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 areas with higher proportions of poor and minority borrowers and in areas where government regulation promotes an increased quantity of lending. 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 lower-income and minority customers.

Keywords: product quality, discrimination, regulation, consumer protection
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1 Introduction

Policymakers have long been concerned about unequal and unfair treatment of poor and minority customers by financial institutions. Several consumer protection laws have been enacted to address discrimination and, in particular, to promote equal access to credit for those living in low-income and minority neighborhoods.[1] The Department of Justice (DoJ) often enforces provisions of these legislations to protect these consumers against discriminatory lending practices.[2] 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 low-income customers. Recent research has also looked at the effect of race on financial market outcomes such as the cost of education bonds issued by historically black colleges (Dougal, Gao, Mayew, and Parsons, 2018). 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. Specifically, our study allows us to take a closer look at a quantity-quality trade-off in this market by investigating the following research question: do consumer protection laws that promote increased access

[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

to credit (i.e., a higher quantity of credit), come at the expense of a lower quality of financial services for such consumers? This is a policy-relevant question for a wide range of regulations in the U.S. and around the world that are primarily focused on increasing the quantity of loans to marginalized borrowers.

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. These complaints are economically important from the financial institution's and regulator's perspective as well. For example, the CFPB uses these complaints as an input in its enforcement decisions, and since its formation, it has fined almost $10 billion to financial institutions to protect consumers.[3]

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.[4] For many consumers, acquiring and choosing a home mortgage product involves difficult choices between various complex products (e.g., Amromin, Huang, Sialm, and Zhong, 2018; Agarwal, Ben-

[3]As an example, in 2012 the CFPB issued warning letters to about a dozen mortgage lenders about deceptive advertising practices. As per their press release: "Today's actions stem from a joint "sweep," a review conducted by the CFPB and the FTC of about 800 randomly selected mortgage-related ads across the country, including ads for mortgage loans, refinancing, and reverse mortgages. The agencies looked at public-facing ads in newspapers, on the Internet, and from mail solicitations; *some came to the attention of the CFPB and the FTC from consumers who complained about them.*" (emphasis added. See https://www.consumerfinance.gov/about-us/newsroom/consumer-financial-protection-bureau-warns-companies-against-misleading-consumers-with-false-mortgage-advertisements/)

[4]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.

David, and Yao, 2017). These transactions leave many potential borrowers at a substantial information disadvantage compared to sophisticated financial institutions (e.g., Campbell, 2006; Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff, 2014; Carlin and Gervais, 2012). 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, and the effect of high-minority status is two-to-three times larger than the effect of low income or low education. In a multivariate setting, a one-standard-deviation increase in the minority share of the population leads to a 16% increase in complaints, whereas the corresponding effects for area income is 8%. 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. These results show that groups that are often the intended targets of consumer protection laws experience much worse outcomes on the quality dimension.

We next investigate the quantity-quality trade-off in this market using a key quantity-based lending regulation in the U.S. In light of concerns about discrimination in lending markets. Several regulations have been enacted in the U.S. over the years to provide better access to credit to low-income 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, i.e., on the *quantity* and *price* of credit. There now exists a large body of empirical work examining the impact of these regulations on consumers' access to credit and pricing, which are easy to measure (see Ladd, 1998, for a literature review). However, the potential effects of such regulations on product *quality* are ambiguous. For example, regulations targeting a higher quantity of loans in an area may also improve the quality of financial services received by poor and minority borrowers, especially 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 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 quantity 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 (also called low- to moderate-income, or LMI). While the regulation is intended to target areas based solely on income, the quantity of lending to minority customers is a key evaluation metric used by regulators in assessing a bank's compliance with CRA regulations.[5] Thus, CRA-target areas experience a positive shock to the quantity of credit supplied to low-income and minority customers. 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 put pressure on lenders to increase

[5]Focus on minority lending is evident by looking at the CRA evaluation template used by regulators, congressional testimony on this topic, and actual evaluation reports of banks. We provide a detailed example using Wells Fargo in Section 2.1 and provide an excerpt from the CRA examination template in Appendix B which shows the importance of lending to minorities in performing well on the CRA evaluation.

lending to customers in these areas beyond what they normally would have. Thus, we can estimate the effect of regulation-induced quantity shock on the quality of financial services by comparing the incidence of poor customer service, fraud and mis-selling across areas with higher quantity pressure from the CRA with carefully chosen control areas that do not have such pressure.

The CRA designations are at the census tract level, but our complaints data are at the zip code level. Therefore, we aggregate census-tract-level population data to the zip code level by computing the share of the population that lives within the CRA-target tracts in the given zip code. Due to this aggregation, we are unable to carry out a regression discontinuity design for our empirical approach – zip codes have varying percentages of the population residing in the CRA-target census tracts, so the fraction of the population that is subject to the CRA-supply shock varies continuously across zip codes. Hence, we adopt a matched sample approach for our empirical analysis. We assign a zip code to be a *CRA-target Area* if the majority of the population in the zip code are in LMI census tracts. We define these areas as treatment areas for the quantity-based regulation shock. Zip codes that do not have any LMI census tracts form our control zip codes. Our detailed demographic data at the zip code level and the presence of a very large number of control zip codes allow us to construct counterfactuals that are virtually identical on all important observable dimensions except the CRA-target designation.

In our main test, we exploit within-MSA variation in complaints across the target and control zip codes. Specifically, we find a control group within each MSA for every treatment zip code such that the two groups are very similar along dimensions such as income, education, population, mortgage volume, and house price changes. The empirical design exploits within-MSA variation in the percentage of the population that resides in the CRA-target areas and therefore soaks away variation in complaints rate that may arise due to any potential unobserved MSA-level differences in economic conditions, regulation, culture, and consumers' propensity to complain. Our main test reveals about 25% more complaints in the treatment area, and the estimate is statistically significant at the 1% level. We interpret this finding as an unintended consequence of quantity-based regulation: CRA-target areas putting pressure on lenders to provide a greater quantity of credit results in relatively worse quality.[6]

Comparing quality across CRA-target and control areas shows that borrowers in the targeted areas are receiving worse quality outcomes, irrespective of the racial composition of the area. In our next tests, we examine the difference in complaints across CRA-target and control groups separately for below- and above-median minority share. We find that difference in complaints between CRA-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, the complaint rates are indistinguishable between the CRA-target and control areas. In contrast, we find that within above-median minority share areas in a given MSA, complaints in CRA-target areas are about 35% higher than their observationally similar control areas. While banks face pressure to increase the quantity of lending in every target area, in high-minority areas, they effectively have two sources of pressure for regulatory compliance – lending to low-income customers and lending to minority customers.

These results shed light on an important unintended consequence of quantity-based regulation and highlight the disproportionate impact of these adverse consequences on 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.

We supplement the within-MSA matched sample results with a country-wide matched sample analysis in the next set of tests. The within-MSA results have several attractive

[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. Similarly, Ding and Nakamura (2017) show strong quantity effects of the CRA in a study focusing on changes in CRA-target areas in Philadelphia, and also show the effects are largest for higher-minority neighborhoods.

features as it allows us to control for unobserved differences across zip codes within an MSA. A disadvantage of this approach is that the treatment zip codes, virtually by construction, have slightly lower income than the control groups.[7] To ensure that our results are not driven by differences in income, we find a set of control zip codes from the entire country that are very similar to the treatment zip code, including on the level of income specifically. We find similar results.

