Whose Voice Do We Hear in the Marketplace?: Evidence from Consumer Complaining Behavior*

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Abstract

Consumers' voice has increasingly become a major factor in the marketplace through consumer complaints, but little is known about who chooses to complain and how complainants compare to consumers of the product. Any differences in complaint rates across groups can reflect either different propensities to complain, or different consumer experiences, making it difficult to assess the degree of self-selection. I utilize a set of law enforcement actions to separate these two explanations by comparing characteristics of complaining consumers to those of victims, and find much lower complaint rates in heavily minority areas compared to non-minority areas, relative to their respective victimization rates. I find evidence against information-based accounts for why victims from minority areas are less likely to complain, and in favor of explanations related to lower levels of trust or general social capital. I then provide a statistical weighting approach in order to remedy the problem of self-selection, and apply it to develop an implied victimization rate using complaints from the Consumer Sentinel database.

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1 Introduction

Nearly 50 years ago, Hirschman (1970) highlighted the crucial role that consumer "voice" plays in markets. The Internet has magnified that role through easily accessible user-generated reviews, which have become a major source of information on the quality of products and companies. In this paper, I focus on consumer complaints; policymakers now receive millions of such complaints per year. They use the information in these complaints to learn about company practices and decide whether a company is violating the law.

Despite the growing power of consumers' voice, we know very little about whose voice we hear. Consumers self-select to complain, which could affect both which companies receive complaints and the assessment of quality provided by the complaints. For example, if the demographics of consumers that provide complaints are very different from fraud victims, policymakers may not learn about problems that affect communities that do not complain.

Unfortunately, it is difficult to assess the degree of self-selection in complaining behavior. Higher rates of complaints for a given set of consumers could reflect either differences in a consumer's propensity to vocalize, or in the experience the consumer received. The existing literature on complaining behavior has, in general, only examined data on complaining consumers, and so cannot disentangle these two explanations.

I separate these two explanations through a set of nine law enforcement actions ("cases"), for which I can combine information on affected consumers, whom I will refer to as "victims", with complaints on those companies from the Consumer Sentinel Network.[1] I can thus

[1] The Consumer Sentinel database receives complaints reported to federal and state government agencies as well as private actors such as the Better Business Bureaus (BBBs). See https://www.ftc.gov/enforcement/consumer-sentinel-network for more details on the Consumer Sentinel Network.

compare how the characteristics of complainants differ from consumers for a given company, based on zip code demographics obtained from consumers' addresses. Because the cases I use vary substantially from each other in size, average amount lost, type of fraud, and the demographics of victims, any conclusions about self-selection behavior that hold across cases are likely to hold more generally for fraud related consumer protection matters.

I find that heavily black and Hispanic areas complain substantially less relative to their rate of victimization after controlling for other demographic chracteristics. I examine the differences between complaining consumers and victims through a set of mixed logit models. I find that the complaint rate falls by 61% relative to the victim rate as the percentage of black residents rises from 0% to 100%, and by 43% as the percentage of Hispanic residents rises from 0% to 100%. Across cases, I find effects significantly different from zero for 6 of 9 cases for the percentage of black residents and 5 of 9 cases for the percentage of Hispanic residents. Thus, self-selection in complaining disproportionately reduces the complaint rate for minority communities compared to non minority communities, relative to their respective level of victimization.

I then turn to examining why residents of heavily minority areas complain at much lower rates than other communities, relative to their rate of victimization. The FTC provides several explanations in a recent report to Congress (Federal Trade Commission, 2016) for why black and Hispanic communities may complain less:

> In the FTC's workshops and conferences, however, many have observed a general reluctance and embarrassment to report fraud. Further, despite the higher prevalence of fraud, some have stated that African American and Latino con-

> sumers may distrust the government, may not know where to complain, may believe their complaints will not make a difference, or may have concerns about encountering the government because of their immigration status.

I categorize these explanations as based on differences in either information or levels of social trust. To test explanations due to information differences, I compare cases where consumers lost thousands of dollars to those where consumers lost tens of dollars, as consumers would likely know they were defrauded and have incentives to find out how to complain when they lost large amounts of money. Since minority communities complain less than non-minority communities relative to their rate of victimization for both types of cases, I do not find support for explanations based on information.

In contrast, quantitative evidence from the General Social Survey (GSS), as well as qualitative evidence from sociology and marketing, suggests that minorities have lower levels of social trust. Lower social trust could reduce complaining because of mistrust of government specifically, or because a feeling of societal exclusion reduces pro-social activity. I find evidence against mistrust of government, as surveys do not show substantial racial gaps for trust in government, and non-governmental BBB complaints exhibit similar selection patterns as government complaints.

I then estimate interaction models in order to examine mechanisms for how alienation could affect complaining behavior. I find lower selection effects for the percentage of Hispanic residents in areas with more foreign born residents, or more speakers of languages other than English. While inconsistent with explanations through language barriers or fears of immigration enforcement, these findings would be consistent with greater alienation for later generation Hispanics. The complaint to victim ratio falls with an increase in the percentage of minority residents for both more advantaged and less advantaged areas; thus, explanations through societal exclusion cannot be narrowly based on the socioeconomic status of minority residents.

Consumer complaint rates are often used to understand how victimization rates differ between different communities; with self-selection in complaining, such inferences would be misleading. Weighting complaints based on the propensity to complain is one way to adjust for self-selection; communities that are less likely to complain relative to their rate of victimization would receive greater weight. I use my empirical estimates to construct such weights, and find that complaint rates from majority black areas should receive about double the weight of the median zip code in order for their complaint rates to match the level of victimization.

I then use these weights to construct an implied victimization rate by multiplying 2015 aggregate complaint rates from Consumer Sentinel across US communities by these weights to reflect the degree of victimization. While the aggregate complaint rate is only slightly higher in heavily black communities, compared to communities with few blacks, heavily black areas have more than triple the implied victimization rate. The aggregate complaint rate is about 50% lower in heavily Hispanic communities than areas with few Hispanics, while the implied victimization rates in Hispanic areas follow an inverse U shape pattern with the highest rates in moderately Hispanic communities. My implied victimization rates are consistent with evidence from victimization surveys that has found much higher rates of victimization for minorities (Anderson, 2007, 2013).

This paper relates to a large body of work examining consumer complaining behavior. While a large body of empirical work has examined how demographics affect complaint behavior, it does not control for victimization (Singh, 1989; Oster, 1980; Garrett and Toumanoff, 2010; Ayres et al., 2013). Thus, it is unsurprising that Garrett and Toumanoff (2010) find that the literature is divided on how demographics such as age, income, education, and race affect the likelihood of consumer complaint. Hirschman (1970)'s major question was how market structure affected the likelihood that consumers used voice, as opposed to exit; Gans et al. (2017) build a model based on Hirschman's work that predicts more complaints in more concentrated markets, and find evidence for the model's predictions using tweets to US airlines.

In addition, a more recent literature has examined consumer's reviews on online platforms. Two recent papers focus on accounting for selection in negative reviews. Nosko and Tadelis (2015) show that buyers on eBay typically do not post negative reviews, and that a measure of seller quality based on the fraction of purchases with a review can help to promote higher quality sellers. Fradkin et al. (2017) show that negative experiences are underreported on AirBnB, and that either paying consumers to review or having sellers and buyers simultaneously review can reduce this underreporting.[2]

The paper proceeds as follows. Section 2 details the legal cases and demographics used in this paper, while Section 3 shows how the demographics of complaining consumers compare to victims. Section 4 tests explanations for why victims from heavily minority areas are less likely to complain than victims from other areas. Section 5 provides a solution to the problem of self-selection through weighting. Section 6 then concludes.

[2]In addition, Mayzlin et al. (2014) show evidence of strategic reviewing behavior, as firms place negative reviews of their competitors. Dai et al. (2014) examine how to construct an optimal quality ranking when reviewers vary in the bias and precision of their reviews. Hu et al. (2008) and Ghose and Ipeirotis (2011) examine how the characteristics of reviews and reviewers affect consumer demand.

2 Data

The foundation of this paper is a set of legal cases for which I have data on affected consumers from consumer databases of the company together with complaints for the same company, and for which I can match consumers to area demographics at the zip code level. Below, I detail the Census demographics and legal cases that I use in the analysis.

2.1 Census Demographics

For demographics, I use information at the 5 digit zip code level from the 2008-2012 American Community Survey (ACS).

I examine several demographic factors that likely proxy for cultural and economic factors that could affect the likelihood that a consumer complains. I first include ethnic demographics, including the fraction of the zip code population that is black, that is of Hispanic origin, and that is Asian. I also include the percentage of the zip code located in an urban area.

