obtain the number of complaints filed with the Federal Communication Commission (FCC) by consumers about issues involving telecommunications billing and services. We use the log of FCC complaints ($lnFCC$) for each zip code in 2015-2016 (when the data became available) as a proxy for potential baseline differences in propensity to complain. Because telecom-related complaints are unrelated to mortgage transactions, FCC complaints provide a reasonable control for a baseline "complainer effect" in the area.

Table 3 presents the results, with column (1) reproducing our base case results for comparison on the sample of zip codes that have complete information for this regression. Column (2) presents the specification including $lnFCC$. We do find a positive and significant coefficient on FCC complaints variable, which suggests there are some common factors that explain complaints arising from different aspects of consumers' lives. However, this factor seems orthogonal to the main effect of the relationship between the minority share of the population and complaints.

4.2.2 House price decline

Another potential concern is whether the results could be driven by differences in house price changes across high-minority and low-minority areas within the three-digit zip code. If high-minority zip codes experienced disproportionately large price drop in the aftermath of the subprime mortgage crisis, and if the propensity to complain correlates with a loss in home value, then our results could be explained away by this factor. Recall, our three-digit zip code fixed effects will capture a great deal of variation from such regional shocks, so this mechanism must be working within three-digit zip codes. To test whether this is driving our results, we compute the price change over the past five years leading up to 2012 (*HPgrowth*) for every five-digit zip code in our sample from the Federal Housing Finance Agency for which we can gather such data. We include this house-price change as an additional variable in our regressions. For the few zip codes with no data at that level, we impute those observations with the house-price change of their respective county. Column (3) of Table 3 presents the results. While areas with higher price drop do have more complaints, the coefficient estimate on the minority variable is virtually unchanged.

Similarly, we investigate if our results could be explained away by differences in actual foreclosure rate. If borrowers are foreclosed upon with higher frequency in a zip code, it is likely there could be more complaints to the CFPB. Foreclosure decisions are often an outcome of the bargaining process between the borrower and the lender. To the extent that a higher foreclosure rate is driven by discriminatory differences in forbearance across areas, this variable may contain variation driven by the channel we have been emphasizing in the paper. We compute the foreclosure rate at the five-digit zip code level using data from Zillow and control for this variable in column (4) of Table 3. Areas with higher foreclosure rate do have more complaints, but again this effect does not explain away our key finding. Column (5) includes FCC complaints, house price drop and foreclosure rates together in the model and shows that our results remain intact.

4.2.3 Mortgage Servicing

Our complaints database also includes the identity of the company against which the complaint is filed. Because mortgage servicing rights may be sold to mortgage-servicing specialists, there may be a concern that our results are simply driven by unscrupulous servicers. Complaints to the CFPB about servicers could itself be a result of predatory lending by originating banks in the first place. Still, to make sure these firms are not driving all our results, we manually examine each institution with at least 200 complaints in the CFPB database and identify companies whose primary business is loan servicing (e.g., Ocwen). We exclude complaints made against specialized servicers and estimate the model with remaining data. As shown in column (6) of Table 3, our results are similar.

4.3 The role of regulation

We now present our results using the CRA's low- or moderate-income (LMI) designation (or *CRA-target area*) as a shock to prioritize lending to poor and minority communities as discussed in section 2. We compare outcomes across LMI ("treatment") zip codes to similar non-LMI ("control") zip codes to tease out the effect of supply shock on quality. Figure 3 plots separately the income distribution of LMI and non-LMI zip codes across the country. By the very definition of this regulatory criteria, the treatment zip codes are concentrated in the left tail of income distribution. Thus, simply comparing outcomes across these two areas is not particularly meaningful. Since the LMI designation relies on an area's relative income within the MSA, there are many zip codes with similar absolute income as the areas in LMI group that do not carry the LMI regulatory designation. This overlap provides us with a meaningful set of treatment and control groups that are similar in many dimensions, but differ in the supply-side pressure on lenders to serve the area.

There are 3,049 LMI (treatment) zip codes in the sample spread all over the country including all 50 states and the District of Columbia. The vast geographical dispersion of treatment zip codes across the country makes our empirical design even more powerful: it ensures that our results are not driven by effects that are unique to a particular locale. To ensure that our treatment and control zip codes lie on the common support of income distribution, we truncate the sample at the 1st percentile of the non-LMI income distribution and the 99th percentile of the LMI distribution.[11] The remaining sample includes 1,987

[11] The results are not sensitive to using these particular criteria and are robust to examining the full, unrestricted sample. This restriction simply ensures the comparisons are most sensible and particularly avoids

treatment zip codes and 11,726 control zip codes which have average household incomes in the range of \$33,173 to \$112,484.

To find suitable control observations with which we can construct counterfactuals for each target area, we estimate the propensity score for LMI designation using a probit model, with the number of mortgages, population, income, education, and house price changes as key predictors. To provide greater flexibility to our matching, we include the continuous value of these variables, indicator variables for each decile of the respective dimension, and state of the zip code in our matching exercise.[12] Regarding matching methodology, our base estimator uses kernel-weighted propensity score matching to construct the counterfactual for target areas. For the kernel weighting, we use a gaussian kernel with a bandwidth of 0.03.[13] Figure 4 shows the comparability of treatment and control observations before and after matching. The plot shows the standardized bias for each of the five matching variables, which is calculated as the difference in means across the treated and control group divided by the standard deviation of the respective variable. The matching procedure drastically reduces the bias for each covariate. While there is not a well-developed literature on formally assessing standardized bias, each covariate falls well below the 20% threshold that Rosenbaum and Rubin (1985) call "large" and comfortably within the bounds of the balancing tests (e.g., post-match covariate variance ratio) proposed in Rubin (2001).

Main matching results

Table 4 presents the base result in column (1). The treated zip codes have about 32% ($e^{0.28} - 1$) more complaints than control zip codes. Thus, the regulation-induced supply shock results in a substantially higher number of complaints about fraud, mis-selling, and poor customer service in the LMI, CRA-treated areas.

potential concerns about the sparseness of control observations in the lower tail of the income distribution.

[12]In untabulated results, we find that requiring matches be in the same state, rather than using "state" as a predictor variable in propensity score, yields similar results.

[13]Robustness tests presented later show that the results are not driven by these specific modeling choices.

Our matching criteria ensures comparability along a number of most important dimensions that can be correlated with unobserved factors related to complaints. One may still be concerned about differences in the cost of living across treatment and control zip codes since the matches, by construction, are located at different points in the MSA income distribution. For an extreme example consider San Francisco and Los Angeles MSAs in California. An area with a median family income of $75,000 in San Francisco falls at the 25th percentile of income distribution in that MSA. Hence this area carries an LMI CRA-target area designation. In contrast, an area with the same level of income in Los Angeles falls at the 65th percentile of the MSA's distribution, and hence it does not fall under the LMI CRA-target category. Suppose our matching exercise picks up the Los Angeles area as the control for the treated area in San Francisco. One may be concerned that cost-of-living differences are so high across the two areas that they do not constitute a good match.