Finally, we directly relate the quantity of lending to quality. A two-stage regression specification, as in an instrumental variable (IV) setting, naturally lends itself to tease out this relationship. In the first stage of the regression, we use the *CRA-target area* designation as an instrument for the quantity of lending activity in that zip code during our sample period. In the second stage, we regress the number of complaints in the zip code on the predicted value of lending from the first-stage regression. The second stage estimate provides the marginal effect of quantity on quality for the areas where the quantity-based regulation was the pivotal factor in increasing lending activity.

We use the number of applications and the number of originations as measures of the quantity of lending activities, as complaints can occur anytime during the chain of mortgage origination: application, origination, servicing, and potential renegotiation of the loan. The first-stage estimates provide evidence supporting the claim that CRA designation increases the quantity of credit – both the number of applications and the number of loans originated – in these areas. This finding is consistent with other studies that show a positive effect of CRA on the supply of lending activity (e.g., see Agarwal et al., 2012; Ding and Nakamura, 2017; Saadi, 2020; Lee and Bostic, 2020). The second-stage estimates show that the marginal increase in lending is associated with higher complaints. Our results are stronger when we use the number of applications as a measure of the quantity of lending activity. We find

[7] The treatment zip codes have a majority of census tracks under the CRA-target area. These areas are below the 80% threshold of the MSA median income, whereas control zip codes have all their census tracts above the 80% threshold. Hence, by construction, treatment areas within an MSA have a slightly higher income than the control areas.

economically similar, but statistically weaker, results for estimates based on the number of originations as the measure of the quantity of lending activity. While both these measures are useful metrics of lending activity, the number of applications is likely a more reasonable measure in our context because it captures the entire process of interaction a consumer has with their financial institution. Overall, these findings are consistent with the notion that regulation that focuses primarily on quantity leads to a dilution in the quality of services provided to customers.

Our work relates to the often-controversial literature on the 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 in detail the quality of financial products and services as reflected by consumers' experience. Piskorski, Seru, and Witkin (2015) and Griffin and Maturana (2016) show compelling evidence of fraud and mis-selling by 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.

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; Ding and Nakamura, 2017) 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 two strands of literature: (a) informational frictions between borrowers and lenders and (b) 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 (e.g., see 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 improper disclosure. Our first set of tests, relating the extent of complaints to levels of income, education, and minority population, is designed to uncover the importance of these frictions in credit markets and establish the baseline patterns in our novel data. Lower-income and less-educated neighborhoods have been shown to be financially less sophisticated, and thus we expect those areas to be more likely to experience a higher incidence of fraud, mis-selling, and poor service.

Our central focus is on the second strand of literature that goes back to the seminal work of multi-tasking by 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 low- to moderate-income and minority individuals. We view this "quantity-based" feature in the regulation 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 the 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, improper disclosure, or generally poor effort in service for lower-income and minority individuals, who are the very people that consumer protection laws are targeted to help.

We begin our examination by relating various demographic characteristics to complaints using standard linear regression techniques. After establishing a strong relationship between areas with lower income, less education, and a higher proportion of minority borrowers and the quality of financial services, we focus our analysis on teasing out the effect of quantity-focused regulations in shaping these outcomes. We do so by examining the effect of a regulation-induced shock to the quantity of lending activity, namely the Community Reinvestment Act (CRA), on the quality of financial services provided to lower-income 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 in lending activities against 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 "underserved" 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 activities to these "underserved" areas.

LMI status is determined at the census-tract level by a simple rule. Tracts with a median family income of 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. Our tests compare outcomes for areas that are similar on observable characteristics, but differ in regulatory designation and thus the pressure for lenders to supply credit to the area.

Our main tests exploit variation in regulatory designation within an MSA, which allows us to rule out the effect of MSA-level unobservable differences on quality outcomes. This analysis compares areas that are very similar on a number of dimensions, but at slightly different points in the income dimension, since the LMI status depends on an area's relative income within an MSA.

We also run tests that exploit variation across the country as a complement to the within-MSA analysis. The strength of this test is that it allows us to get treatment and control areas that are very similar on the absolute level of income dimension as well. For illustration, 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 dimensions such as the residents' marginal propensity to complain. Under this assumption, we can tease out the difference in the quality of financial services caused by differential regulation by comparing the complaint rate across carefully matched areas in the treatment and control groups.

LMI designation is at the census-tract level. Since our data and analyses are at the zip code level, we must aggregate the census tract data to the zip code level. This aggregation renders a regression discontinuity design infeasible, so we proceed with a matched sample design. We define zip codes as *CRA-target areas* if the majority of its population resides in LMI census tracts. These are the areas that receive the quantity-based regulation "treatment" induced by the CRA. Non-LMI (*control*) areas are defined as zip codes that do not have any census tract under the LMI category. Using propensity score (kernel) matching, we use the control zip codes to construct counterfactuals that are very similar to the treatment groups in terms of not only income, but also population, outstanding mortgages, education, and recent house price dynamics.

Our treatment and control groups, by construction, are in relatively lower-income areas of the country. Thus, the difference in outcomes between the treatment and the control groups provides us with the effect of the quantity-focused regulation on quality in lower-income areas, which are the relevant areas that the CRA is aiming to help. While the language and area definitions in the CRA regulation use income tests, the CRA examiners also evaluate performance on "fair lending" laws (FHA, ECOA) and consider discriminatory behavior as grounds for lowering a lender's CRA rating.[8] For example, in Wells Fargo's 2012 CRA Performance Evaluation, their record of discriminatory behavior effectively downgraded them from a top rating (4/4) to a below-par (2/4) rating:

> The bank's overall CRA Performance Evaluation rating was lowered from "Outstanding" to "Needs to Improve" as a result of the extent and egregious nature of the evidence of discriminatory and illegal credit practices, as described in the Fair Lending and Other Illegal Credit Practices section of this document.

In light of this interaction between the CRA and "fair lending" laws, we extend our work further by conditioning the analysis on the racial composition of the CRA-target areas. These regulations reinforce one another, which suggests that the CRA effects may be stronger in high-minority areas. Specifically, we divide zip codes into two groups: below- and above-median minority-share areas. Within each subset, we separately estimate the average

[8]Many industry insiders assert that the link between the CRA and "fair lending" is too strong and, thus, detracts from the original focus on serving low-income areas regardless of race. For example, in a 2014 *American Banker* article, Warren Traiger writes, "In regulators' push to root out lending discrimination based on race or ethnicity, they have co-opted the CRA as a fair lending enforcement tool. The last several years have seen a spate of banks with downgraded CRA ratings based solely on evidence of inadequate compliance with other laws." (American Banker, 2014).

treatment effect of the regulation on the treated group. 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.

Finally, we use a two-stage regression model to directly link the CRA-induced quantity shock to quality. For the first stage, we use the CRA-target designation to predict the quantity of lending activities in that zip code. This predicted value is then used as an explanatory variable for the second stage regression with the number of complaints as the dependent variable. This model allows us to formally establish the economic channel behind our findings. The local average treatment effects we estimate in this IV setup represent the effect of quantity on quality specifically for the marginal quantity that is induced by the CRA regulation.

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.[9] 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.

[9]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.

As we discuss in detail later in the paper, CFPB also uses these complaints for its enforcement actions against banks. Hence these complaints are economically meaningful from the bank's perspective as well.

To file a complaint, 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. 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 only on mortgage-related complaints for a few reasons. First, it is economically less meaningful to compare quality across different products such as mortgages and credit cards. 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. We use the 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 the 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.

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.[10] Table 1 provides the 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 when using the number of raw complaints as the 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

[10]Since 2015, complaints in the database are allowed to include a narrative 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 a total of 212,669 mortgage-related complaints, 182,175 complaints have the five-digit zip code identified. After matching to demographic data, 168,539 complaints remain in the sample and form the basis of our analysis.