Second, I use information on the economic and family situation of the zip code, including the median household income, median household size, median age, the unemployment rate, and the fraction of the zip code population that is college educated. These factors could affect complaining for several reasons. First, filing a complaint takes time, and so consumers with a higher cost of time – such as those with a higher income, who are employed, or who have kids – might be less likely to complain. On the other hand, poorer consumers may have more pressing concerns, such as food, housing, or safety, than consumer fraud. Another reason for different complaint rates could be knowledge of the appropriate authorities to complain to; college educated consumers might be more likely to be informed about authorities that receive consumer complaints and seek to remedy problems.[3]

I exclude zip codes belonging to PO Boxes and Unique Organizations (such as businesses or universities that have their own zip code) and zip codes with a population of less than 100 in 2010.[4] I also exclude zip codes missing the Census demographic variables described above. This process leaves a set of 28,604 zip codes that I use for my main analyses.

2.2 Legal Cases

I match these zip code level demographics to data from nine legal cases. For each case, I have data from consumer databases detailing the victims of a case as well as consumer complaints about the companies involved in the case. In order to obtain these cases, staff at the Federal Trade Commission undertook a search of recent cases involving violations of consumer protection laws.[5] In order to be included in the paper, a given case had to have data from a customer database as well as a list of consumer complaints. In order to have power for statistical analysis, I require that there exist at least 150 consumer complaints on the company. In addition, the litigation with the company must have been completed (all defendants either settled, or a final judgment was entered), and there must be no legal restrictions barring the use of the data. This process led to nine legal cases to use in the analysis.

Consumer complaints come from the Consumer Sentinel Network, which collects data on

[3]In Appendix B, I provide greater detail about the distribution of each of these variables.

[4]The Census has created the Zip Code Tabulation Area (ZCTA) in order to connect Census demographics to zip codes from addresses, because the zip code is not a traditional Census geography. The boundaries of zip codes and ZCTAs do not always perfectly line up, so I exclude zip codes for PO Boxes and Unique Organizations in order to reduce differences between the two.

[5]I am able to access the data used in this paper as part of my duties as an employee of the FTC.

consumer complaints from several sources – federal government agencies such as the Federal Trade Commission (FTC) and Consumer Finance Protection Bureau (CFPB), private actors such as the Better Business Bureaus (BBBs), and state and local government agencies.[6] For each legal case, I obtain complaints either by direct searches of Consumer Sentinel using company names, or from the set of complaints used by law enforcement authorities as part of the case.[7] I only include victims and complaints which report a zip code that can be matched to the set of zip codes I detail in Section 2.1.

I summarize the differences across these cases in Table I. In Appendix A, I provide further details on the cases, including a short description and links to further information. In Table I, I display the number of victims and the number of complaints for each case that can be matched to zip codes with full demographic data, as well as the complaint to victim ratio. In addition, I have included an approximate average loss for consumers based on information from either the FTC legal complaint in the case or from redress data, as well as a simple description of the case. Across the nine cases, the number of victims, the complaint to victim ratio, and the average loss vary substantially.

The first five cases – Case B[8], Ideal, Platinum, WinFixer, and SimplePure – have large numbers of victims, low complaint to victim ratios, and a low average loss per victim. Case B has over 12 million victims and Ideal 2 million victims, while Platinum, WinFixer, and SimplePure have between 50,000 and 1 million victims each. The number of complaints

[6]See https://www.ftc.gov/enforcement/consumer-sentinel-network/reports for the Consumer Sentinel Data Book, which contains further detail on the Consumer Sentinel as well as a wealth of statistics on the complaints included in it.

[7]Because the Consumer Sentinel Network has a five year data retention policy, complaints had to either be relatively recent, or saved by the legal team for the case. I include complaints from all sources, including identity theft and Do Not Call complaints and complaints given directly to the case team from Consumer Sentinel contributors.

[8]For this case, I am unable to disclose the company's name or details on its industry.

ranges from 0.35 and 7.3 complaints per 1,000 victims across cases, while the average victim loss for these cases ranges roughly between \$30 and \$110.

The second four cases – AdvStrategy, Guidance, MoneyNow, and PHLG – each have a much smaller number of victims, a much higher complaint to victim ratio, and a large average loss per victim. The number of victims across cases ranges between 1,800 and 7,000 victims. The number of complaints ranges between 25 and 150 complaints per 1,000 victims, while the average loss per victim is about \$500 in the PHLG case, and over \$2,000 in the other three cases.

Beyond these massive differences in the number of victims, the complaint to victim ratio, and average loss per victim, the different cases reflect a wide variety of different alleged fraudulent activity. The Ideal and Platinum cases are based on defrauding victims who filed payday loan applications, the WinFixer case is about spyware and computer security scans, and SimplePure about advertising and purchasing herbal supplements. Guidance, MoneyNow, and AdvStrategy are all cases involving business opportunities or business coaching, while PHLG involves the money transfer element of imposter scams.

3 Are the Demographics of Complainants and Victims Different?

In this section, I first show that controls for victimization are necessary because victim demographics vary substantially across the different cases. I then use the set of legal cases to show how the demographics of complainants differ from those of victims, and find that

Table I Cases with Victim Lists

Case	Number of Victims	Number of Complaints	Complaints per 1,000 Victims	Average Loss	Case Description
Case B	12,311,307	4,271	0.35	≈ \$40-\$90	
Ideal	2,010,169	1,403	0.70	≈ \$30-\$40	Payday Loan Apps
Platinum	69,576	510	7.3	≈ \$110	Payday Loan Apps
WinFixer	304,493	1,062	3.5	≈ \$60	Computer Security
SimplePure	681,124	650	0.95	≈ \$90	Dietary Supplements
AdvStrategy	11,361	322	28.3	≈ \$2,200	Business Opportunity
Guidance	6,696	193	28.8	≈ \$1,600 - \$8,000	Business Coaching
MoneyNow	1,801	259	143.8	≈ \$2,800	Business Opportunity
PHLG	2,641	289	109.4	≈ \$500	Money Transfer for Imposter Scams

Note: The number of victims and number of complaints reflects all victims and complaints that can be matched to zip codes in Section 2.1, after duplicate entries were removed. The average loss per victim is approximate and based on available information from the FTC legal complaint, press releases, or redress information.

residents of heavily minority areas complain less than residents of other areas relative to their degree of victimization.

3.1 Why Control for Victimization?

Because the degree of victimization varies across demographic groups, the demographics of complainants will, in general, be different than the demographics of the general population even without any selection in who complains. I show in this section that the demographics of victims varies across cases, and that the demographics of victims affects the demographics of complaints. Thus, after controlling for victimization through the ratio of complaints to victims, I can examine how the propensity to complain varies across demographics.

Differences in the demographics of victims across cases likely reflect the behavior at issue in these cases, and make it important to control for victimization in order to examine complaining behavior. For example, victims in the Ideal and Platinum cases applied for payday loans, victims in the MoneyNow, Guidance, and AdvStrategy cases wanted to create their own business, victims in the WinFixer case had to have computers in order to have spyware, and victims in the SimplePure case were interested in purchasing dietary supplements.

In Figure 1, I demonstrate these differences by showing the per capita victim rate from majority black zip codes across the legal cases. I define the victim rate as the number of victims in a zip code divided by the 2010 Census population. Since the absolute number of victims varies widely across cases, I normalize the victim rate in majority black areas by dividing by the overall average victim rate for the case; in both cases, I weight across zip codes using population weights. A value of one thus indicates that majority black zip codes have the same per capita victim rate as the average across all zip codes. Bars in black represent the normalized victim rate for zip codes with a greater than 50% black population.

Four cases have a substantially larger per capita victim rate from majority black zip codes relative to national averages. The per capita victim rate in majority black zip codes is 50% higher than national averages for Case B, 120% higher for PHLG, 162% higher for Ideal, and 185% higher for Platinum. In the SimplePure, WinFixer, AdvStrategy, and MoneyNow cases, the per capita victim rate from majority black zip codes is similar to national averages. The per capita victim rate in majority black zip codes is 22% lower for Guidance.

These differences in victim rates also affect per capita complaint rates. The grey bars in Figure 1 represent the average normalized complaint rate for zip codes with a greater than 50% black population. I define the complaint rate in the same way as the victim rate. The complaint rate is the the number of complaints in a zip code divided by the 2010 Census population; I normalize by dividing by the overall average complaint rate in the case and use population weights. For the cases with a much larger per capita victim rate from majority black zip codes, the per capita complaint rate from majority black zip codes is 82% higher than the national average for Ideal, 42% higher than the national average for Platinum, and 145% higher than the national average for PHLG. Thus, differences in complaint rates do not solely reflect differences in the propensity to complain across demographic groups.

I control for victimization by examining the complaint rate divided by the victim rate, which I call the *complaint to victim ratio*, for majority black or Hispanic zip codes. I normalize this by dividing by the national average for the case, so values less than one indicate that the number of complaints to victims is lower for these zip codes compared to the national average. Figure 2 depicts these estimates. The complaint to victim ratio is higher for majority black zip codes than national averages for only one case, PHLG, and is higher for majority Hispanic zip codes than national averages for two cases, Guidance and PHLG. In all of the other cases, the complaint to victim ratio is 13% to 67% lower in majority black zip codes relative to national averages, and 13% to 49% less in majority Hispanic zip codes relative to national averages. Thus, I consistently find lower complaint to victim ratios in majority black or Hispanic areas compared to the national average across the different legal cases.