To address this issue, we divide the sample into MSA-level income buckets that are $10,000 wide and require control zip codes to come from the same bucket as the treatment zip codes. We then repeat the analysis requiring matches to be in the same $5,000 bucket. Such requirements further ensure that we do not compare areas in high cost-of-living MSA (e.g., San Francisco in the example) to places that have relatively lower cost-of-living (Los Angeles). Columns (2) and (3) in Table 4 present the results, and the results are similar to the baseline test. We perform similar analysis by directly stratifying the sample by absolute income. This matching effectively places more weight in the matching on income (and thus less on other dimensions). Columns (4)-(5) present the results, which show slightly smaller point estimates, but still economically and statistically significant effects. These results paint a clear and consistent picture that perturbation on the supply side of credit leads to a substantial dilution in the average quality of financial services provided by the lenders. Thus, regulations aimed at increasing the quantity of lending to poor borrowers seem to have an adverse impact on the quality dimension.

Regulation and Race

We now examine heterogeneity in the effect of regulation based on the minority share of the population, which allows us to separately consider the effect of supply shock on the quality of financial services received by high-minority area consumers. We break this analysis into two parts. In the first part, we investigate whether our results relating race to quality and then regulation to quality are coming from the same zip codes. Said differently, if the distinction between LMI and non-LMI groups is effectively divided along high-minority/low-minority lines, then the effects of race and regulation may be confounded. To isolate the effect of regulation beyond any effects of local minority population share, we extend our matching criteria to include the racial composition of the area as an additional covariate in the propensity score matching. Specifically, we include both the percentage of minority population and the rank decile of zip codes on this dimension as additional covariates in matching procedure. Thus, the new set of treatment and control groups are similar along several demographic dimensions such as income, education, and minority population. We present this result in column (2) of Table 5. Compared to the base case estimate of 0.28, the difference between treatment and control areas drops to 0.18 when we additionally match on racial composition. Thus, even after controlling for racial composition, areas with credit supply shock have about 20% ($e^{0.18} - 1$) more complaints than observationally similar control areas. Both these sources of variation – race and regulation – have independent explanatory power in explaining differences in quality across zip codes.

In the second part of the analysis, we explore the interactive effects: does the supply shock disproportionately hurt the minority consumers? We do so by estimating the matched sample test separately for areas with relatively large and small minority population. We break all zip codes into two groups based on whether they have below- or above-median share of minority population (median minority population is 12.1% for the matching sample). Following the base matching technique, we now find a set of control areas for each treated area within the same minority-population bucket. Said differently, target areas in above-median (below-median) minority population are matched with comparable control areas in above-median (below-median) minority population only. Table 5 presents the results in columns (3)-(4). A stark pattern emerges: in low-minority population areas, treatment areas have 9% more complaints than the control areas, whereas the corresponding difference is about four-times larger at 42% ($e^{0.35} - 1$) for the high minority areas. The difference-in-difference of 33% across low and high-minority population areas is significant at 1%. The results are even more stark when requiring matches within $10,000 MSA income strata as shown in columns (5)-(6). In this specification, above-median minority areas experience a 49% ($e^{0.42} - 1$) increase in complaints for LMI CRA-target areas as compared to non-LMI areas, while the regulation effect is not statistically different from zero for below-median minority areas. In sum, the regulation-induced shock to the supply side of lending has a disproportionately large detrimental impact on the quality of service received by areas with a higher minority share of the population. Overall, these results provide strong evidence on the role of shocks to the supply-side of credit in affecting the quality of services received by minority consumers.

Placebo Tests and Alternative Matching Strategies

Our results so far exploit the institutional feature that areas below 80% of the median MSA-income are classified as target areas for CRA lending. We conduct two sets of placebo tests by varying the cut-off points in artificial ways to show that it is CRA's actual LMI cut-off point of 80% that drives our results. Specifically, we examine the complaints frequency around 70% and 90% thresholds.

For the 70% threshold analysis, we consider all zip codes that are below 80% cutoff and assume that all zip codes below the 70% cutoff are in the CRA-target areas, whereas those above this threshold are not. Thus, we are artificially considering some of the zip codes that lie between 70% and 80% of the MSA median area as non-treated zip codes. In reality, all these zip codes are below the actual threshold of 80%, and hence they are all treated by the CRA. For the placebo test at 90% threshold, we symmetrically only consider zip codes that are above 80% of the MSA-level median income. Thus, in this test, we artificially consider zip codes between the 80%-90% of MSA income area as treated zip codes, whereas those above 90% are considered non-treated. Thus, each of the placebo tests allows us to examine nearby cutoffs (varying the income threshold) while making sure that we do not compare across the actual treatment-control threshold.

Using matching technique describe earlier, we present the results of placebo tests in Table 6. A stark pattern emerges from this analysis. There is some difference, though much smaller and nearly always statistically insignificant, in the quality of financial services across the placebo treatment and control group thresholds. This supports the notion that income is a driver of the quality of financial services. But there is a sharp discontinuity in this effect at the 80% threshold compared to the artificial thresholds at 70% and 90%. For example, when we match treatment and control zip codes in the most stringent specification, requiring MSA median income to be within the same $5,000 MSA income bucket, the difference in number of complaints across the treatment and control groups in placebo tests is 0.01 and statistically insignificant. In contrast, the corresponding difference at the actual threshold of 80% is 0.22 (p-value<0.01). Overall, these tests alleviate a number of concerns: (i) our results are unlikely to be driven by pure income differences across treatment and control areas; (ii) our results are unlikely to be driven by any unobserved difference in the characteristics of the two zip codes as long as they do not discontinuously jump at the threshold of 80%; and (iii) our results are unlikely to be driven by any correlation between cost-of-living differences (i.e., differences in relative income) across areas that differ slightly in relative income.

Our main tests use kernel-weighted propensity matching. The kernel-weighting allows us to efficiently use more data to construct our matched counterfactual in places where there are many possible matches. We also present several alternative estimates in Table 7 using different matching strategies to show that our results do not hinge on a particular matching scheme. Columns (1)-(2) vary the kernel bandwidth from 0.01 to 0.05 and show similar estimates to the base estimate using a bandwidth of 0.03. Columns (3)-(4) use nearest neighbor propensity score matching using one and three nearest neighbors, respectively. The results are similar. Finally, we dispense with propensity score matching and use Mahalanobis distance nearest neighbor matching.[14] Columns (5) and (6) present the results, with Column (6) using the additional constraint that the matched zip code must be in the same $5,000 income strata. Again, our results indicate an economically significant increase in complaints for CRA-target zip codes as compared to their observationally similar counterparts in areas that lack the extra regulatory pressure to lend.

In other unreported robustness tests omitted for brevity, we pick control zip codes by also matching on the number of FCC complaints or foreclosures, in addition to all the matching criteria used in the base case (i.e., number of mortgages, population, income, education, and house price changes). This additional matching criterion further ensures that the two groups are similar in their baseline propensity to complain and instances of housing distress. Our results remain similar for these matching criteria as well.

5 Cross-sectional Variation in Complaints Type

We have made no distinction in the nature of complaints filed by borrowers in our tests so far. Complaints vary along a number of meaningful dimensions such as the type of mortgage products (e.g., fixed rate versus adjustable rate) involved in the complaint, their timing (e.g., at the time of credit decision or later), or final resolution of complaints (e.g., resolved with compensation versus not). We now exploit these variations to shed further light on the relationship between minority population and quality of services they receive.