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 loan signing/closing. The majority, about 85%, of complaints arise after the origination involving problems in the course of loan servicing such escrow maintenance, 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 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. 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 minority (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 broadly representative of the 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.[11] We use this measure 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 a large drop in home value during the great recession.

CRA-target area, as discussed above in Section 2, represents whether the zip code has the CRA regulation-induced upward pressure on lending activities. CRA-target area equals one if the majority of the zip code population is in an LMI tract, zero if none of the population is in an LMI tract, and omitted (coded as missing) if a positive, but the minority of the population lives in an LMI tract. Defining the variable this way allows us to create matched treatment and control variables that, while virtually identical on other dimensions, face sufficiently different degrees of regulatory pressure. This classification yields about 2,000 CRA-target areas and about 7,000 potential controls across 355 MSAs. Given the particular specification and matching requirements (e.g., requiring overlap, restricting matches to MSA or income strata), fewer observations are used in the estimation.

4 Results

We begin by providing some new facts about the overall variation in quality across demographic characteristics. We then move to the central focus of our analysis: the quantity-quality trade-off.

[11] 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.

4.1 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:

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

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 independent 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 MSA level.

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 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 these effects such as using ten or 100 buckets or a flexible polynomial approach.

We also include fixed effects at the MSA level (ζ_{MSA}) 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 MSA, which allows us to estimate the relationship between demographic characteristics and complaints after soaking away differences in local economic and regulatory considerations.

Table 2 presents the estimates of the regression in equation (1). In column (1) we only include MSA fixed effects in the model as explanatory variables and find R^2 of 42% 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 79%. Columns (3)-(5) present our main demographic results where we estimate the relationship for each characteristic one at a time. One standard deviation decrease in income is associated with about 11% more complaints, whereas the corresponding effect for lower education is comparable at 5%. The effect of the minority share of the population, on the other hand, is considerably higher at about 17%.[12] Since all the explanatory variables are standardized and the dependent variable is the log of complaints for all models, we can directly compare these coefficients as the relative economic importance of the respective variables. Needless to say, these demographic variables are correlated. Column (6) separates the relative importance of each of these three variables by including them all in the model. The independent effect of education is explained away by the other variables. The effect of income remains relatively strong, but the minority population of the zip code clearly is both economically larger and statistically stronger. The effect of the *Minority* variable is about twice as large as that of income.

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

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

the following regression:

$$
\begin{aligned}
lnComplaints_{zip5} = &\sum_{r=2}^{5} \psi_r MinorityGroup_{r,zip5} + \\
&\sum_{b=2}^{50} \left(Mort_{b,zip5} + Pop_{b,zip5} + Inc_{b,zip5} + CollEd_{b,zip5} \right) + \zeta_{MSA} + \nu_{zip5} \quad (2)
\end{aligned}
$$

MinorityGroup 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 the highest minority concentrations, with areas above 80% minority population having nearly double the complaints compared to those with below 20% minority population.

4.2 Quantity-quality trade-off

We now present the results of quantity-quality trade-off based on the research design discussed in Section 2. We compare outcomes for *CRA-target* ("treatment") zip codes to similar non-LMI ("control") zip codes to tease out the effect of a quantity supply shock on the quality of mortgage products and services. Figure 3 plots the income distribution of CRA-target areas and the pool of potential non-LMI control zip codes across the country. By the very definition of this regulatory criterion, the treatment zip codes are concentrated in the left tail of income distribution.

To find suitable control observations with which we can construct counterfactuals for each CRA-target area, we estimate the propensity score for LMI designation using a probit model with the following variables: the logged values of mortgages, population, and income; share of the population with at least a bachelor's degree; the state; and house price changes. For the tests where we allow matches from anywhere in the country (and thus a much larger pool of potential matches), we also include indicator variables for each decile of the respective continuous variables above. 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 an epanechnikov kernel with a bandwidth of 0.03.[13]

Figure 4 shows the comparability of treatment and control observations before and after matching when we require matches to be within the same MSA, anywhere in the country, and within \$10,000 of income strata at the MSA level. The plot shows the standardized bias for each of the main 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).

4.2.1 Within-MSA matching results

In our main test, the treatment and control groups are restricted to the same MSA, allowing us to exploit *within-MSA* variation in the regulatory shock. A key advantage of this approach is that we are able to soak away all the local variation at the MSA level such as differences in state regulation, economic activities, housing and banking market characteristics, and the cost of living. Column (1) of Table 3 presents the main result. The treated, CRA-target areas have about 28% ($e^{0.25} - 1$) more complaints than their matched

[13]Robustness tests discussed later in Section 5 show that the results are not driven by these specific modeling choices.

control zip codes within their same MSA. Thus, the regulation-induced supply shock results in a substantially higher number of complaints about fraud, mis-selling, and poor customer service in the CRA-target areas.

4.2.2 Regulation and race

The role and importance of (race-based) fair lending laws in the CRA evaluations leads us to examine heterogeneity in the effect of regulation based on the minority share of the population. We do so by estimating the matched sample test separately for areas with relatively higher and lower minority shares of the 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 used above, we now find a set of control areas for each CRA-target area within the same minority-share-of-population bucket. Said differently, CRA-target areas with above-median (below-median) minority population are required to be matched with comparable control areas that also have above-median (below-median) minority population. Table 3 presents the results in columns (2)-(3). A stark pattern emerges: in low-minority-population areas, the CRA-target areas have statistically indistinguishable complaints than the control areas. Within above-median minority-share areas, however, the corresponding difference is 42% ($e^{0.35} - 1$). The difference-in-difference across low- and high-minority population areas is statistically significant at 1%. In sum, the regulation-induced shock to the supply of lending has a disproportionately large detrimental impact on the quality of service received by areas with a higher minority share of the population.

4.2.3 Across-the-country matching results

We complement the within-MSA matching estimator with a country-wide matching estimator, by finding a set of matched zip codes from anywhere in the country using the same criteria as above. The strength of these tests is that there is a much broader pool of control zip codes to match from. Table 4 presents the base result in column (1). The treated zip codes have about 58% ($e^{0.46} - 1$) more complaints than the control zip codes. The effect is much larger in areas with a higher share of minority population, while barely statistically significant in areas with a relatively low minority population. These results are consistent with the within-MSA estimates presented earlier. To further ensure that the CRA-target and control zip codes are close on the dimension of absolute income level, we force matches to be within the same $10,000 strata and repeat the estimates. Columns (4)-(6) in Table 4 present the results. All the results are similar to the baseline test.

These results paint a clear and consistent picture that regulatory pressure 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 lower-income and minority borrowers seem to adversely impact quality.

4.2.4 Evidence from loan applications and originations

We directly relate the quantity of lending activity induced by the CRA regulation to the quality of financial services received by borrowers using a two-stage regression model. Our model is as follows:

$$quantity_{zip5} = \phi(CRA\text{-}target_{zip5}) + \Gamma X_{zip5} + \zeta_{MSA} + \nu_{zip5} \quad (3)$$

$$lnComplaints_{zip5} = \psi(\widehat{quantity}_{zip5}) + \Theta X_{zip5} + \zeta_{MSA} + \epsilon_{zip5} \quad (4)$$

The first-stage regression uses the CRA target-area designation as an instrument for the quantity of lending activity. We use two measures of quantity: either the log of the number of loan applications or the log of the total number of loans originated in 2012-16. *CRA-target* is one for the treatment zip codes as defined earlier, and zero for control zip codes. The identifying assumption is that the designation of a zip code as the target area affects the number of complaints in the second stage regression only through its affect on the quantity of lending activity. The regression is estimated at the five-digit zip code level with MSA fixed effects, which coincides the within-MSA matched sample approach presented earlier.