3.2 Which Demographic Communities Have a Higher Propensity to Complain?

In Figure 2, I showed that, for most of the legal cases, majority black and Hispanic communities have lower numbers of complaints relative to victims compared to national averages.

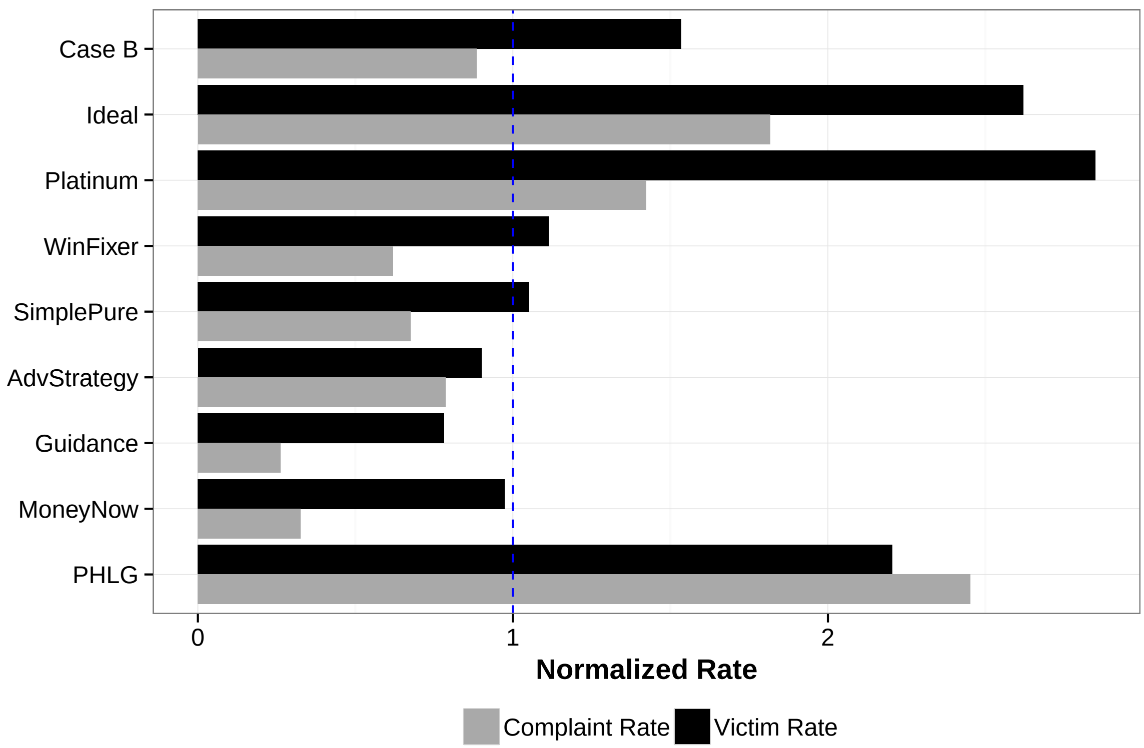


Figure 1 Victim and Complaint Rate for Majority Black Zip Codes, Relative to National Averages, Across Cases

Note: The graph depicts the victim rate (in black) and complaint rate (in grey) for majority black zip codes, for each of the nine legal cases, relative to the corresponding national average (where the national average is the population weighted average across zip codes). The blue vertical line indicates a value of one, so majority black zip codes have the same complaint or victim rate as the national average.

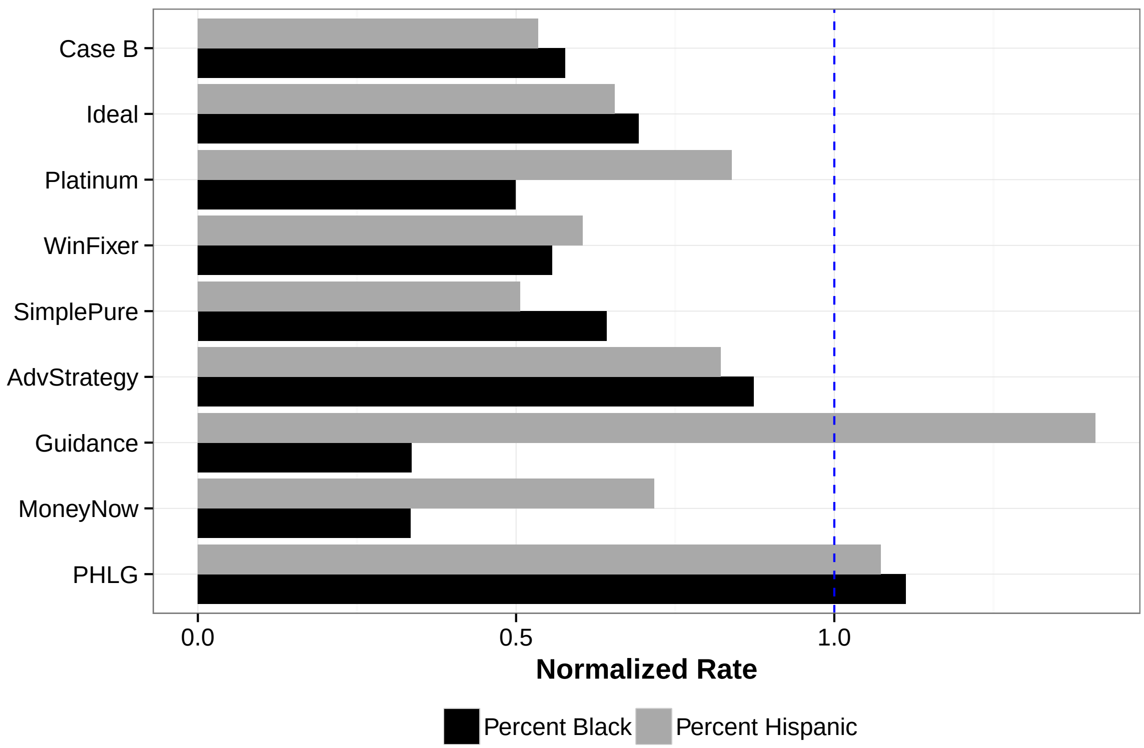


Figure 2 Complaint to Victim Ratio for Majority Black and Hispanic Zip Codes, Relative to National Averages, Across Cases

Note: The graph depicts the complaint to victim ratio, the complaint rate divided by the victim rate, from majority black zip codes (in black) and majority Hispanic zip codes (in grey), for each of the nine legal cases, relative to the national average in the same case (where the national average is the population weighted average across zip codes). The blue vertical line indicates a value of one, so majority black or Hispanic zip codes have the same ratio of complaint rate to victim rate as the national average.

However, any differences in complaining behavior could be due to other factors, such as differences in income and education across communities. Thus, I now examine all of the demographic characteristics in Section 2.1, and show that heavily black and Hispanic communities continue to have less complaints relative to their victimization rates compared to non-minority communities, after controlling for other demographic characteristics.

I do so by jointly modeling the per capita complaint rate and per capita victim rate for each company at the zip code level. I identify differences in complaining behavior across communities through the differential effect of demographics on the complaint rate relative to the victim rate. In order to estimate this specification, I first construct a dataset with two observations for each zip code-company combination, the per capita complaint rate and victim rate. I include all 28,604 zip codes detailed in Section 2.1 for all nine companies. I then estimate the following panel logit model:

$$y^*_{ijk} = \sum_s (\beta^j_s + \gamma_{ks}) D_{is} + \delta^j_k + \eta^j \log(Pop_i) + \rho_i + \epsilon_{ijk}. \tag{1}$$

In the equation above, i represents zip code, j whether the observation reflects a complaint rate or victim rate, and k represents company. The dependent variable y^*_{ijk} is a latent variable for the complaint rate or victim rate. I include all the demographic variables mentioned in Section 2.1 in D_{is}. The variables included are the percentage of black residents, the percentage of Hispanic residents, the percentage of Asian residents, the percentage of urban residents, the local unemployment rate, the percentage of college graduates, as well as, in logarithmic form, the median age, median household income, and median household size.

My main goal is to understand how the complaint rate and victim rate vary with demographics; β_s^j allow each demographic variable D_{is} to separately affect the complaint rate and the victim rate. Since the complaint to victim ratio is the ratio of the complaint rate and victim rate, the difference $\beta_s^C - \beta_s^V$ indicates how demographics affect the complaint to victim ratio.[9]

The effect of demographics can vary by company as well, in order to capture the differences shown in the previous subsection, through γ_{ks}. I also allow the complaint rate and victim rate to differ by company through δ_k^j. Finally, η^j allow the zip code's population to affect the complaint rate and the victim rate. I also include zip code random effects in ρ_i. All observations are weighted using 2010 Census population weights. The coefficients from this regression, and all other models estimated in this paper, are detailed in Web Appendix D.[10]

In Figure 3, I depict the estimated percent change in the complaint to victim ratio from changing each of the demographic factors. The y-axis indexes a change in each of the demographic factors. For each such factor, I plot the mean effect and the confidence interval around that mean. A null effect indicates that changing a demographic factor affects the victim rate and complaint rate symmetrically, after controlling for all other demographic variables, and so the complaint to victim ratio remains constant.