[14]For this matching technique, we match on mortgages, population, income, education and home price changes, but do not match on the deciles of these variables to keep the dimensions of matching manageable.

5.1 Variation in the timing of complaints

As discussed earlier, there are a variety of laws such as Fair Housing Act (FHA), Equal Credit Opportunity Act (ECOA) and Community Reinvestment Act (CRA) that try to protect the interests of minorities by making it illegal to treat them differently.[15] These laws focus on the quantity of lending, and often they evaluate a bank's performance based on discrimination at origination. That is, they expose lenders to particularly acute legal liability for discriminatory behavior in the quantity of lending during the credit decision and origination process. Thus we expect banks to be relatively less discriminatory on the quality dimension at the time of loan origination, when regulatory scrutiny is higher, as compared to post-origination issues. As a concrete example, we expect higher quality dilution towards minorities on issues involving loan servicing than issues involving falsification of loan applications. In addition, it is relatively easier to establish a claim of dilution in the quality of service at the time of credit origination than at a later stage. In the spirit of Holmstrom and Milgrom (1991), banks have stronger incentives to not discriminate on more-easily measurable dimension than on the difficult-to-measure dimension of quality. It is reasonable to assume that post-origination issues are harder to measure compared to at-issuance origination, and hence we expect stronger quality dimension on post-origination matters.

Motivated by these arguments, we break complaints into two groups depending on whether they are related to issues at the time of origination or at a later stage. If the complaint takes place at the time of loan application, underwriting decision, or signing and closing of the documents, then we classify it as an at-origination complaint; if the complaint is about loan modification, collection, foreclosure, escrow accounts, or other servicing issues, we classify it as a post-origination complaint. Finally, we are unable to classify some loans in either of these two categories due to insufficient information: we club such complaints under the "other" category. 12.6% of all complaints fall under at-origination category, 85.16% under

[15] These laws also prohibit discrimination based on religion, national origin, sex, marital status, the presence of children, age, or because an applicant receives income from a public assistance program.

post-origination, and the remaining 2.21% under other.

We now estimate our regression model separately across at- and post-origination categories of complaints. Breaking complaints into at- or post-origination issues results in many zip codes with no complaints at all, so we estimate the regressions using standardized number of complaints (mean zero, unit standard deviation) rather than the log of complaints. Table 8 presents the results. Columns (1) and (2) show the baseline results with *log(Complaints)* and then the standardized number of complaints, respectively, as the dependent variables. Column (3) presents the estimate relating income, education, and race to the number of complaints at origination, while column (4) presents results based on complaints post origination. One standard deviation increase in minority population is associated with an increase of 0.11 standard deviation in at-origination complaints, whereas the corresponding magnitude is 0.20 for post-origination complaints. These results support the notion that quality is especially lower for activities that are harder to measure. Overall this finding provides further support to the quantity-quality trade-off in line with Holmstrom and Milgrom (1991).

5.2 Variation Across Mortgage Products

Are our results driven by a specific type of mortgage product? About 29% of mortgage complaints are related to conventional fixed-rate mortgages, whereas the remaining complaints come from products such as adjustable-rate mortgages, home equity line of credit, FHA loans, and other complex hybrid products. One potential concern with our analysis could be that minorities are more likely to get certain mortgage products, and such products have higher complaints rate for reasons related to product complexity. To directly address this concern we estimate our model for each mortgage product category separately. We estimate these regressions using standardized number of complaints rather than the log of complaints to ensure we do not leave out zip codes that have zero complaints in a given product category. Table 9 presents the results, with column (1) presenting the estimate using all complaints for reference. The results indicate that the effects are fairly similar across all product categories: it is the minority proportion of the population that drives our result, not the specific product type.

5.3 Variation in Resolution of Complaints

Are our results driven by frivolous complaints made by minority borrowers? If minority borrowers are more likely to make such complaints, then this introduces a concern that is similar to the complainer effect channel we discussed earlier in the paper. One additional way in which we address this concern is by examining the resolution of the complaints. As discussed in Section 3, about 10% of complaints are closed explicitly *with* relief and so are most likely from the most egregious behavior (e.g., fraud) on the part of the financial institution. About 82% are coded by the CFPB as "closed with explanation". These complaints may be of lesser severity, but they likely include issues that are typical of mis-selling such as rate adjustments that were higher than promised at origination or other ways in which the borrower feels misled. Only about 5% are closed explicitly *without* relief. Table 10 presents the baseline specification estimated with the dependent variable as the standardized total number of complaints (column 1), complaints with no relief (column 2), complaints closed with explanation (column 3), and complaints with relief (column 4). Our results remain similar across different compliant resolution types and lend support to the claim that our results are not driven by an abundance of frivolous complaints from high-minority areas.

6 Robustness Tests

In addition to the additional tests in Tables 3 and 7, we now consider some further robustness tests.

Community action groups:

Some community groups are active in educating their members about their consumer rights and legal protections available to them against large corporations. If these groups are especially active in minority areas (and not so much in other areas), then part of our results could be driven by the activism of these groups. To address this concern, we conduct an additional test that is based on the idea that such complaints are typically bunched together in time in response to the campaign by the activist group. We limit the number of complaints in a zip code to one complaint per month to ensures that we do not pick up droves of complaints clustered together in time at a specific location and re-estimate our base regression. Our results are similar with a point estimate on *Nonwhite* of 0.14 (p-value$<$0.01) compared to our baseline estimate of 0.16 (p-value$<$0.01).

Price and quantity effects:

Are minority borrowers complaining simply because of high-priced loans they may have received or because of higher denial rates? To better address this issue, we estimate our model with a control for the share of high-priced loans and the denial rate in mortgage market in the given zip code. We obtain these measures from the HMDA database and use them as control variables in the base regression model. Our results are robust to the inclusion of these variables with the coefficients ranging from 0.12-0.16 (p-value$<$0.01) depending on the particular specification used for the estimation. Thus, the quality dimension we focus on in this paper is not merely an artifact of quantity or price effects.

Geographical variation:

We also estimate our model separately across different geographical areas of the country to assess whether our results are pervasive or driven by just a couple of areas. We do so by estimating our results separately for different 1-digit zip codes. This estimation gives us separate coefficients for 10 different parts of country. Figure 5 presents the results graphically. The coefficient is positive for every region and remains economically and statistically significant in nine of ten broad areas of the country.

7 Discussion & Conclusions

Since the very beginning of modern finance, there have been concerns about the exploitation of low-income and minority consumers by large, sophisticated banks. Market failures such as banks' market power, high search costs, and asymmetric information problems make consumer finance an area that is particularly vulnerable to such behavior. Using mortgage-related consumer complaint data relating to fraud, mis-selling, and poor service from the Consumer Financial Protection Bureau, we show that areas with low income, low educational attainment, and high shares of minority consumers receive a substantially lower quality of financial services. Most striking, the relationship between high-minority concentration and complaints is exceptionally strong even after controlling for income, education, and other potentially confounding factors such as house price changes. These effects can be quite harmful to these consumers, especially to the extent that these experiences of poor treatment from the financial sector result in general mistrust, withdrawal, or exclusion from the formal financing sector.