As discussed earlier, zip codes that fall below the 80% threshold of average MSA income are designated as the CRA target area. We only include zip codes whose average income is in the range of 60% to 100% of the MSA-level median family income in this model to ensure that our zip codes are comparable on several other dimensions that could potentially independently affect the number of complaints (i.e., for reasons other than increased quantity due to the CRA designation). This sample selection criteria effectively gives us a well-balanced set of zip codes, some of which are above and some below the 80% threshold. Hence, our exclusion restriction – that the CRA designation affects complaints only through the quantity channel – is likely to hold. In addition, the model includes the following control variables (X): number of mortgages, population, education, house price dynamics as well as the area's relative income. We also include relative income interacted with each of the other control variables.

In the estimation of the second-stage regression equation (4), we use the number of complaints in the zip code as the dependent variable and the predicted values of the quantity of lending activity (applications or originations) as the key explanatory variable. The second-stage estimate provides the local average treatment effect, which economically represents the marginal effect of a unit increase in quantity in lending activity that comes from CRA-target status on the number of complaints.[14]

Table 5 presents the results. Columns (1) and (2) present the baseline OLS relationship between the quantity of lending and complaints. We present our estimates of the first stage regression in columns (3) and (4). We find that CRA-target areas have significantly higher lending activity, with about 7% higher quantity of loan applications and about 5% higher quantity of loan originations. Column (5) presents the reduced form estimate linking

[14]Since our instrument is a binary variable, the second-stage coefficient is simply the Wald estimator, namely the difference in the conditional expectation of complaints across the treated (instrument value=1) and control (instrument value=0) areas scaled by the conditional expectation of quantity across the two areas.

CRA-target areas to the number of complaints and indicates that the target areas have approximately 13% more complaints. Note that this reduced form regression coefficient is the regression-based analog of our matching estimator presented earlier.

The second-stage regression results are provided in columns (6) and (7). Areas with higher loan applications and originations have significantly higher complaints. The regression coefficients represent the elasticity of complaints to the respective quantity variable since we measure them both in log terms. One percentage increase in applications is associated with a 1.88% increase in the number of complaints. This result establishes a clear connection between the regulation-induced quantity shock and the quality of financial products and services. We find similar results using the number of loans originated as the measure of quantity. One percentage point increase in origination leads to 2.67% higher complaints. However, for this specification, the F-statistic in the first stage regression is below the conventional threshold of 10, and we interpret this estimate with the caveat that it may suffer more from the weak instrument bias.

Overall, these results highlight an important link between regulation-induced pressure to increase the quantity of lending activity and the quality of these financial services.

5 Robustness tests & economic significance

5.1 Alternative measures of complaints intensity

In our main analyses, we use the (log) number of complaints as the main dependent variable. We control for the number of mortgages in flexible parametric and non-parametric ways across the different tests. As an alternative approach, we estimate all our main results using the number of complaints divided by the number of mortgages in the zip code.[15] The

[15] In unreported tests, we also scale by the number of new originations during the sample period and find similar results.

resulting measure can be viewed as the complaint rate per mortgage in a given zip code. To ease interpretion, we standardize the ratio to mean zero and unit standard deviation. Table 6 presents the estimates of difference in these standardized rates between CRA-target areas and control areas. Our main findings remain the same. Column (1) of Table 6 shows the within-MSA estimates, which show that the CRA-target areas (our treatment group) have about 0.4 standard deviations higher complaint rates compared to the control areas. Columns (2) and (3) further show that the results are similar if we allow our matching criteria to include zip codes from all over the country (unconstrained) and across the country, but within $10,000 income strata.

5.2 Variation in the Resolution of Complaints

Are our results driven by frivolous complaints made by minority borrowers? If borrowers in the CRA-target areas are more likely to make such complaints, then this introduces a concern that our results are simply driven by variation in the propensity to complain and not the actual quality of products and services delivered. 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. As we subdivide the complaints into these categories, we naturally get more zip codes with zero complaints of a given type, making it infeasible to use the log of complaints as the dependent variable. Thus, for these tests, we use the standardized (mean zero, unit standard deviation) number of complaints. Table 7 presents the baseline, within-MSA specification estimated with the dependent variable as the standardized total number of complaints (column 1), complaints with relief (column 2), complaints closed with explanation (column 3), and complaints with no 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 the CRA-target areas.

5.3 Other robustness tests

For our matching estimator, we rely on a kernel-weighted propensity score method to construct counterfactuals to compute the average treatment effect on the treated (ATET) on CRA-target zip codes. The kernel is epanechnikov with 0.03 bandwidth in the results presented so far. In Table 8, after reproducing the baseline result in column (1), we produce the estimation results from different bandwidths (columns 2 and 3), using local linear regression (column 4), and using one, three, and five nearest-neighbor matches. Our results are robust to these alternative matching techniques.

Additionally, we do not find any significant time-series variation in our results. Specifically, our base estimates are similar during the first-half and second-half of the sample.

5.4 Economic Significance

How meaningful are these consumer complaints from an economic perspective? Clearly, consumers who are taking the time to complain to the CFPB find it valuable from their individual perspective, but what about the banks and regulators? While it is hard to pin down the precise economic costs of complaints, we provide a number of arguments, and some empirical tests to shed some light on their economic importance.

Appendix C provides some anecdotal examples on how these complaints are important for the CFPB's enforcement actions. As these examples show, the CFPB uses these complaints as an important input to spur or aid in investigations of wrong-doing by a bank. These investigations can lead to large fines against the offending institutions. These examples also provide anecdotal evidence supporting the claim that the CFPB's information is used for other regulations such as the assessment of CRA compliance by a bank.

One formal way to study the economic significance of these complaints is to examine the relationship between the number of complaints and the amount of fines banks have paid since the inception of CFPB. This data is available for only the largest banks of the country, so we have a limited number of observations for this analysis. Hence, the analysis presented here highlight the economic importance of complaints in an approximate sense only.[16]

In Figure 5, we provide a scatter plot of log complaints against log of dollar value of fines imposed against the institution. There is a clear positive correlation between the two variables: banks with more complaints paid significantly higher fines. We estimate an OLS regression of log(fines) on log(complaints) and the best fit line is give by the following equation: $logFines = 8.44 + 0.88 \times logCompliants$. The coefficient estimate on logComplaints is significant at 1%. Since we have data on complaints for only 26 institutions, the regression estimate should be interpreted with caution. With that caveat, the broad correlation is clear: banks with higher complaints paid significantly higher fines.

Our estimation suggests an elasticity of 0.88 between complaints and fines. The two-stage regression estimates provided us with an elasticity of 1.88 between loan quantity and complaints (Table 5). Combining the two elasticity estimates, we can arrive at a back-of-the-envelope calculation of the dollar value of quantity-quality trade-off. One percentage point increase in quantity results in 1.88% more complaints, which in turn results in 1.65% (1.88×0.88) more fines. The key takeaway from these rough estimates is that the consumer complaints we are studying strongly relate to economically meaningful actions by regulators against banks.

[16] A more formal analysis of the drivers of fines against financial institutions must also take into account several other motivations, including legal, political, and social forces, on the imposition of fines. These issues are beyond the scope of our paper.

6 Discussion & Conclusions

Since the very beginning of modern finance, there have been concerns about the exploitation of lower-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. A number of banking regulations such as the Community Reinvestment Act have been enacted to tackle this market failure. These regulations typically focus on the quantity, not on the quality, of financial services received by these consumers. While such regulation may be successful in providing a higher *quantity* of credit to borrowers in these areas, our results show that the *quality* of products and services is substantially lower in areas that are targeted by these regulations. 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 highlight a new cost of such quantity-focused regulations by showing that the consumers in lower-income and high-minority areas that are targeted for help by the CRA experience worse outcomes along the quality dimension.