Residents of heavily minority communities have much lower numbers of complaints rel-

[9]Formally, for complaint rate r_i^C and victim rate r_i^V in zip code i, the change in the complaint to victim ratio $\frac{r_i^C}{r_i^V}$ from a change in demographic factor D_{is} from X to Y is:

$$\frac{r_i^C(D_{is}=Y)}{r_i^V(D_{is}=Y)} \Big/ \frac{r_i^C(D_{is}=X)}{r_i^V(D_{is}=X)} = \frac{r_i^C(D_{is}=Y)}{r_i^C(D_{is}=X)} \Big/ \frac{r_i^V(D_{is}=Y)}{r_i^V(D_{is}=X)} = \frac{\exp(\beta_s^C(Y-X))}{\exp(\beta_s^V(Y-X))}$$
$$= \exp((\beta_s^C - \beta_s^V)(Y-X)).$$

[10]I also include a robustness analysis using discretized demographic variables in Web Appendix C. I continue to find lower complaint to victim ratios in heavily minority communities compared to non-minority communities using discretized demographic variables, although the effects for the percentage of Hispanic residents are more nonlinear.

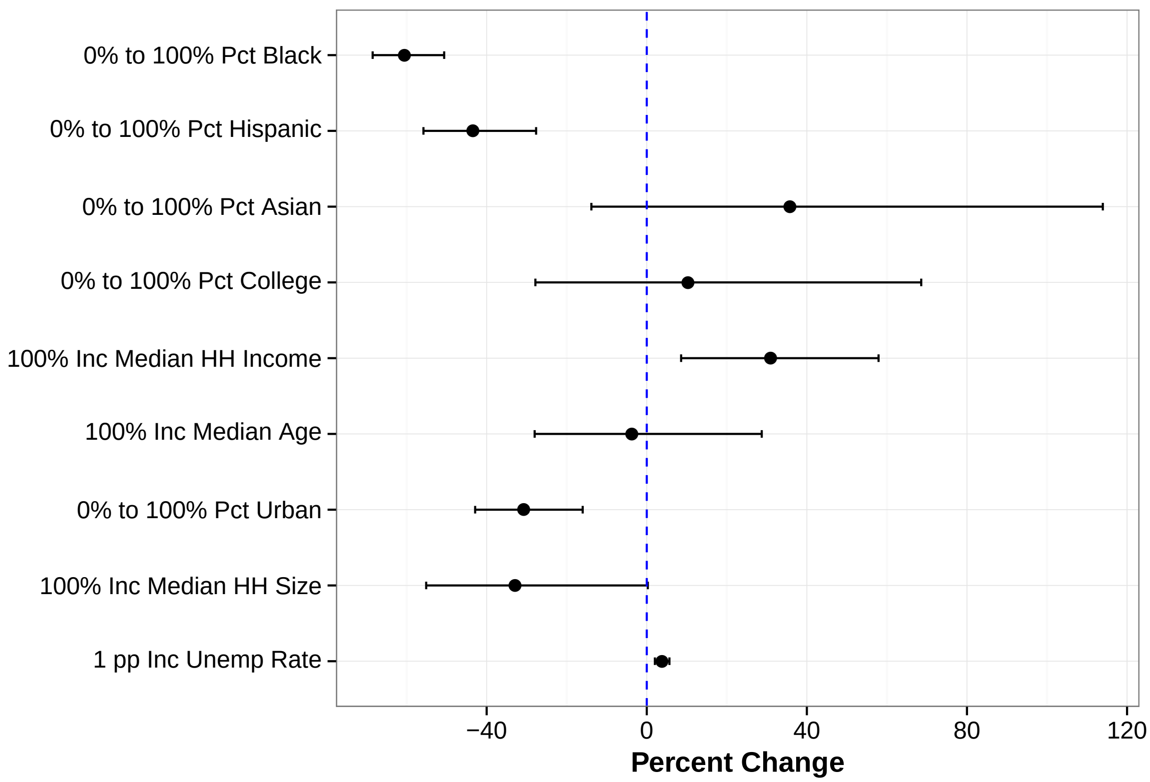


Figure 3 Percent Change in Complaint to Victim Ratio by Demographic Factors

Note: The graph depicts the estimated percent change in the complaint to victim ratio (the complaint rate divided by the victim rate) for changes in different demographic factors, as well as the associated 95% confidence interval. The blue, dashed vertical line indicates a value of zero, so changing the demographic factor does not differentially affect the complaint rate and victim rate and so the complaint to victim ratio is constant.

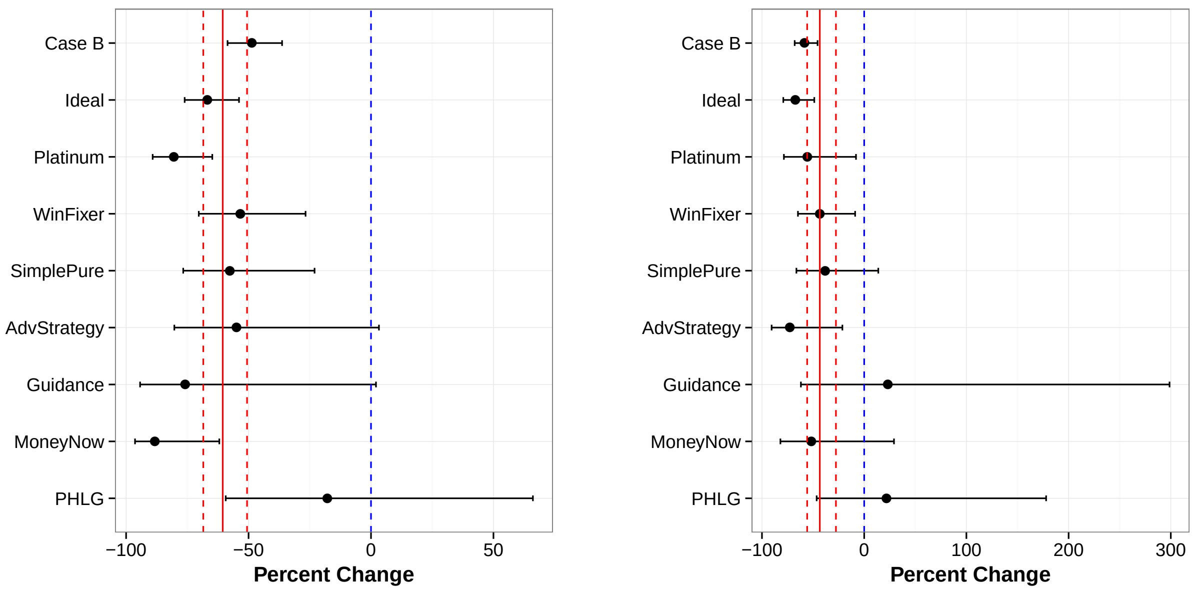
ative to victims. The complaint to victim ratio falls by 61% as the percentage of black residents in the zip code increases from 0% to 100%, and by 43% as the percentage of Hispanic residents in the zip code increases from 0% to 100%. The associated confidence intervals imply selection effects for complaining that are greater than 25%.

I find smaller selection effects for the other demographic variables. The estimates indicate that the complaint to victim ratio rises by 31% with a 100% increase in median income, falls by 31% with the percentage of the zip code that is urban rising from 0% to 100%, and rises by 4% with a 1 percentage point increase in the local unemployment rate. The confidence intervals for these effects exclude zero. In addition, the complaint to victim ratio falls by 33% with a 100% increase in median household size, rises by 10% as the percent of residents with a college education increases from 0 to 100%, and falls by 4% with a 100% increase in the median age, although I cannot reject null effects for these variables.

I examine the robustness of the main finding of lower numbers of complaints relative to victims as the fraction of minority residents rises by estimating equation (1) for each company individually.[11] In Figure 4, I depict the effects across cases; the y-axis indexes different cases, and the red solid and dashed vertical lines depict the estimated effect and confidence interval using all companies. For the percentage of black residents, I find a small (18%) and insignificant reduction in the complaint to victim ratio when moving from a 0% to 100% black community for only one case (PHLG). For all the other 8 cases, the estimates indicate a 49% to 88% reduction in the number of complaints relative to the number of victims as the percentage of black residents increases from 0% to 100%.

For the percentage of Hispanic residents, I estimate small (22 to 23%) increases in the

[11] In these specifications, I exclude random effects.