Because of concerns about unequal access to credit for low-income and minority areas, regulations such as the Community Reinvestment Act provide strong incentives to lenders to serve areas that are defined as low-to-moderate-income relative to the median MSA income. Such regulation may, at the margin, provide a higher *quantity* of credit to borrowers in these areas, but we show that the average *quality* of products and services are substantially lower in these areas. Further, the dilution in quality is disproportionately larger for high-minority areas. While we cannot make a general statement about the overall welfare consequences of such regulations, our results show that consumers in low-income and minority areas experience worse outcomes along the quality dimension.

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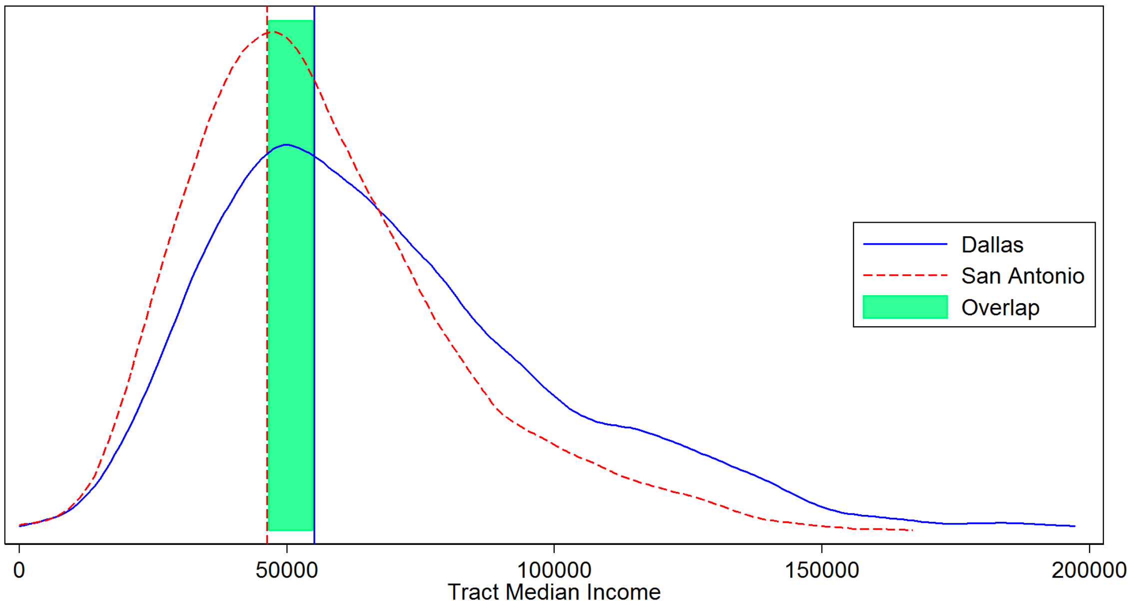

Figure 1: Example Geographical Variation in Low- to Moderate-Income Designation This figure presents a kernel densities of 2010 census tract incomes for the Dallas-Plano-Irving ("Dallas") and San Antonio-New Braunfels ("San Antonio") metropolitan statistical areas (MSA) in Texas. The vertical lines at \$55,120 and \$46,240 represent 80% of the respective median MSA incomes for Dallas and San Antonio. The shaded "Overlap" region between those two lines indicate the income range where, despite identical median family income (e.g., \$50,000), Dallas tracts are designated low- to moderate-income (LMI), but San Antonio tracts are not.

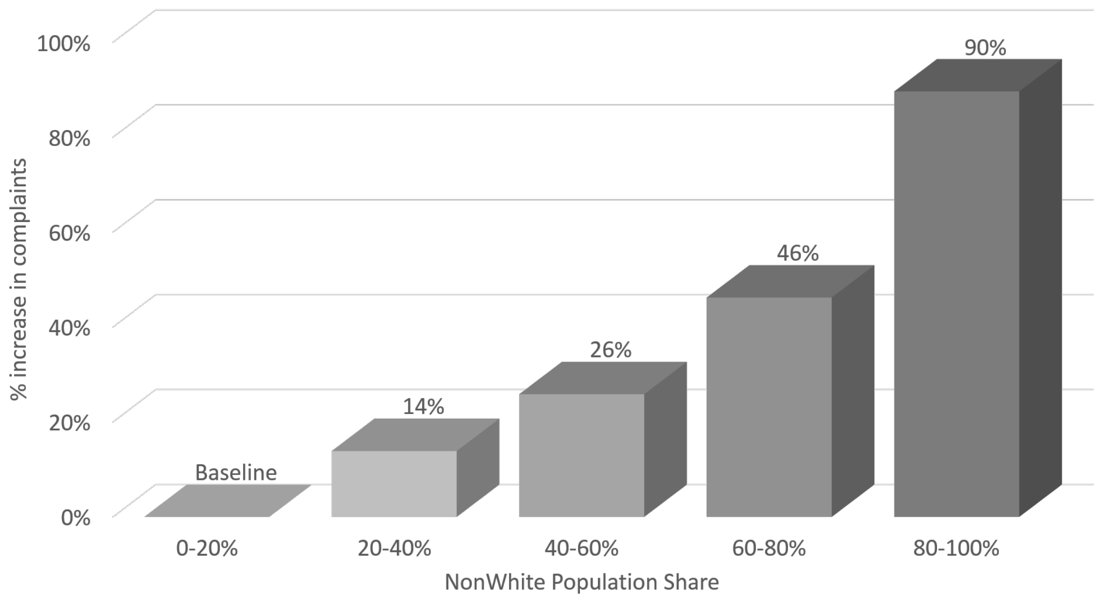

Figure 2: Minority Share and Quality
This figure presents a bar chart of the point estimates from the following regression: $lnComplaints_i = \sum_{r=2}^{5} \psi_r NWgroup_{r,i} + \sum_{b=2}^{50} \left(Mort_{b,i} + Pop_{b,i} + Inc_{b,i} + CollEd_{b,i} \right) + \zeta_{zip3} + \nu_i$. $NWgroup$ represents indicator variables for minority population share in the zip code: 0-20% (omitted base category in the regression), 20-40%, 40-60%, 60-80%, and 80-100%. $Mort$, Pop, Inc, $CollEd$ respectively represent indicator variables for 50 equally populated buckets of the number of mortgages outstanding, population, income, and education for a zip code. Point estimates from the regression are translated into percent increase above the base category for this figure.