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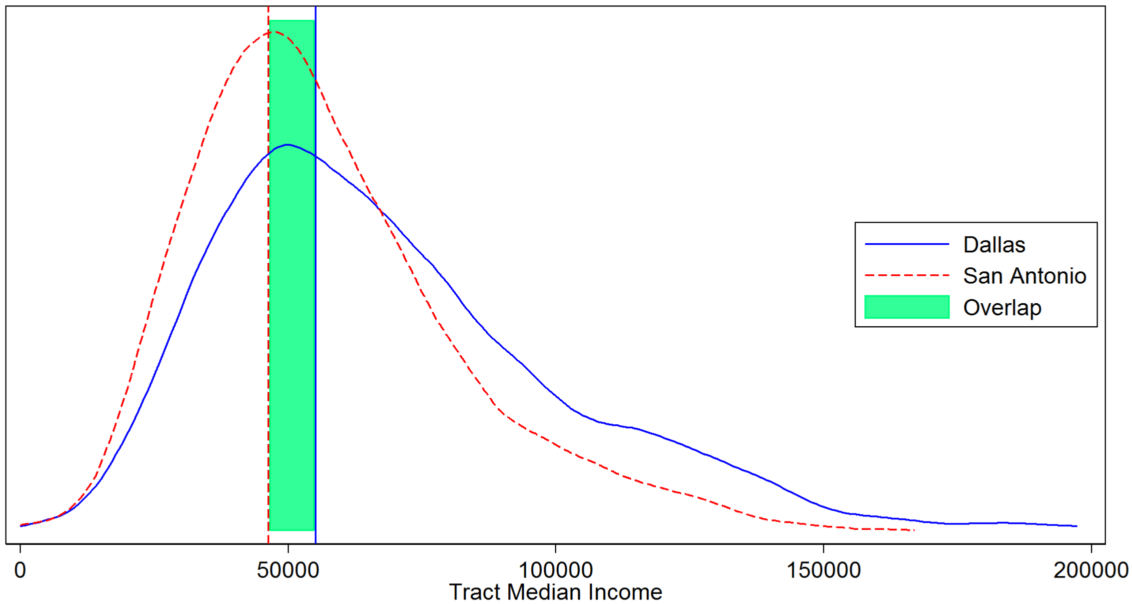

Figure 1: Example Geographical Variation in Low- to Moderate-Income Designation
This figure presents kernel densities of 2010 census tract incomes for the Dallas-Plano-Irving ("Dallas") and San Antonio-New Braunfels ("San Antonio") metropolitan statistical areas (MSA) in Texas. The vertical lines at $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.

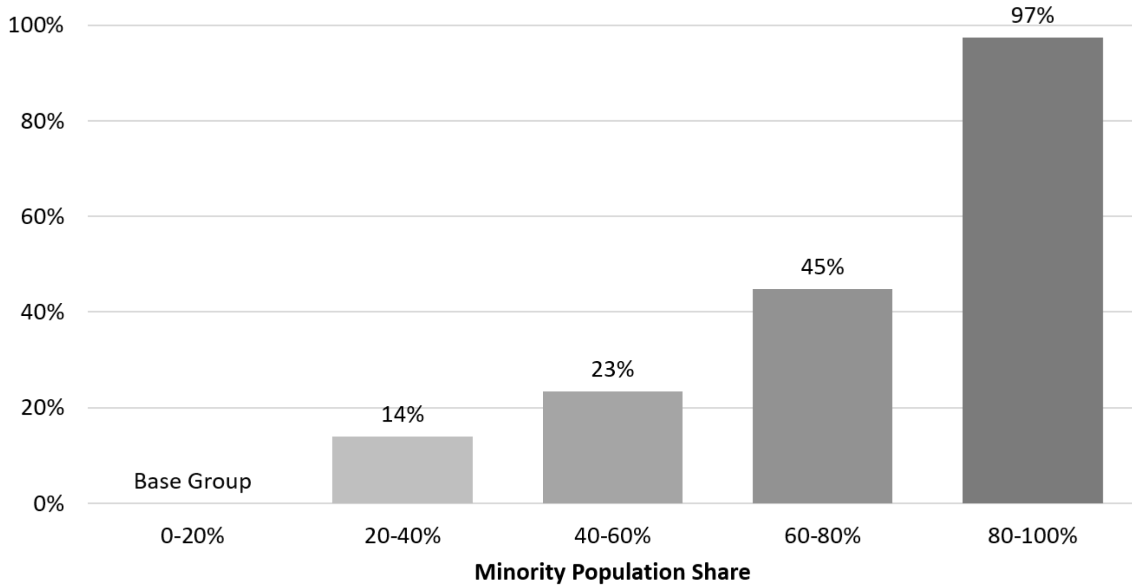

Figure 2: Minority Share and Quality
This figure presents a bar chart of the point estimates from the following regression:

$$lnComplaints_i = \sum_{r=2}^{5} \psi_r Minority_{r,zip5} + \sum_{b=2}^{50} \left(Mort_{b,zip5} + Pop_{b,zip5} + Inc_{b,zip5} + CollEd_{b,zip5} \right) + \zeta_{MSA} + \nu_{zip5}$$

Minority 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 percentage increase above the base category for this figure.

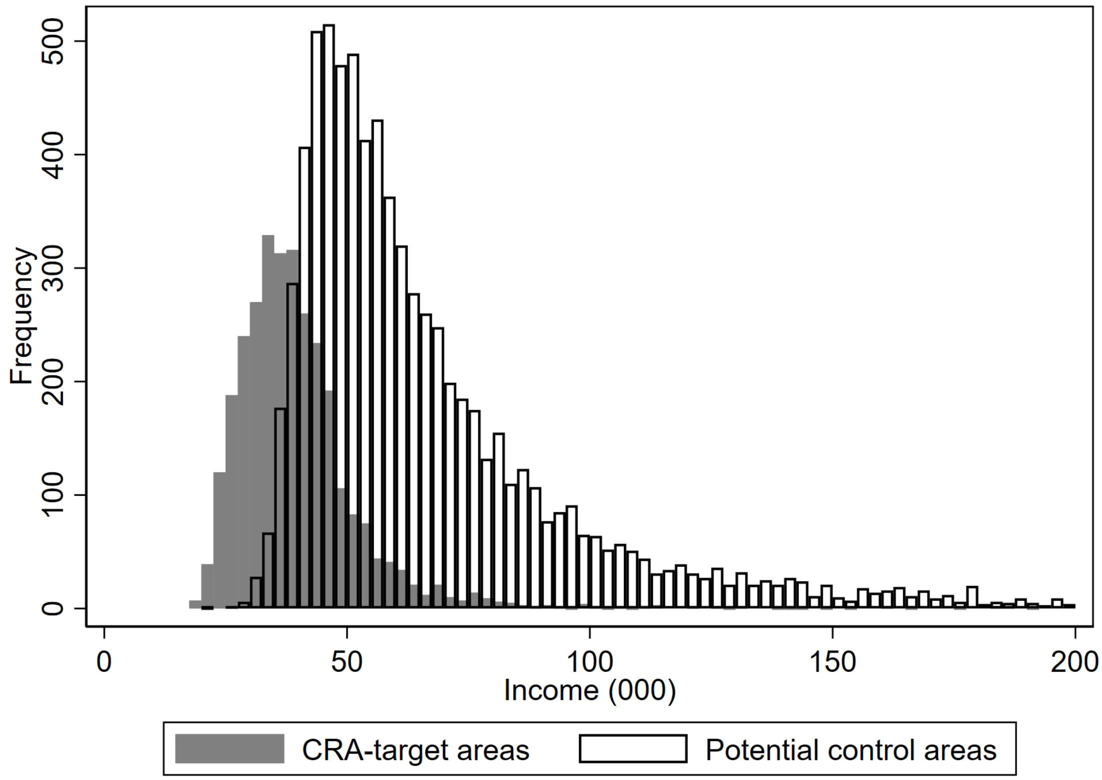

Figure 3: Area Income and CRA-target Status
This figure presents a histogram of income separately for CRA-target areas and control zip codes *CRA-target* areas are those where the majority of residents live in census tract designated as low-to-moderate income (LMI) by the CRA. Census tracts are designated LMI when the median family income is below 80% of the median MSA income. Control zip codes are those with zero population in LMI census tracts.