(a) Percent Black

(b) Percent Hispanic

Figure 4 Percent Change in Complaint to Victim Ratio by Racial Demographics

Note: The graph depicts the estimated percent change in the complaint to victim ratio, or the complaint rate divided by the victim rate, for changes in different demographic factors, as well as the associated 95% confidence interval. The red, solid vertical line depicts the mean effect using all companies depicted in Figure 3, while the red, dashed vertical line depicts the 95% confidence interval around this effect. The blue, dashed vertical line indicates a value of zero, so changing the demographic factor does not differentially affect the complaint rate and victim rate, and so the complaint to victim ratio is constant.

complaint to victim ratio when moving from a 0% to 100% Hispanic community for only 2 cases (PHLG and Guidance), although these are measured with considerable error and I cannot reject either null effects or large negative effects. For all the other 7 cases, the number of complaints relative to the number of victims fall by 38% to 73% as the percentage of Hispanic residents increases from 0% to 100%. The confidence intervals imply significant non-zero effects for six of nine cases for heavily black communities, and five of nine cases for heavily Hispanic communities.

To sum up, I find strong evidence that residents of heavily black and heavily Hispanic areas complain at lower rates than non-minority areas compared to their level of victimization;

these effects are consistent across cases and are generally statistically significant.

4 Why Do Victims From Heavily Minority Areas Complain at Lower Rates?

In the previous section, I demonstrated that residents of heavily minority areas have lower complaint rates than residents of other areas relative to their rate of victimization. In this section, I examine potential explanations for this finding based on information or social trust. I do not find evidence for explanations based on differences in information, or based on mistrust of government. I do find limited evidence that differences in social trust based on alienation from society could explain a lower propensity to complain for residents of minority areas.

4.1 Information

Differences in a consumer's information set can affect complaining behavior in two major ways. First, consumers may not know that they have been defrauded. Take for example, the Ideal case, in which Ideal bought payday loan application details and charged consumers without providing any service. Consumers may not have checked their bank statements and seen the payment to Ideal Financial, or may not have realized that they never received any services from Ideal. Second, some consumers may not know who to complain to, or how to complain. They may thus only complain to the company involved, and not to the BBBs or consumer protection agencies.

I examine both of these explanations by using the variation across cases in the average amount of loss. I compare the five cases with an average amount of loss between $30 and $110 – Case B, Ideal, WinFixer, Platinum, and SimplePure – to the three cases with an average loss above $2,000 – Guidance, AdvStrategy, and MoneyNow.[12] All three of the latter cases were business opportunity or business coaching cases where victims never received the promised business opportunity. With an average loss an order of magnitude larger than the first five cases, victims will almost certainly know they were victimized. In addition, given the large loss they suffered, victims would likely be willing to spend time to research who they should complain to in order to recoup their losses, if their reason for not complaining was they did not know who to complain to. With a small loss, it may not be worth the time or effort to find out who to complain to. As Table I shows, the aggregate complaint to victim ratios are one to two orders of magnitude higher on average for the large loss cases than for the small loss cases.

I estimate equation (1) separately for the large loss and small loss cases, and depict the percent change in the complaint to victim ratio for percent black and percent Hispanic in the first two rows of Figure 5. Black circles depict the percent change from an increase in the fraction of black residents from 0% to 100%, and grey triangles the percent change from an increase in the fraction of Hispanic residents from 0% to 100%. Heavily minority communities have lower complaint rates, relative to their rate of victimization, for both large loss and small loss cases. The complaint to victim ratio falls by 52% as the share of black residents increases from 0% to 100% using the small loss cases, compared to 80% for the

[12] I exclude the PHLG case, as its loss value was intermediate at about $500, and because 90% of complaints were to Western Union or MoneyGram (because these companies sent payments in the case) rather than the BBBs or government entities.

large loss cases. The complaint to victim ratio falls by 76% as the share of Hispanic residents increases from 0% to 100% using the small loss cases, compared to 47% for the large loss cases. Thus, the selection effects are substantial, and statistically significant, for both small loss and large loss cases for both the percentage of blacks and Hispanics.

4.2 Alienation, Trust, and Social Capital

Another potential explanation for lower complaint rates in heavily minority communities is that residents of those communities are alienated from mainstream institutions, or from society more generally. For example, Orlena Blanchard, speaking about her experience in marketing to black communities at the 2016 FTC Changing Demographics workshop[13], noted that:

> [Y]ou're wondering why you don't get a lot of reporting from the African American community, or it doesn't compare in terms of reporting fraud or anything like that, you have to wonder why. And you have to look very deeply into sort of the lifestyle and experience and cultural identity as to why ... And thinking about really trust issues and consideration for government agencies and where they see themselves in terms of having an equal place in society as citizens. ... When picking up the phone to report or considering that they have just as much right to report an issue and feel that they're going to get an equal response that any other citizen would get. This is a really important consideration for this particular group.

[13] See https://www.ftc.gov/news-events/events-calendar/2016/12/changing-consumer-demographics for videos and transcripts.

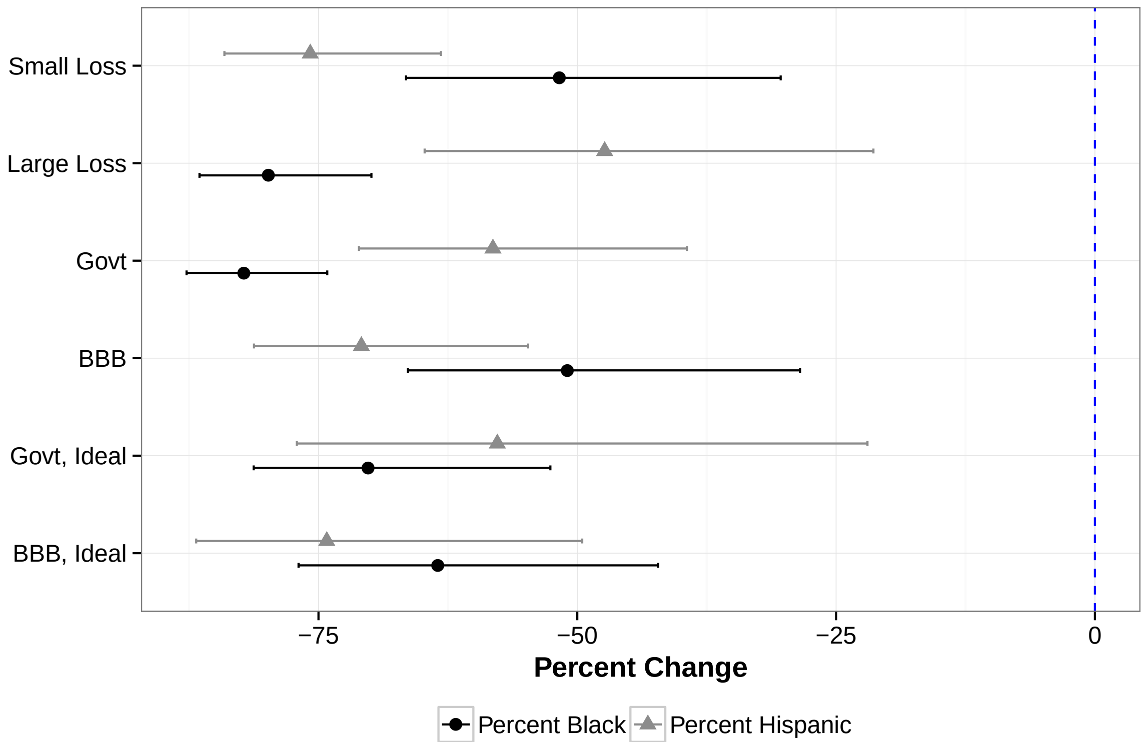


Figure 5 Percent Change in Complaint to Victim Ratio by Demographic Factors

Note: The graph depicts the percent change in the complaint to victim ratio for percentage of black residents (in black circles) and Hispanic residents (in grey triangles) across different specifications. The first row represents estimates for the small loss cases (combining Case B, Ideal, WinFixer, Platinum and SimplePure), while the second row represents estimates for the large loss cases (combining Guidance, AdvStrategy, and MoneyNow). The third row represents estimates using only government complaints, and fourth row only BBB complaints, for all cases except PHLG and WinFixer. The fifth row represents estimates using only government complaints, and sixth row only BBB complaints, for the Ideal case. The blue, dashed vertical line indicates a value of zero, so changing the demographic factor does not differentially affect the complaint rate and victim rate and so the complaint to victim ratio is constant.

Considerable qualitative and quantitative evidence indicates that members of minority groups have lower levels of trust than whites. The General Social Survey (GSS) regularly asks a question on trust: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" This measure has become a standard measure of trust, and is known to be lower for blacks relative to whites (Alesina and La Ferrara, 2002; Brehm and Rahn, 1997; Glaeser et al., 2000; Putnam, 2001). In the first three rows of Table II, I report the proportion of people that say that one "can trust" by race and ethnicity using data from 2000 and after, as well as related questions that ask whether people would try to be fair, or try to take advantage ("Fairness") and whether people usually try to be helpful, or are mostly looking out for themselves ("Helpfulness"). For all three questions, there is a substantial racial gap, with blacks and Hispanics having much lower levels of trust than non-Hispanic whites. For example, 39% of whites say that one usually can trust people, compared to 16% of blacks and 17% of Hispanics. For fairness, 57% of whites think that people are generally fair and 50% that they are generally helpful, compared to 33% and 39% for blacks and 36% and 32% for Hispanics. These racial gaps in trust survive extensive controls; for example, Alesina and La Ferrara (2002) report a 24 to 26 percentage point gap between whites and blacks on trust after controlling for income, education, sex, age, marital status, and religion, among other covariates.