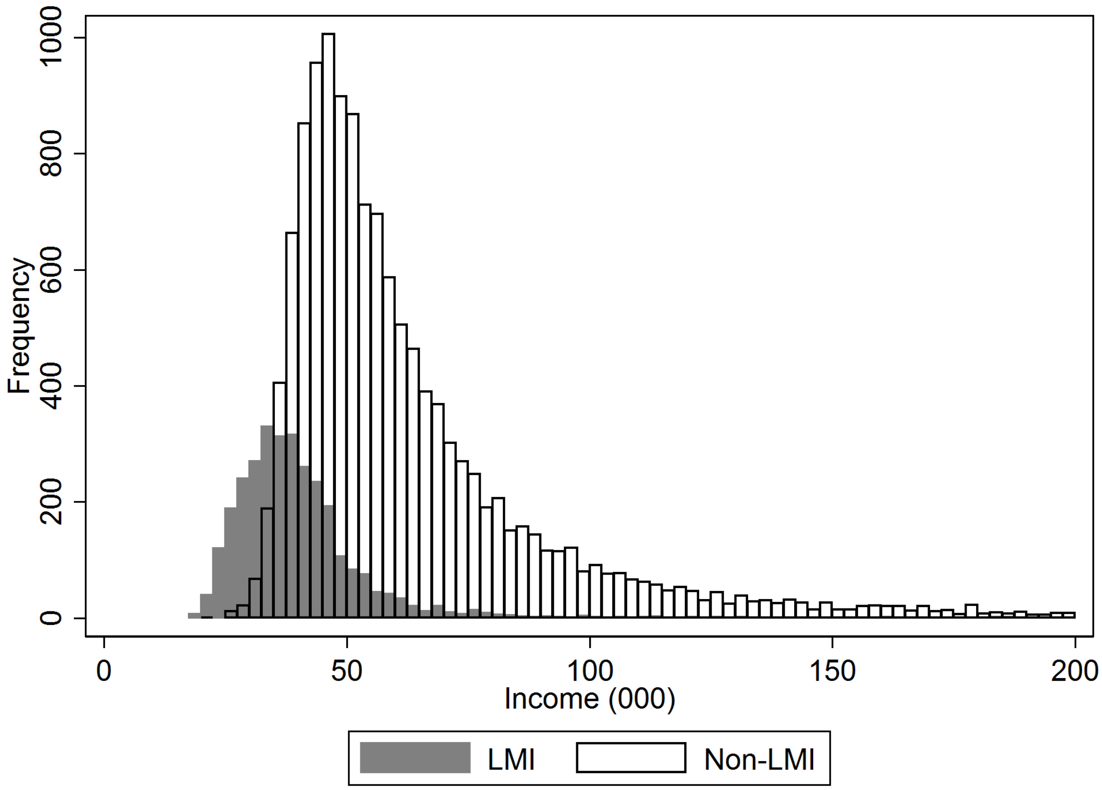

Figure 3: Area Income and Low- to Moderate-Income Status
This figure presents a histogram of income separately for low- to moderate-income (LMI) zip codes and non-LMI zip codes. Census tracts are designated LMI when the median family income is below 80% of the median MSA income. LMI zip codes are those with a majority of its population in low- to moderate-income tracts in 2010.

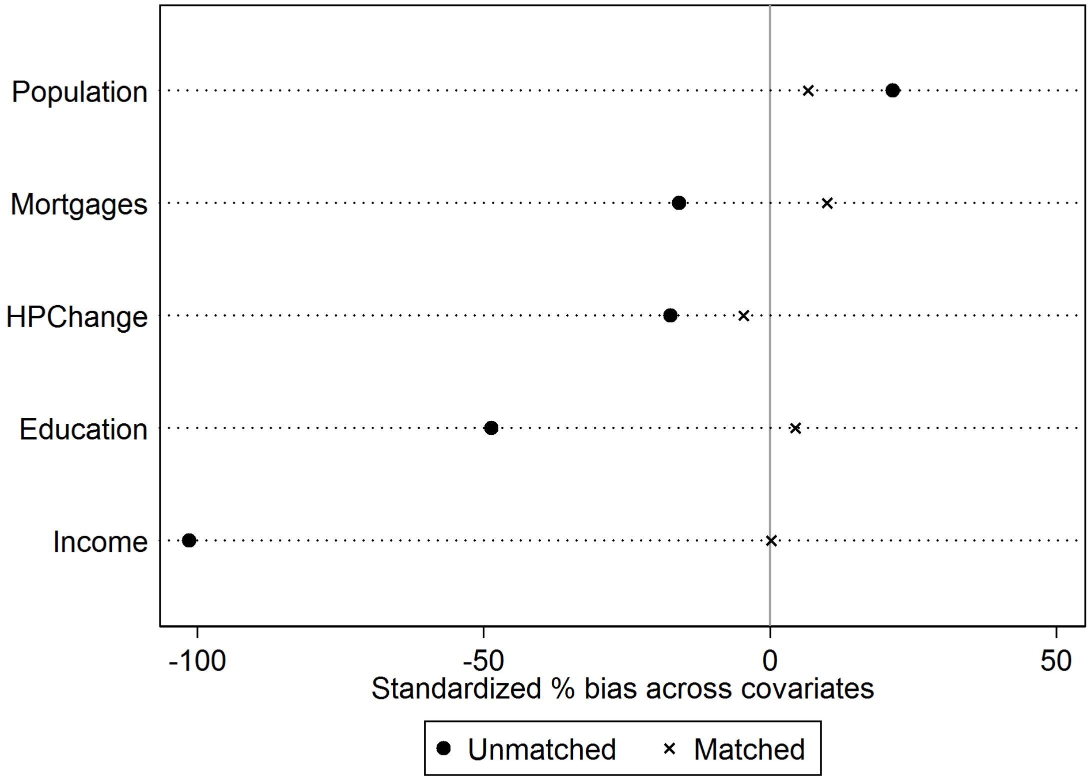

Figure 4: Covariate Balance for Raw and Matched Samples
This figure presents the difference in means between low- to moderate-income (LMI) zip codes for the number of mortgages, population, income, education, and house price index changes. The circles (•) represent raw pre-match difference and the the x's (×) represent the post-match differences. The difference is measured by the standardized % bias, which is the percent difference in means divided by the sample standard deviation or the variable.

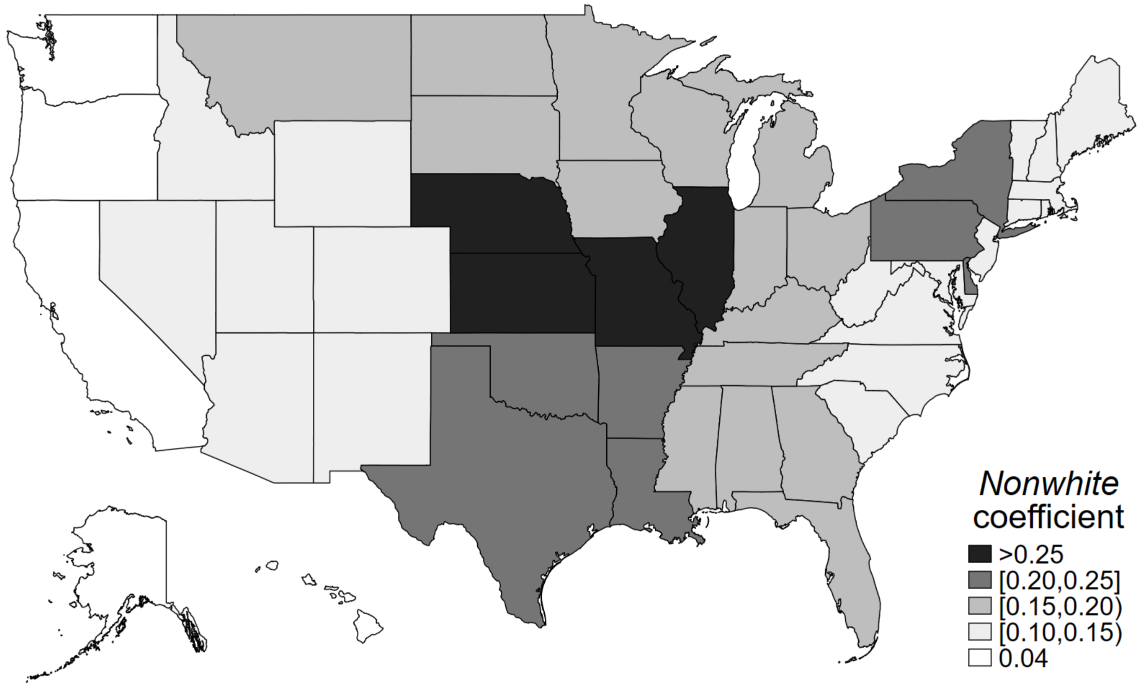

Figure 5: The Role of Race Around the Country
This figure presents the magnitude of the point estimate on $\hat{\rho}$ on *Nonwhite* in the following regression for each 1-digit zip code:

$$lnComplaints_{zip5} = \rho(Nonwhite_{zip5}) + \sum_{b=2}^{50} \left(Mort_{b,zip5} + Pop_{b,zip5}\right) + \zeta_{zip3} + \nu_{zip5}$$