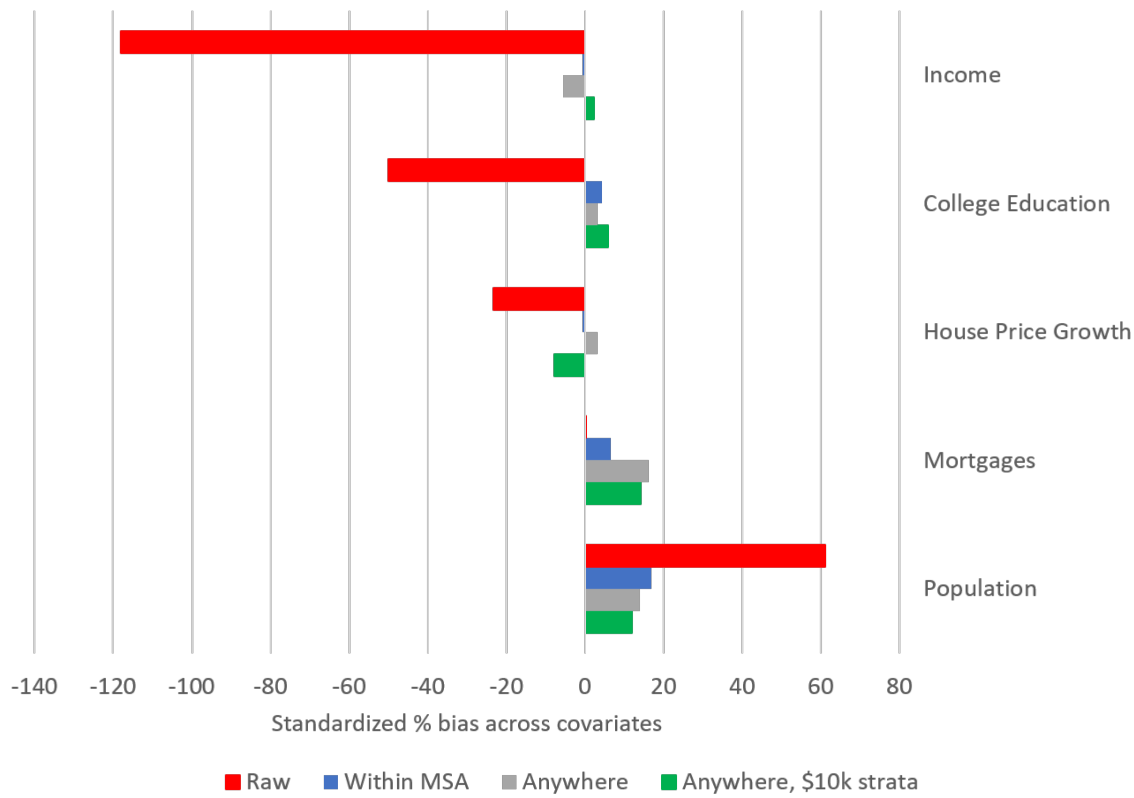

Figure 4: Covariate Balance for Raw and Matched Samples
This figure presents the difference in means between CRA-target zip codes and controls zip codes for the number of mortgages, population, income, education, and house price index changes. The difference is measured by the standardized % bias, which is the percent difference in means divided by the sample standard deviation of the variable. The *raw* differences are the base, unmatched comparisons. *Within MSA* represents the differences when matches are required to be in the same MSA as the CRA-target zip code. *Anywhere* represents the differences when matches for the CRA-target zip code can come from anywhere in the U.S. *Anywhere, $10k strata* represents the differences when matches for the CRA-target zip code can come from anywhere in the U.S. but must be in the same $10,000 income strata.

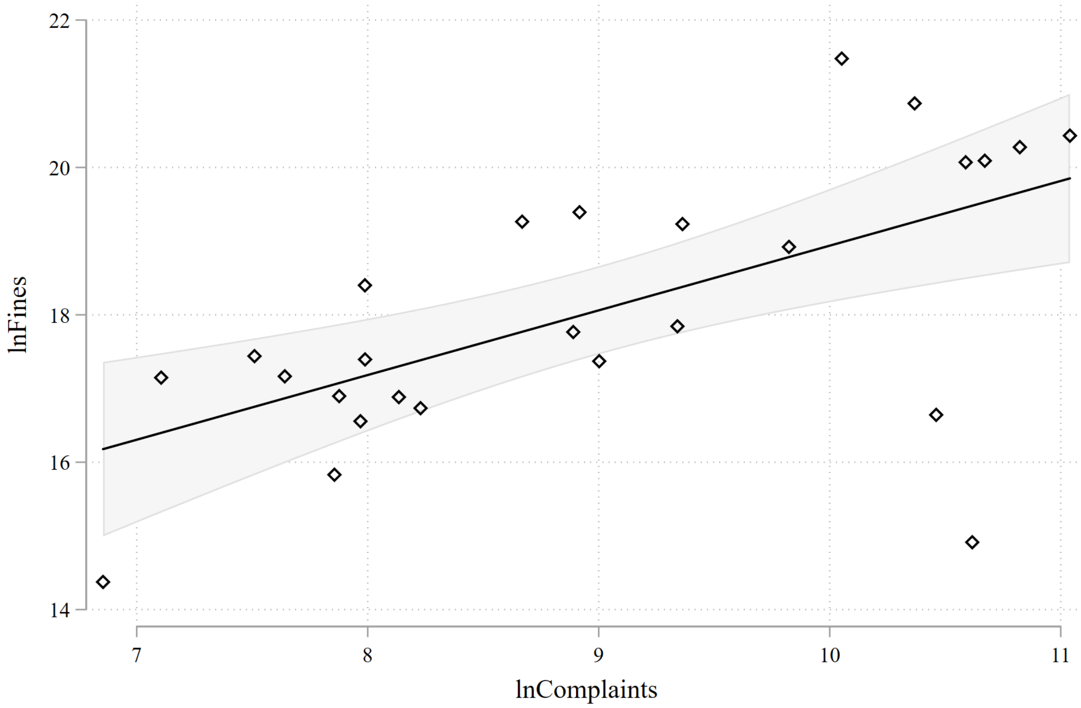

Figure 5: Consumer Complaints & Fines Paid By Banks
This figure plots the (log) number of complaints against (log) dollar fines paid by the bank due to CFPB's enforcement actions.

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, *Income* is the mean household adjusted gross income in the five-digit zip code for 2012, *lnIncome* 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. *Minority* is the share of the zip5 population that non-white for 2012. *CRA-target* is an indicator variable equal to one for zip codes with a majority of its population in low- to moderate-income tracts in 2010, zero if none of the population is in an LMI tract, and dropped for zip codes with a positive but less-than-majority of the population in LMI tracts. *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), 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
Income (000)	64.06	52.97	18.65	42.05	51.23	67.61	1464.53	16,309
lnIncome	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
Minority	0.21	0.21	0.01	0.05	0.13	0.30	0.90	16,309
CRA-target	0.28	0.45	0.00	0.00	0.00	0.00	1.00	10,974
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

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) , *lnIncome* is the log of the average adjusted gross income of households in each zip5 for 2012, *CollegeEducated* is the share of the zip5 adult population for 2012 with at least a bachelor's degree, and *Minority* 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 MSA.