The qualitative literature in sociology and marketing has also found evidence that members of minority groups experience more alienation from society, and have less trust. Anderson (2000), examining poor black communities in North Philadelphia, contrasts between "decent" families, who adopt more mainstream values, and "street" families who adopt an "oppositional culture [that] is a product of alienation". This alienation may be due to lower

Table II Beliefs on Trust from the General Social Survey by Race and Ethnicity

Variable	Non-Hispanic White	Non-Hispanic Black	Hispanic
Trust	0.39	0.16	0.17
	(0.005)	(0.008)	(0.009)
Fairness	0.57	0.33	0.39
	(0.005)	(0.011)	(0.012)
Helpfulness	0.50	0.36	0.32
	(0.005)	(0.011)	(0.012)
Trust in Govt Admins	0.24	0.26	0.31
	(0.009)	(0.019)	(0.02)
Trust People in Govt	0.24	0.25	0.30
	(0.008)	(0.018)	(0.02)

Note: All variables are from the General Social Survey (GSS). Trust is defined as individuals saying they "can trust" people for the trust variable, fairness that people are generally fair using the fairness variable, and helpfulness that people mostly try to be helpful using the helpful variable. Trust in government administrators is defined as individuals saying they strongly agree or agree that most government administators can be trusted to do what is best for the country using the poleff17 variable, and trust people in government is defined as people saying strongly agree or agree that most of the time we can trust people in government using the govdook variable. Trust, fairness, and helpfulness are using all GSS years between 2000 and 2016; trust in government administrators is based on the 2006, 2012, and 2016 GSS years and trust people in government is based on the 2004, 2010, and 2014 GSS years. Estimates take into account sample weights, and standard errors are in parentheses.

self-efficacy (Bandura, 1977), where minorities do not believe they can succesfully navigate mainstream institutions, or learned helplessness (Seligman, 1975), in which past negative experiences have left minorities to conclude that engaging with mainstream institutions is fruitless. For examples of both of these channels, Bone et al. (2014) report that minorities seeking business financing are less likely than whites to receive information on loan terms, more likely to be asked for documentation and financial statements, more likely to see obtaining financing as an uphill journey in which they are in a subservient position, and more likely to experience rejection negatively if they are primed to think about race. Such alienation does not have to be associated with members of minority groups; for example, MacLeod (2018) follows a set of low income white friends who are extremely alienated from mainstream values and society, and a set of low income black friends who are not. However, such alienation is likely more prevalent in minority communities.

The lack of trust documented above could also lead minorities to feel that victimization is "normal" and so their own fault for being too trusting, rather than abnormal and worth correcting by complaining to the authorities. For example, Anderson (2000) describes the alienated worldview of the most extreme of street families as:

> Highly alienated and embittered, they exude generalized contempt for the wider scheme of things and for a system they are sure has nothing but contempt for them. ... For them, people and situations are best approached both as objects of exploitation and as challenges possibly "having a trick to them", and in most situations their goal is to avoid being "caught up in the trick bag." Theirs is a cynical outlook, and trust of others is severely lacking, even trust of those they

are close to.

I examine multiple different channels through which a lack of trust could affect complaint rates. First, members of minority groups may mistrust the government in the sense that government officials will misuse information given to them or will not do the best they can. Second, they may feel that sending a complaint may not make a difference, either because it is not possible to improve things or that their complaint will benefit a society which they feel excluded from. I find evidence against the first explanation of governmental mistrust.

4.2.1 Mistrust of Government

One way a lack of trust could reduce complaint rates from minority areas is that residents of these areas mistrust the government. The GSS asks multiple questions in particular years about mistrust of government officials; one question asks whether most government administrators can be trusted to do what is best for the country, while another asks whether most of the time we can trust people in government. Blacks and Hispanics are more likely to express trust in government administrators or trust in people in government. In the last two rows of Table II, I report the proportion of people that agree or strongly agree to these questions by race and ethnicity. 26% of blacks and 31% of Hispanics agree or strongly agree that one can trust government administrators, and 25% of blacks and 30% of Hispanics agree or strongly agree that one can trust people in government, compared to 24% for whites for both questions.[14] The lack of a racial gap for questions specifically on trust in government cast some doubt that mistrust of government can explain lower complaint to victim ratios

[14] Answers to these questions may be influenced by the party in power in Washington, but Alesina and La Ferrara (2002) report much smaller racial gaps for similar questions on confidence in government entities than they find for trust over a much different sample period.

in minority areas.

Another way to test this explanation by examining which organizations complainants complain to. If mistrust of government is the reason for lower complaint rates relative to victim rates in minority areas, one would expect less selection in complaining to the non-governmental BBBs than to government sources.[15] I test this proposition using data from 7 cases for which I can identify the source of the complaint for all complaints.[16] For these cases, examining only government or BBB complaints, government complaints are 55% of complaints for AdvStrategy, 4% for Case B, 59% for Guidance, 54% for Ideal, 85% for MoneyNow, 46% for Platinum, and 79% for SimplePure.

I then estimate equation (1) separately using only BBB complaint rates or only government complaint rates, after excluding the PHLG and WinFixer cases. In the third and fourth rows of Figure 5, I depict the change in the complaint to victim ratio for government complaints compared to BBB complaints. I find similar selection in complaints received by both groups. The complaint to victim ratio falls by 82% for government complaints, compared to 51% for BBB complaints, as the percent of black residents rises from 0% to 100%, and falls by 58% for government complaints, compared to 71% for BBB complaints, as the percentage of Hispanic residents rises from 0% to 100%.

The share of government complaints can be imbalanced across cases – only 4% for Case B, and 79% for SimplePure, for example, which could affect the estimates detailed above if the degree of selection in complaining varies across cases. I thus also estimate equation (1)

[15] Of course, consumers may be mistrustful of authority in general, may believe that the BBBs are a government agency, or might correctly realize that information reported to the BBBs could be accessed by law enforcement authorities.

[16] The complaint source was not kept for most WinFixer complaints, while almost all complaints for the PHLG case are not to government or BBB sources.

using only Ideal Financial complaints, as this case both had a large number of complaints and victims and a balanced share of government and BBB complaints. In this specification, I again use either government complaint rates or BBB complaint rates when estimating equation (1). These results are depicted in the fifth and sixth rows of Figure 5; I continue to find substantial selection in complaining for both BBB and government complaints. Using only Ideal data, the complaint to victim ratio falls by 70% for goverment complaints, compared to 63% for BBB complaints, as the percent of black residents rises from 0% to 100%, and falls by 58% for government complaints, compared to 74% for BBB complaints, as the percentage of Hispanic residents rises from 0% to 100%. Thus, for the Ideal case, I cannot reject that the degree of selection in complaining is the same for government and BBB complaints.

4.2.2 Interactions with Education or Income

A different channel for how lower levels of trust or social capital could affect complaining behavior is that residents of minority communities feel excluded from mainstream institutions, feel that complaints will not benefit their community, or that victimization is normal and so not worth complaining about. The sociological literature finds that such alienation is more likely in poorer, less educated communities. For example, Anderson (2000) finds that the share of alienated "street" families increases as the author ventures to poorer parts of the black community in Philadelphia. Since poorer, less educated minority areas have a larger proportion of such alienated residents, we might expect even larger declines in complaint rates in such localities.

I test this proposition by estimating a set of interaction models. In each model, I interact the percentage of black residents and percentage of Hispanic residents with a different variable

– the (logged) median household income, the percentage of residents in poverty, the share of college educated graduates, or the average credit score. I examine credit score because economists have viewed credit score as a measure of social capital (Bricker and Li, 2017).[17] I estimate models with interactions by reestimating equation (1) including both variables and their interaction as part of the set of demographic variables D_{is}.

I present these estimates in Figure 6 by reporting the effect of changing the percentage of black residents, or percentage of Hispanic residents, from 0% to 100% at different values of the interaction variable. I find that the complaint rate falls relative to the victimization rate as the percentage of minority residents rises for both low income, low education, and low credit score areas, as well as for high income, high education, and high credit score areas. In general, the estimates of interactions are imprecise and I cannot reject the hypothesis that the selection effects I estimate are the same for both more disadvantaged and less disadvantaged areas. While effects for Hispanic residents in general indicate less selection in complaining in more advantaged areas (with the largest effect for college education), selection effects for black residents sometimes increase when conditioning on a more advantaged area.