The point estimate is positive for each 1-digit zip code and statistically significant for all regions except for those beginning with 9 (west coast).

Table 1: Sample Summary Statistics

This table presents the sample summary statistics. *Complaints* is the number of mortgage-related complaints filed to the CFPB in a given five-digit zip code in a given year winsorized at the 1% tails, *lnComplaints* is the log of Complaints, *AGI* is the mean household adjusted gross income in the five-digit zip code for 2012, *lnAGI* is the log of adjusted gross income, *College Education* is the portion of the adult population in the five-digit zip code with at least a bachelor's degree in 2012. *NonWhite* is the share of the zip5 population that is a minority race for 2012, *LMI* is an indicator variable equal to one for zip codes with a majority of its population in low- to moderate-income tracts in 2010, *Mortgages* is the number of mortgages in the five-digit zip code in 2012 measured by IRS filings with reported mortgage interest, *Population* is the zip code population in 2010, $\%\Delta HP$ is the percentage point change in zip5 house price growth (county house price growth is used for observations with no zip code level house price data), *Foreclosures* is the total zip5 foreclosures for 2012-2016 as reported by Zillow, and *lnFCC* is the log of the number of complaints to the Federal Communications Commission from 2015-2016 (data begin in 2015). All variables are winsorized at the 1% level.

variable	mean	sd	min	p25	p50	p75	max	N
Complaints	10.33	13.25	1.00	2.00	5.00	13.00	71.00	16,309
lnComplaints	1.63	1.22	0.00	0.69	1.61	2.56	4.26	16,309
AGI Income (000)	64.06	52.97	18.65	42.05	51.23	67.61	1464.53	16,309
lnAGI	10.93	0.44	10.12	10.65	10.84	11.12	12.54	16,309
College Education	0.27	0.16	0.05	0.15	0.22	0.35	0.76	16,309
Nonwhite	0.21	0.21	0.01	0.05	0.13	0.30	0.90	16,309
LMI	0.19	0.39	0.00	0.00	0.00	0.00	1.00	16,309
Mortgages (000)	1.97	2.07	0.04	0.41	1.19	2.92	9.54	16,309
Population (000)	17.20	15.18	0.62	4.78	12.66	26.11	67.05	16,309
$\%\Delta\text{HP}_{2007-2012}$	-17.73	15.07	-58.3	-26.75	-15.50	-6.35	8.99	15,867
$\text{Foreclosures}_{2012-2016}$	254.69	253.92	0.00	59.08	182.04	368.37	1241.18	9,740
lnFCC	2.97	1.3	0	2.08	3.14	3.99	5.32	15,806

Table 2: Income, Education, and Race

This table presents OLS estimates from the regression of complaints (*lnComplaints*) for a given five-digit zip code (zip5) on measures of income, education, race, and various sets of fixed effects. *lnComplaints* is the log number of mortgage-related complaints filed to the CFPB in a given zip5 during the sample period (2012-2016) , *lnAGI* is the log of the average adjusted gross income of households in each zip5 for 2012, *CollEd* is the share of the zip5 adult population for 2012 with at least a bachelor's degree, and *NonWhite* is the share of the zip5 population that is a minority race for 2012. *MortBucket50* represents a set of dummy variables for 50 equally populated buckets of the number of mortgages outstanding in the zip code (e.g., 700-750 mortgages) measured by IRS filings with reported mortgage interest for 2012. Similarly, *PopBucket50* represents dummy variable for 50 zip code population buckets for 2012. All continuous independent variables are standardized to have a mean of zero and unit variance Standard errors are clustered by three-digit zip code (zip3).

	(1)	(2)	(3)	(4)	(5)	(6)
lnAGI			-0.10***			-0.02*
			(<0.01)			(0.10)
CollEd				-0.08***		-0.06***
				(<0.01)		(<0.01)
NonWhite					0.17***	0.16***
					(<0.01)	(<0.01)
MortBucket50 FE	No	Yes	Yes	Yes	Yes	Yes
PopBucket50 FE	No	No	Yes	Yes	Yes	Yes
zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16309	16309	16309	16309	16309	16309
R^2	0.47	0.80	0.81	0.81	0.82	0.82

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Focusing on Race: Alternative Channels

This table presents OLS estimates from the regression of complaints (*lnComplaints*) for a given five-digit zip code (zip5) on measures of income, education, race, and various sets of fixed effects. *lnComplaints* is the log number of mortgage-related complaints filed to the CFPB in a given zip5 during the sample period (2012-2016) , *NonWhite* is the share of the zip5 population that is a minority race for 2012, *lnFCC* is the log of the number of complaints to the Federal Communications Commission from 2015-2016 (data begin in 2015), $\%\Delta HP_{2007-2012}$ is the percentage point change in zip5 house price growth (county house price growth is used for observations with no zip code level house price data), $Foreclosures_{2012-2016}$ is the total zip5 foreclosures for 2012-2016 as reported by Zillow, *MortBucket50* represents a set of dummy variables for 50 equally populated buckets of the number of mortgages outstanding in the zip code (e.g., 700-750 mortgages) measured by IRS filings with reported mortgage interest for 2012. Similarly, *PopBucket50*, *IncomeBucket50*, *CollEdBucket50* respectively represents dummy variable for 50 zip code population, income, and education buckets. All tests in this table are limited to observations with full data on each variable for ease of comparability. Column (6) measures complaints excluding specialized mortgage servicers. All continuous independent variables are standardized to have a mean of zero and unit variance. Standard errors are clustered by three-digit zip code (zip3).