	(1)	(2)	(3)	(4)	(5)	(6)
lnIncome			-0.11***			-0.08**
			(<0.01)			(0.03)
CollegeEducated				-0.05**		-0.01
				(0.01)		(0.83)
Minority					0.17***	0.16***
					(<0.01)	(<0.01)
MortBucket50 FE	No	Yes	Yes	Yes	Yes	Yes
PopBucket50 FE	No	No	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16309	16309	16309	16309	16309	16309
R^2	0.42	0.79	0.79	0.79	0.80	0.80

p-values in parentheses

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

Table 3: CRA-target Areas and Complaints: Within MSA

This table presents matching estimates for complaints (*lnComplaints*) for a given five-digit zip code (zip5) for CRA-target zip codes as compared to matched non-target zip codes, where *CRA-target* 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 from control zip codes from the same MSA as the treatment zip code to compute the average treatment effect on the treated (ATET). The kernel is epanechnikov with 0.03 bandwidth. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnIncome*, *CollegeEducated*, $\%\Delta\text{HP}_{2007-2012}$, and state indicator variables. Column (1) presents the baseline, full sample estimate. Columns (2)-(3) respectively restrict the sample to zip codes with below- (*Low minority share*) and above-median (*High minority share*) minority share of the population. Ntreat and Ncontrol represent the number of matched observations in the treatment and control groups. Standard errors are clustered by MSA.

	(1) Base	(2) Low minority share	(3) High minority share
CRA-target	0.25***	-0.04	0.35***
	(<0.01)	(0.47)	(<0.01)
N	7082	3431	3430
Ntreat	1701	352	1294
Ncontrol	5381	3079	2136

p-values in parentheses

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

Table 4: CRA-target Areas and Complaints: Across The Country

This table presents matching estimates for complaints (*lnComplaints*) for a given five-digit zip code (zip5) for CRA-target zip codes as compared to matched non-target zip codes from anywhere in the country. *CRA-target* 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 epanechnikov with 0.03 bandwidth. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnIncome*, *CollegeEducated*, $\%\Delta HP_{2007-2012}$, indicator variables for each decile of those five variables, and state indicator variables. Columns (1)-(3) use all possible zip codes within the country for matching. Columns (4)-(6) restrict the set of matching zip codes to areas that fall within a $10,000 income strata with treated area. Columns (2)-(3) and Columns (5)-(6) restrict the sample to zip codes with below- (*LowMinority*) and above-median (*HighMinority*) minority share of the population as indicated. Ntreat and Ncontrol represent the number of matched observations in the treatment and control groups. Standard errors are clustered by MSA.

	All			Income Strata		
	(1) All	(2) LowMinority	(3) HighMinority	(4) All	(5) LowMinority	(6) HighMinority
CRA-target	0.46***	0.09*	0.56***	0.40**	0.12**	0.48*
	(<0.01)	(0.07)	(<0.01)	(0.03)	(0.03)	(0.09)
N	8786	4192	4391	6947	2584	3285
Ntreat	1978	378	1598	1777	343	1333
Ncontrol	6808	3814	2793	5170	2241	1952

p-values in parentheses

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

Table 5: Quantity-Quality Trade-Off: Two-Stage Regressions

This table presents regression estimates that link the quantity of lending activity to the quality of financial services. The two measures of the quantity of lending activity are the (log) number of applications (*lnApps*) for mortgages and (log) number of mortgages originated (*lnOrigs*) in the zip code during our sample period. Columns (1) and (2) estimate the effect of these measures of the quantity on number of complaints using an OLS regression model. Columns (3) and (4) present the first-stage regression estimates where the instrument is the CRA-target area, which is an indicator variable that equals one if the majority of the population in the zip code are in tracts classified as low-to-moderate income by the CRA, and zero if the zip code contains no lmI census tracts. Columns (5) provides the reduced-form estimation result linking CRA-target status to the (log)number of complaints (*lnComplaints*). Columns (6)-(7) provide the second stage estimation for applications and originations, respectively. *Controls lnMortgages*, *lnPopulation*, *CollegeEducated*, $\%\Delta HP_{2007-2012}$ the area's income relative to MSA-level median family income. *Controls Interactions* contains the interactions of the control variables with the area's relative income. We also include relative income interacted with each of the other control variables. First-stage F-statistics are presented at the bottom of the table. All estimations include MSA fixed effects, and standard errors are clustered at the MSA level.

	OLS		First Stage		Reduced Form	IV	
	(1) lnComplaints	(2) lnComplaints	(3) lnApps	(4) lnOrigs	(5) lnComplaints	(6) lnComplaints	(7) lnComplaints
CRA-target			0.071***	0.050**	0.134***		
			(<0.01)	(0.02)	(<0.01)		
lnApps	0.172***					1.884***	
	(<0.01)					(<0.01)	
lnOrigs		0.100***					2.666**
		(<0.01)					(0.02)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3126	3126	3126	3126	3126	3126	3126
Instrument						CRA-target	CRA-target
First-Stage F-Statistic						11.225	5.445

p-values in parentheses

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

Table 6: Alternative Measure: Complaint Ratio

This table presents matching estimates for an alternative measure of complaints: number of complaints divided by the number of mortgages in the zip code during the sample period. We standardized this ratio to have mean zero and unit standard deviation. The estimates measure the difference (in standard deviations) in this measure of complaints between CRA-target zip codes and matched non-target zip codes. 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 epanechnikov with 0.03 bandwidth. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnIncome*, *CollegeEducated*, $\%\Delta \mathrm{HP}_{2007-2012}$, indicator variables for each decile of those five variables, and state indicator variables. Column (1) presents the estimate where matches are required to be in the same MSA. Column (2) allows matches from anywhere in the country, and column (3) restricts them to matches to be within the same $10,000 income strata as the treated zip code. Ntreat and Ncontrol represent the number of matched observations in the treatment and control groups. Standard errors are clustered by MSA.

	Within MSA (1)	Match Anywhere (2)	Match within $10k Strata (3)
CRA-target	0.40**	0.30***	0.40**
	(0.04)	(<0.01)	(0.03)
N	5765	8526	6757
Ntreat	457	1735	1603
Ncontrol	5308	6791	5154

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Complaints by Resolution

This table presents matching estimates based on the resolution of complaints. The dependent variable is the standardized (mean zero, unit standard deviation) number of complaints of the relevant type for the zip code. The estimates measure the difference (in standard deviations) in the number of complaints between CRA-target zip codes and matched non-target zip codes. The matching method uses a kernel-weighted propensity score to construct counterfactuals to compute the average treatment effect on the treated (ATET), and matches are required to be in the same MSA. The kernel is epanechnikov with 0.03 bandwidth. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnIncome*, *CollegeEducated*, $\%\Delta HP_{2007-2012}$, and state indicator variables. Column (1) presents the estimate for the entire sample. Columns (2)-(4) are based on complaints that were resolved with relief, with explanations, and without relief, respectively. Ntreat and Ncontrol represent the number of matched observations in the treatment and control group. Standard errors are clustered by MSA.