The complaint to victim ratio falls by 61% as the percentage of black residents in the zip code increases from 0% to 100% for a median household income of $30,000, compared to 66% for a median household income of $100,000. The complaint to victim ratio falls by 49% as the percentage of Hispanic residents in the zip code increases from 0% to 100% for a median household income of $30,000, compared to 38% for a median household income of $100,000. For high poverty areas (30% poverty share), the complaint to victim ratio falls by 55% as

[17]For estimates with credit scores, I have to exclude 1,399 zip codes where I do not have credit score information.

the percentage of black residents rises from 0% to 100%, and by 45% as the percentage of Hispanic residents rises from 0% to 100%. For low poverty areas (5% poverty share), the complaint to victim ratio falls by 70% as the percentage of black residents rises from 0% to 100%, and by 34% as the percentage of Hispanic residents rises from 0% to 100%. For low credit score areas (an average credit score of 630), the complaint to victim ratio decreases by 60% as the percentage of black residents rises from 0% to 100%, and by 48% as the percentage of Hispanic residents rises from 0% to 100%. For medium credit score areas (an average credit score of 710), the complaint to victim ratio falls by 82% as the percentage of black residents rises from 0% to 100%, and by 46% as the percentage of Hispanic residents rises from 0% to 100%.[18]

The interaction with college education is the only interaction for which the selection effect is smaller for both the percent of black residents and percentage of Hispanic residents in more advantaged areas. At a percentage of college educated residents of 10%, the complaint to victim ratio falls by 66% as the percentage of black residents rises from 0% to 100%, and by 53% as the percentage of Hispanic residents rises from 0% to 100%. For areas with a college educated percentage of 60%, the complaint to victim ratio falls by 53% as the percentage of black residents rises from 0% to 100%, and by 23% as the percentage of Hispanic residents rises from 0% to 100%. The Hispanic selection effect is insignificantly different from zero for areas with a college educated percentage of 60%, although it is also insignificantly different from the effect for areas with a college educated percentage of 10%.

[18]In 2010, about 25% of Americans had a credit score below 650, and 53% had a credit score above 700. See https://www.sec.gov/comments/s7-14-11/s71411-316.pdf.

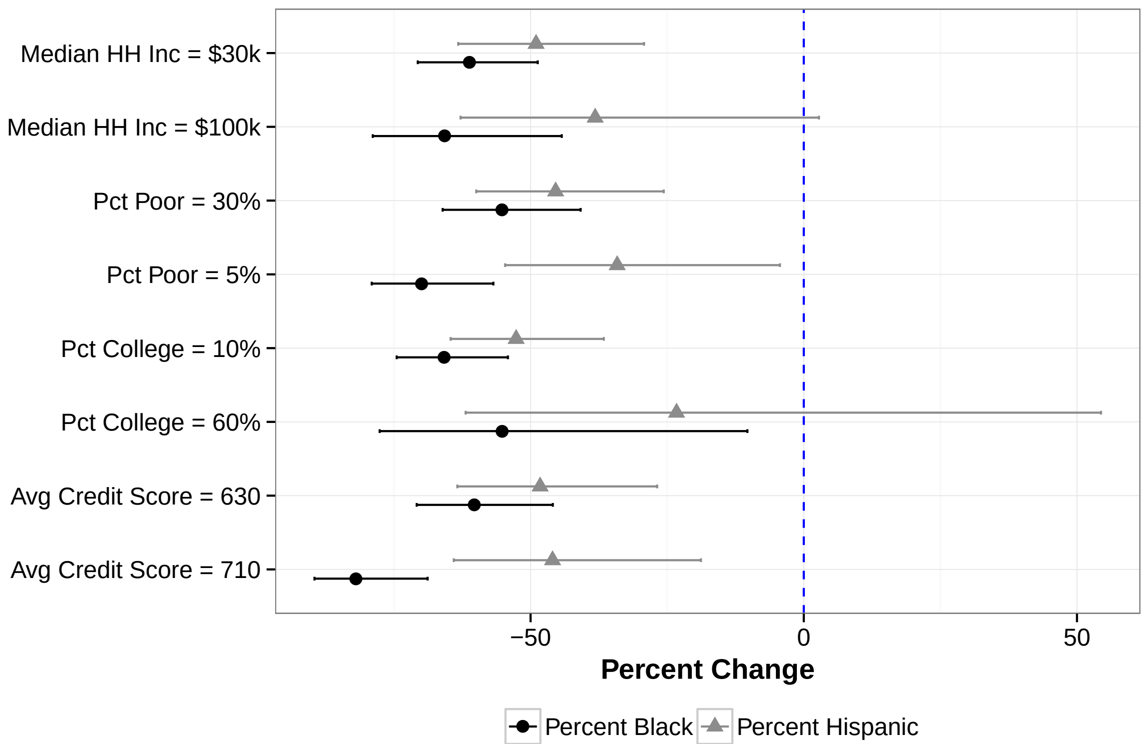


Figure 6 Percent Change in Complaint to Victim Ratio by Racial Demographics, with Interactions

Note: The graph depicts the estimated percent change in the complaint to victim ratio, or the complaint rate divided by the victim rate, for changes in the percentage of black residents (black circles) or Hispanic residents (grey triangles), as well as the associated 95% confidence interval at different levels of a given interaction variables. The blue, dashed vertical line indicates a value of zero, so changing the demographic factor does not differentially affect the complaint rate and victim rate, and so the complaint to victim ratio is constant.

4.2.3 Hispanic Specific Explanations

For Hispanic victims specifically, language barriers or fears of immigration enforcement could also lead to lower complaint rates. The FTC and other government agencies take complaints in Spanish both over the phone and online, but Hispanic victims may be unaware of this fact and so may be less likely to complain. Another specific reason for mistrust of government could be fear that information provided to law enforcement authorities could be used for immigration enforcement. For example, Alsan and Yang (2018) find that the takeup of government programs such as food stamps and the Affordable Care Act decline with increases in immigration enforcement.

I examine these concerns by interacting the percent of Hispanic residents with the percent of foreign born residents, or with the percentage of residents speaking a language other than English, with a similar specification to the interaction models described above.[19] In Figure 7, I depict these results. While the standard errors around these effects are somewhat imprecise, I find results inconsistent with either a language barrier or immigration enforcement explanation; the sign of the selection effect reverses for areas with a high proportion of foreign born residents, or residents speaking another language. The complaint to victim ratio falls by 57% as the percentage of Hispanic residents rises from 0% to 100% in areas that have 10% of the population foreign born, compared to a 52% *rise* in areas that have 50% foreign born. Similarly, the complaint to victim ratio falls by 45% as the percentage of Hispanic residents rises from 0% to 100% in areas that have 10% of the population speaking

[19] These interactions, unfortunately, may suffer from collinearity problems; the percentage of Hispanic residents is correlated at 0.69 for percentage of foreign born residents and 0.88 for percentage of residents speaking another language.

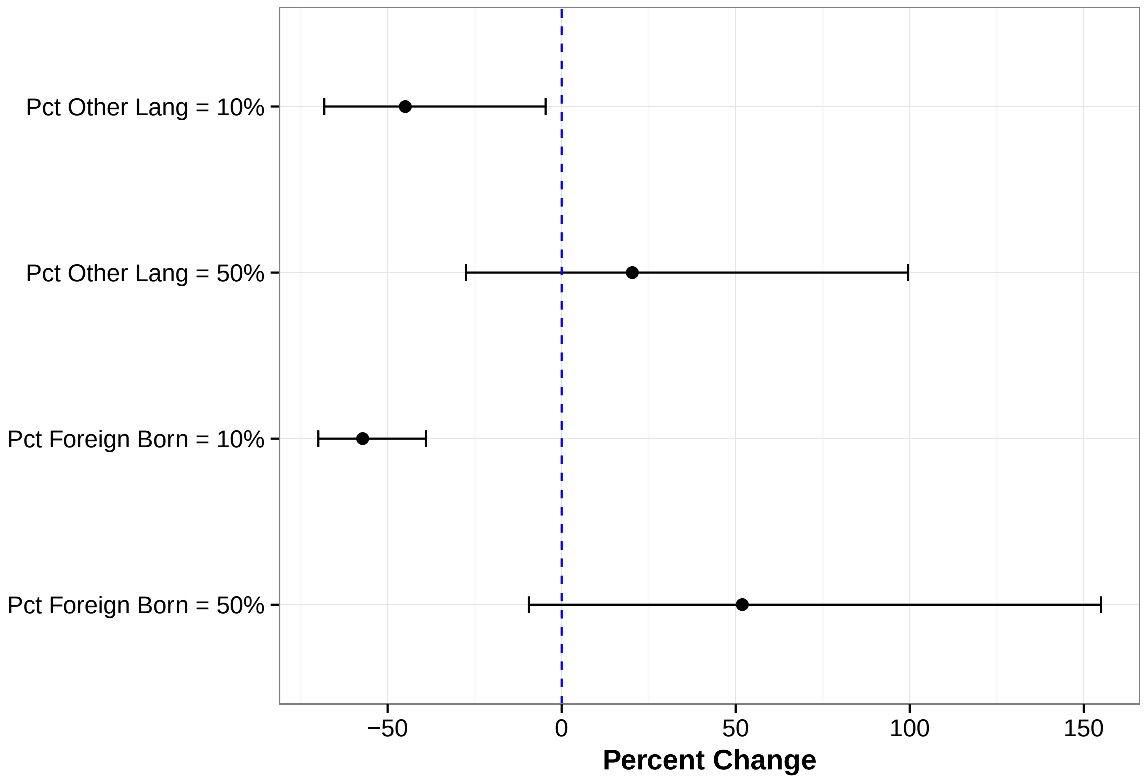


Figure 7 Percent Change in the Complaint to Victim Ratio with Hispanic Specific Interactions

Note: The graph depicts the estimated percent change in the complaint to victim ratio, or the complaint rate divided by the victim rate, for changes in the percentage of Hispanic residents, as well as the associated 95% confidence interval, at different levels of a given interaction variable. The blue, dashed vertical line indicates a value of zero, so changing the demographic factor does not differentially affect the complaint rate and victim rate, and so the complaint to victim ratio is constant.

another language, compared to a 20% rise in areas that have 50% of residents speaking another language. These results could be consistent with an explanation of alienation, if second or third generation Hispanics are more alienated than first generation Hispanic immigrants.