	All					NoServicers
	(1)	(2)	(3)	(4)	(5)	(6)
NonWhite	0.14***	0.15***	0.13***	0.13***	0.13***	0.12***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
lnFCC		0.11***			0.10***	0.09***
		(<0.01)			(<0.01)	(<0.01)
$\%\Delta HP_{2007-2012}$			-0.14***		-0.12***	-0.12***
			(<0.01)		(<0.01)	(<0.01)
$Foreclosures_{2012-2016}$				0.06***	0.05***	0.05***
				(<0.01)	(<0.01)	(<0.01)
MortBucket50 FE	Yes	Yes	Yes	Yes	Yes	Yes
PopBucket50 FE	Yes	Yes	Yes	Yes	Yes	Yes
IncomeBucket50 FE	Yes	Yes	Yes	Yes	Yes	Yes
CollEdBucket50 FE	Yes	Yes	Yes	Yes	Yes	Yes
zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9234	9234	9234	9234	9234	9234
R^2	0.81	0.81	0.81	0.81	0.81	0.80

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regulation and Quality

This table presents matching estimates for complaints (*lnComplaints*) for a given five-digit zip code (zip5) for LMI zip codes as compared to matched non-LMI zip codes, where *LMI* is an indicator variable equal to one for zip codes with a majority of its population in low- to moderate-income tracts in 2010. The matching method uses a kernel-weighted propensity score to construct counterfactuals to compute the average treatment effect on the treated (ATET). The kernel is gaussian with 0.03 bandwidth. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnAGI*, *CollEd*, $\%\Delta\text{HP}_{2007-2012}$, indicator variables for each decile of those five variables, and state indicator variables. Column (1) presents the base estimate. Columns (2)-(3) respectively divide the sample into $10k and $5k strata based on MSA-median income and require matches be within-strata. Columns (4)-(5) place similar restrictions using zip code income strata. The number of matched observations decreases with more stringent requirements.

		MSA Strata		Income Strata	
	Base	10k	5k	10k	5k
	(1)	(2)	(3)	(4)	(5)
LMI (atet)	0.28***	0.31***	0.22***	0.21***	0.21***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
N	13713	13083	12521	11337	10151
Ntreat	1987	1864	1823	1891	1888
Ncontrol	11726	11219	10698	9446	8263

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Race and Regulation

This table presents matching estimates for complaints (*lnComplaints*) for a given five-digit zip code (zip5) for LMI zip codes as compared to matched non-LMI zip codes, where *LMI* is an indicator variable equal to one for zip codes with a majority of its population in low- to moderate-income tracts in 2010. The matching method uses a kernel-weighted propensity score to construct counterfactuals to compute the average treatment effect on the treated (ATET). The kernel is gaussian with 0.03 bandwidth. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnAGI*, *CollEd*, $\%\Delta \mathrm{HP}_{2007-2012}$, indicator variables for each decile of those five variables, and state indicator variables. Column (1) presents the base estimate. Column (2) presents the estimate when *NonWhite* and indicator variables for each decile of *NonWhite* are used in the matching scheme. Columns (3)-(4) provide the base estimates when splitting the sample to below- and above-median *NonWhite* share (*Low NW* and *High NW*). Columns (5)-(6) perform the split-sample estimation while also requiring that matches be in the same \$10k MSA-median income strata. The number of matched observations decreases with more stringent requirements.

		Match on	Base		MSA Strata	
	Base	NonWhite	Low NW	High NW	Low NW	High NW
	(1)	(2)	(3)	(4)	(5)	(6)
LMI (atet)	0.28***	0.18***	0.09*	0.35***	0.05	0.40***
	(<0.01)	(<0.01)	(0.07)	(<0.01)	(0.27)	(<0.01)
N	13713	13713	6705	6856	5131	6239
Ntreat	1987	1987	470	1517	437	1391
Ncontrol	11726	11726	6235	5339	4694	4848

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Placebo Tests: The Low-to-Moderate-Income Threshold

This table presents matching estimates for complaints (*lnComplaints*) for a given five-digit zip code (zip5) for LMI zip codes as compared to matched non-LMI zip codes, where *LMI* is an indicator variable equal to one for zip codes with a majority of its population in low- to moderate-income tracts in 2010. The matching method uses a kernel-weighted propensity score to construct counterfactuals to compute the average treatment effect on the treated (ATET). The kernel is gaussian with 0.03 bandwidth. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnAGI*, *CollEd*, $\%\Delta \mathrm{HP}_{2007-2012}$, indicator variables for each decile of those five variables, and state indicator variables. Row *80% (LMI)* presents the base estimates using the true LMI threshold of 80% of the median MSA income. Row *70%* presents estimates using a placebo LMI threshold of 70% of the median MSA income. All observation in Row *70%* are below the true LMI threshold and are thus all in the treatment group in all other tests. Row *90%* presents estimates using a placebo LMI threshold of 90% of the median MSA income. All observation in Row *90%* are above the true LMI threshold and are thus all in the control group in all other tests. *Base* tests estimate the results in the framework described above. *Within 10k MSA* and *Within 5k MSA* respectively divide the sample into \$10k and \$5k strata based on MSA-median income and require matches be within the same strata. *Nt* and *Nc* represent the number of treatment and control observations for each test.

	Base		Within 10k MSA		Within 5k MSA	
Threshold	ATET	Nt / Nc	ATET	Nt / Nc	ATET	Nt / Nc
70%	0.09	883 / 1102	0.09	784 / 993	0.01	784 / 993
	(0.19)		(0.39)		(0.94)	
80% (LMI)	0.28***	1987 / 11726	0.31***	1864 / 11219	0.22***	1823 / 10698
	(<0.01)		(<0.01)		(<0.01)	
90%	0.09**	2085 / 9641	0.03	2048 / 9186	0.01	2018 / 8807
	(0.01)		(0.48)		(0.78)	

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Alternative Matching Strategies

This table presents matching estimates for complaints (*lnComplaints*) for a given five-digit zip code (zip5) for LMI zip codes as compared to matched non-LMI zip codes, where *LMI* is an indicator variable equal to one for zip codes with a majority of its population in low- to moderate-income tracts in 2010. The matching methods in Columns (1) and (2) use a kernel-weighted propensity score to construct counterfactuals to compute the average treatment effect on the treated (ATET) using gaussian kernels with 0.01 and 0.05 bandwidths, respectively. Columns (3) and (4) using nearest neighbor propensity score matching with one and three nearest neighbors, respectively. The propensity scores are estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnAGI*, *CollEd*, $\%\Delta\text{HP}_{2007-2012}$, indicator variables for each decile of those five variables, and state indicator variables. Column (5) performs mahalanobis matching using the five continuous variables, and Column (6) further requires matches be in the same $5,000 income strata. The number of matched observations vary according to the available matches using a particular strategy.

	Kernel Bandwidth		PS Nearest Neighbor		Mahalanobis	
Desc	bw=0.01 (1)	bw=0.05 (2)	PS-1NN (3)	PS-3NN (4)	NN (5)	NN, 5k strata (6)
LMI (atet)	0.28***	0.28***	0.33***	0.27***	0.16***	0.17***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
N	13713	13713	13668	13663	13713	13650
Ntreat	1987	1987	1946	1941	1987	1986
Ncontrol	11726	11726	11722	11722	11726	11664

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regulatory Focus and the Timing of Quality Dilution

This table presents OLS estimates from the regression of complaints (*lnComplaints* or *Complaints*) for a given five-digit zip code (zip5) on measures of income, education, race, and various sets of fixed effects. Columns (1) and (2) present results with the dependent variable of log complaints and the standardized number of complaints. The dependent variable is columns (3) and (4) are the standardized number of complaints related to actions likely at-origination and post-origination, respectively. *lnComplaints* is the log number of mortgage-related complaints filed to the CFPB in a given zip5 during the sample period (2012-2016) , *lnAGI* is the log of the average adjusted gross income of households in each zip5 for 2012, *CollEd* is the share of the zip5 adult population for 2012 with at least a bachelor's degree, and *NonWhite* is the share of the zip5 population that is a minority race for 2012. *MortBucket50* represents a set of dummy variables for 50 equally populated buckets of the number of mortgages outstanding in the zip code (e.g., 700-750 mortgages) measured by IRS filings with reported mortgage interest for 2012. Similarly, *PopBucket50* represents dummy variable for 50 zip code population buckets for 2012. All continuous independent variables and *Complaints* are standardized to have a mean of zero and unit variance Standard errors are clustered by three-digit zip code (zip3).