		Resolution of Complaint		
	All	Relief	Explanation	No Relief
	(1)	(2)	(3)	(4)
CRA-target	0.28***	0.19**	0.28***	0.19**
	(<0.01)	(0.04)	(<0.01)	(0.04)
N	5987	5987	5987	5987
Ntreat	606	606	606	606
Ncontrol	5381	5381	5381	5381

p-values in parentheses

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

Table 8: Alternative Matching Criteria

This table presents matching estimates for alternative matching techniques. The dependent variable is the log number of complaints in the zip code. *CRA-target* is one for zip codes where the majority of the population is in low-to-moderate (LMI census tracts as designated by the CRA. Control zip codes are those with zero population in LMI census tracts. The estimates measure the difference in this measure of complaints between CRA-target zip codes and matched non-target zip codes. Columns (1)-(3) uses kernel-weighted propensity score to construct counterfactuals to compute the average treatment effect on the treated (ATET). The kernel is epanechnikov with bandwidth of 0.03, 0.02, and 0.04 in columns (1), (2) and (3), respectively. Column (4) uses local linear regression matching technique, instead of kernel-weighting. Columns (5) - (7) are based on nearest-neighborhood matching criteria using one, three, and five nearest neighbors respectively. The propensity score is estimating using probit regression and includes *lnMortgages*, *lnPopulation*, *lnIncome*, *CollegeEducated*, $\%\Delta\text{HP}_{2007-2012}$, and state indicator variables. Each estimate requires matches to be from the same MSA as the CRA-target zip code. Ntreat and Ncontrol represent the number of matched observations in the treatment and control group. Standard errors are clustered by MSA.

Scheme	(1) k(0.03)	(2) k(0.02)	(3) k(0.04)	(4) llr(0.03)	(5) nn(1)	(6) nn(3)	(7) nn(5)
CRA (atet)	0.25	0.17	0.39	0.43	0.50	0.51	0.39
	(<0.01)	(0.02)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
N	5924	5874	6004	7064	7064	7064	7064
Ntreat	543	493	623	1683	1683	1683	1683
Ncontrol	5381	5381	5381	5381	5381	5381	5381

p-values in parentheses

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

A 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

B CRA Examination Procedures

The following presents a portion of the instructions for performing Community Reinvestment Act examinations for Large Institutions.[17] This excerpt illustrates the important link between the CRA and Fair Housing laws, which focus on discrimination. As discussed in Section 2.1 in the paper, poor performance on this section alone can have substantial effects on a lender's overall CRA rating.

> Review the results of the most recent compliance examination and determine whether evidence of discriminatory or other illegal credit practices that violate an applicable law, rule, or regulation should lower the institution's preliminary overall CRA rating, or the preliminary CRA rating for a state or multistate MSA.[4] If evidence of discrimination or other illegal credit practices by the institution in any geography, or in any assessment area by any affiliate whose loans have been considered as part of the bank's lending performance, was found, consider the following:
>
> 1. The nature, extent, and strength of the evidence of the practices;
> 2. The policies and procedures that the institution (or affiliate, as applicable) has in place to prevent the practices;
> 3. Any corrective action the institution (or affiliate, as applicable) has taken, or has committed to take, including voluntary corrective action resulting from self-assessment; and
> 4. Any other relevant information.
>
> Assign final overall rating to the institution. Consider: The preliminary rating; and any evidence of discriminatory or other illegal credit practices, and discuss conclusions with management.
>
> [4] "Evidence of discriminatory or other illegal credit practices" includes, but is not limited to: (a) Discrimination against applicants on a prohibited basis in violation, for example, of the Equal Credit Opportunity Act or the Fair Housing Act; (b) Violations of the Home Ownership and Equity Protection Act; (c) Violations of section 5 of the Federal Trade Commission Act; (d) Violations of section 8 of the Real Estate Settlement Procedures Act; and (e) Violations of the Truth in Lending Act regarding a consumer's right of rescission.

[17] https://www.ffiec.gov/cra/examinations.htm

C Economic Importance

We provide some examples below from CFPB, other government agencies, consumer counseling agencies, and actual complaints as some anecdotal evidence in support of the economic importance of CFPM complaints.

- **Evidence from CFPB:** Warning Letter for False Advertising: On November 19, 2012, CFPB issued a warning letter to approximately a dozen mortgage lenders and brokers regarding misleading advertisement practices. In their press release, they specifically mention the use of CFPB complaints as an input to their decision to take this action. Here is an excerpt from their press release:

  > "Today's actions stem from a joint "sweep," a review conducted by the CFPB and the FTC of about 800 randomly selected mortgage-related ads across the country, including ads for mortgage loans, refinancing, and reverse mortgages. The agencies looked at public-facing ads in newspapers, on the Internet, and from mail solicitations; some came to the attention of the CFPB and the FTC from *consumers who complained about them.*
  >
  > The CFPB and the FTC were looking for potential violations of the 2011 Mortgage Acts and Practices Advertising Rule, which prohibits misleading claims concerning government affiliation, interest rates, fees, costs, payments associated with the loan, and the amount of cash or credit available to the consumer. The CFPB and the FTC share enforcement authority for the rule. Companies that the CFPB finds have violated prohibitions on misleading advertising could be subject to enforcement actions." (emphasis added)

- **Evidence from consumer counseling agencies:** A HUD-approved housing counseling agency, MSU Extension described the use of consumer complaints to its consumers:

  > "*The CFPB uses the data it collects to launch investigations, guide its oversight of banks, and fine for wrongdoing.* To date, it has issued hundreds of millions of dollars in penalties to clamp down on financial exploitation of consumers. For example, Wells Fargo Bank was fined $1 billion for practices on its auto loans and mortgages. Chase, Citibank and American Express had to pay $537 million in refunds and penalties for deceptive credit-card marketing. U. S. Bank was fined $48 million for charging 420,000 borrowers who never received identity theft protection services they paid for. It also busted nationwide mortgage modification scams requiring large up-front fees to fake lawyers for promised lower rates they never received." (emphasis added)

- **Evidence from other government agencies:** CFPB complaints are also used in the assessment of Community Reinvestment Act (CRA) compliance. Here is an excerpt from the recent CRA evaluation report:

> "Pursuant to 12 CFR 25.28(c) or 195.28(c), respectively, in determining a national bank's or federal savings associations (collectively, bank) CRA rating, the OCC considers evidence of discriminatory or other illegal credit practices in any geography by the bank, or in any [assessment area] by an affiliate whose loans have been considered as part of the banks lending performance. As part of this evaluation process, the OCC consults with other federal agencies with responsibility for compliance with the relevant laws and regulations, including the U.S. Department of Justice, the U.S. Department of Housing and Urban Development, and the *Bureau of Consumer Financial Protection*, as applicable. The OCC has not identified that this institution has engaged in discriminatory or other illegal credit practices that require consideration in this evaluation." (emphasis added)

- **Evidence from press article:** An example of direct action based on a consumer's complaint:[18]

> "When Harry of Hull, Mass., learned that his son Ari, a soldier about to be deployed to Iraq, was struggling with a predatory auto loan that was targeted to service members, he knew just what to do. He wrote to the Consumer Financial Protection Bureau. Harry's complaint (the CFPB would not give us his last name) launched an investigation that uncovered deceptive practices by U.S. Bank and one of its nonbank partners, Dealers' Financial Services, in selling subprime auto loans to active-duty service members. As a result, U.S. Bank and DFS were ordered to return more than $5.5 million to those affected. "It's great to have someone in our corner," Ari said.

[18]Source: https://www.consumerreports.org/cro/news/2015/07/how-to-complain-and-get-results-with-the-consumer-financial-protection-bureau/index.htm. Also documented at the CFPB's website: https://files.consumerfinance.gov/f/201407_cfpb_everyone-has-a-story_meet-harry-and-ari.pdf.