	lnComplaints (1)	Complaints (2)	AtOrig (3)	PostOrig (4)
lnAGI	-0.02*	-0.02	0.03*	-0.03**
	(0.10)	(0.16)	(0.05)	(0.02)
CollEd	-0.06***	-0.09***	-0.00	-0.09***
	(<0.01)	(<0.01)	(0.83)	(<0.01)
NonWhite	0.16***	0.20***	0.11***	0.20***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
MortBucket FE	Yes	Yes	Yes	Yes
PopBucket FE	Yes	Yes	Yes	Yes
zip3 FE	Yes	Yes	Yes	Yes
Observations	16309	16309	16309	16309
R^2	0.82	0.76	0.57	0.74
Share of Total	100.00%	100.00%	12.63%	85.16%

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Complaints Across Mortgage Product Type

This table presents OLS estimates from the regression of *Complaints* for a given five-digit zip code (zip5) on measures of income, education, race, and various sets of fixed effects. *Complaints* is the number of mortgage-related complaints filed to the CFPB in a given zip5 during the sample period (2012-2016) for the full sample (column 1) or the particular mortgage product type (columns 2-9). The mortgage product types are conventional fixed-rate mortgages (FRM), conventional adjustable-rate mortgage (ARM), FHA mortgages, home-equity or line of credit (HELOC), VA mortgages, reverse mortgages, second mortages, or others. *lnAGI* is the log of the average adjusted gross income of households in each zip5 for 2012, *CollEd* is the share of the zip5 adult population for 2012 with at least a bachelor's degree, and *NonWhite* is the share of the zip5 population that is a minority race for 2012. *MortBucket50* represents a set of dummy variables for 50 equally populated buckets of the number of mortgages outstanding in the zip code (e.g., 700-750 mortgages) measured by IRS filings with reported mortgage interest for 2012. Similarly, *PopBucket50* represents dummy variable for 50 zip code population buckets for 2012. All continuous variables are standardized to have a mean of zero and unit variance Standard errors are clustered by three-digit zip code (zip3).

	All	FRM	ARM	FHA	HELOC	VA	Reverse	2nd	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lnAGI	-0.02	-0.05***	0.05***	-0.13***	0.06***	-0.05***	0.01	0.00	0.01
	(0.16)	(<0.01)	(0.01)	(<0.01)	(<0.01)	(<0.01)	(0.60)	(0.83)	(0.61)
CollEd	-0.09***	-0.02	-0.06***	-0.11***	-0.00	-0.04**	-0.04*	-0.02	-0.12***
	(<0.01)	(0.13)	(<0.01)	(<0.01)	(0.77)	(0.03)	(0.06)	(0.30)	(<0.01)
NonWhite	0.20***	0.15***	0.16***	0.23***	0.02	0.09***	0.06***	0.04**	0.20***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.22)	(<0.01)	(0.01)	(0.02)	(<0.01)
MortBucket FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PopBucket FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
zip3 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16309	16309	16309	16309	16309	16309	16309	16309	16309
R^2	0.76	0.66	0.58	0.48	0.37	0.22	0.11	0.09	0.68

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Complaint Resolution

This table presents OLS estimates from the regression of complaints (*lnComplaints* or *Complaints*) for a given five-digit zip code (zip5) on measures of income, education, race, and various sets of fixed effects. *Complaints* is the number of mortgage-related complaints filed to the CFPB in a given zip5 during the sample period (2012-2016) , *lnAGI* is the log of the average adjusted gross income of households in each zip5 for 2012, *CollEd* is the share of the zip5 adult population for 2012 with at least a bachelor's degree, and *NonWhite* is the share of the zip5 population that is a minority race for 2012. *MortBucket50* represents a set of dummy variables for 50 equally populated buckets of the number of mortgages outstanding in the zip code (e.g., 700-750 mortgages) measured by IRS filings with reported mortgage interest for 2012. Similarly, *PopBucket50* represents dummy variable for 50 zip code population buckets for 2012. Column (1) uses all complaints, column (2) contains complaints for which there was explicitly no relief given to the borrower, column (3) contains complains that were closed with an explanation, and column (4) contains complaints was there was explicit relief given to the borrower. All continuous variables are standardized to have a mean of zero and unit variance Standard errors are clustered by three-digit zip code (zip3).

	(1) All	(2) No Relief	(3) Explanation	(4) With Relief
lnAGI	-0.02	-0.02	-0.02	-0.02
	(0.16)	(0.28)	(0.23)	(0.11)
CollEd	-0.09***	-0.06***	-0.09***	-0.03**
	(<0.01)	(<0.01)	(<0.01)	(0.02)
NonWhite	0.20***	0.13***	0.21***	0.13***
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
MortBucket FE	Yes	Yes	Yes	Yes
PopBucket FE	Yes	Yes	Yes	Yes
zip3 FE	Yes	Yes	Yes	Yes
Observations	16309	16309	16309	16309
R^2	0.76	0.41	0.74	0.52

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix: Complaint Example

The following is an example complaint presented exactly as it appears in the Consumer Financial Protection Bureau (CFPB) Database. This particular example includes a consumer narrative, which consumers were given the option to display starting from 2015. For such data entries, the five-digit zip code is redacted to a three-digit zip code to protect the anonymity of the filer. The observations used in our analysis have no consumer narrative and so will include all the data items below with the consumer narrative left blank. The database can be viewed and downloaded from `http://www.consumerfinance.gov/data-research/consumer-complaints/`

Date received	8/9/2016
Product	Mortgage
Sub-product	Conventional fixed mortgage
Issue	Application, originator, mortgage broker
Sub-issue	[blank]
Consumer complaint narrative	I contacted Wells Fargo Home Mortgage to refinance my current mortgage. I informed them that I was behind and I filed bankruptcy about 6 years ago. They said no problem they could do it. My credit score was XXXX which they said was good. I applied and then they said that I had to pay {$11.00} for the credit report and {$530.00} for the appraisal in order to continue on with the application process. So I paid them the {$540.00}. I never received the appraisal on my home. They never contacted the appraisal company to schedule a date or time. They denied my application based on behind on mortgage and bankruptcy. I would like my {$530.00} back for the appraisal the I never received. I have called several times and left messages and no one has returned my calls. What does Wells Fargo do with all the money they get from people that don't qualify for refinance?
Company public response	Company has responded to the consumer and the CFPB and chooses not to provide a public response
Company	Wells Fargo & Company
State	ND
ZIP code	580XX
Tags	[blank]
Consumer consent provided?	Consent provided
Submitted via	Web
Date sent to company	8/9/2016
Company response to consumer	Closed with monetary relief
Timely response?	Yes
Consumer disputed?	No
Complaint ID	2050804