5 How Can One Account for Self-Selection in Complaining?

The evidence above demonstrates that communities with different demographic groups complain at substantially different rates relative to their degree of victimization. This type of self-selection may distort inferences that policymakers make from complaint data. Take, for example, a policymaker that wants to know whether victimization rates are higher in minority communities, and uses average complaint rates as a proxy for victimization.

In Figure 8, I plot how complaint rates vary across communities with different concentrations of blacks and Hispanics using all fraud-related complaints to Consumer Sentinel in 2015; Raval (2018) provides a more detailed analysis of how aggregate complaint data varies with demographics, and how this relationship varies by product category and data contributor.[20] The black solid and grey dashed lines depict the average complaint rate for communities defined by their share of population that is black and Hispanic, respectively. The estimates are based upon a nonparametric loess regression, with the grey area surrounding each graph representing the 95% confidence interval.

While the average complaint rates are not monotonic, Figure 8 demonstrates that the average complaint rate tends to be lower in areas with a greater share of Hispanic residents. After a small rise in complaint rates from areas that are close to 0% Hispanic to areas that are 15% Hispanic, the complaint rate steadily falls as areas become more Hispanic. Communities that are close to 100% Hispanic have about half the complaint rate of areas

[20] This analysis thus excludes identity theft and do not call complaints.

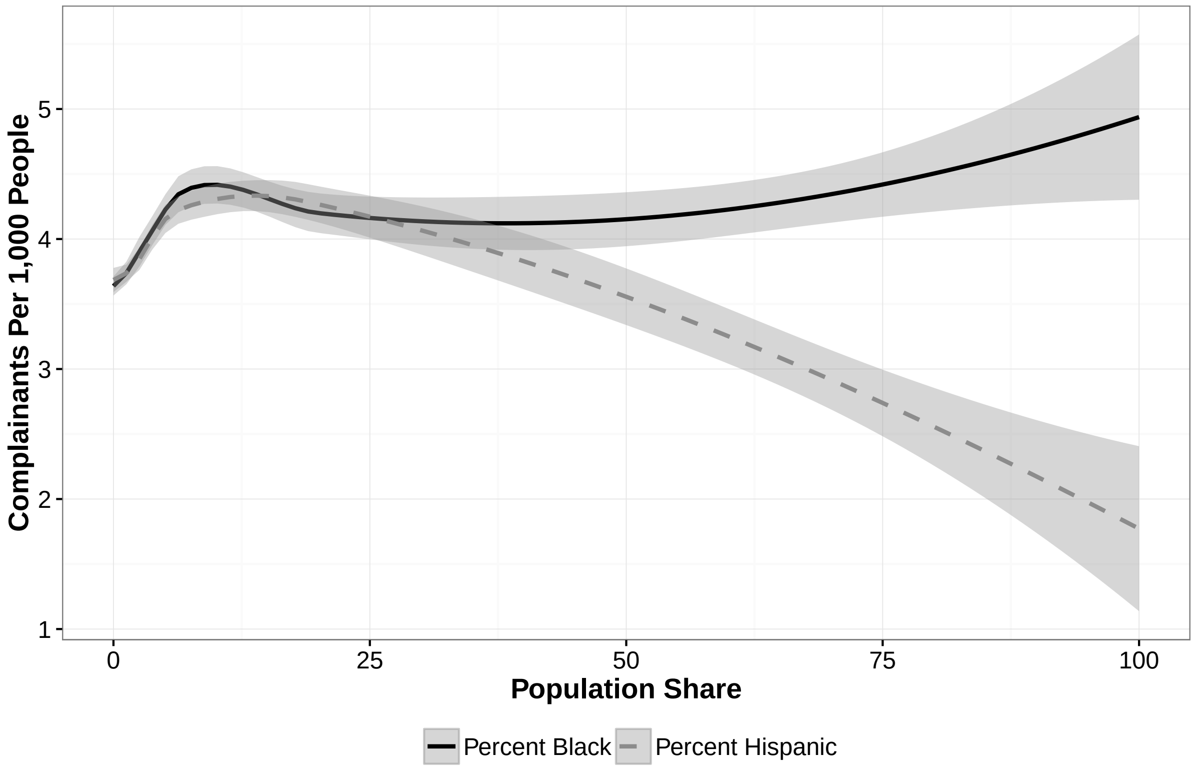


Figure 8 Complaint Rates For Black and Hispanic Communities in 2015

Note: The graph depicts the nonparametric loess regression of the zip code per capita complaint rate on the share of percent black or percent Hispanic in the zip code, based on all 2015 Fraud and Other complaints to Consumer Sentinel. Black solid lines reflect percent black, and grey dashed lines reflect percent Hispanic.

that are 0% Hispanic. For black communities, by contrast, the complaint rate is much more constant with respect to the share of the population that is black. Communities that are almost 100% black have only about a 10 percent higher complaint rate than communities that are 10% black, and a 30 to 40 percent higher complaint rate compared to communities that are 0% black.

A policymaker might take away from Figure 8 that victimization is lower in heavily Hispanic areas, and only slightly higher in heavily black areas. However, the previous section demonstrated that complaint rates can diverge substantially from victimization rates, and victims in heavily minority areas are much less likely to complain, so one cannot simply take complaints as a proxy for victimization.

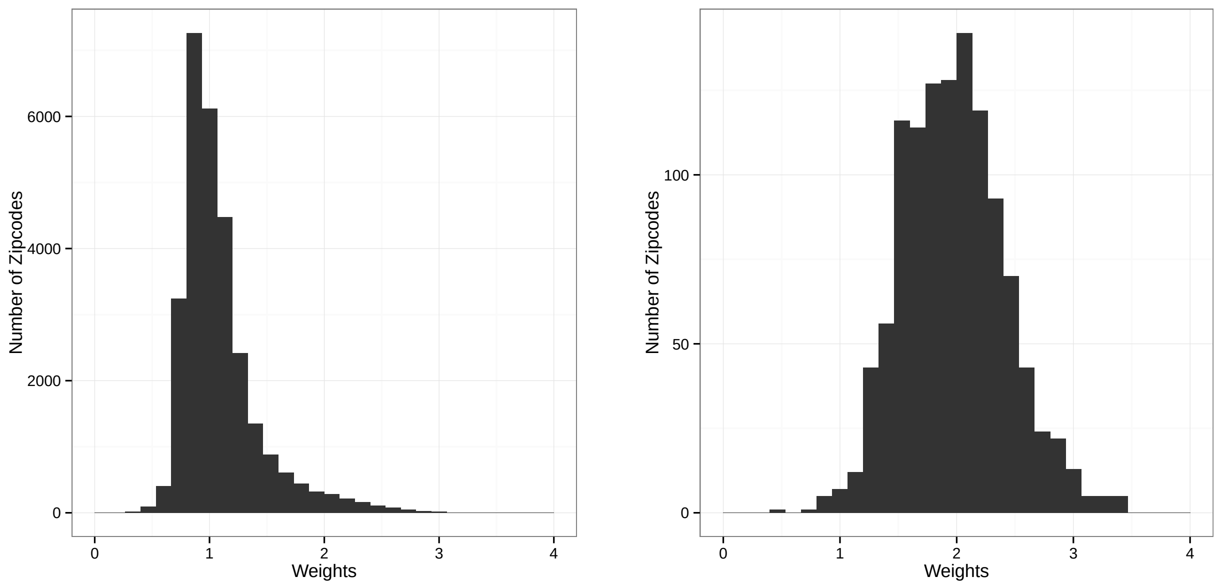
One way to account for self-selection in complaints in order to reflect victimization is through statistical weighting. Such weights would overweight complaints from groups that complain less than their rate of victimization, relative to national averages. I construct such weights w_i for each zip code i as follows. The per capita victim rate in a given zip code i, r_i^V, is equal to the per capita complaint rate in zip code i, r_i^C, multiplied by the ratio of the victim rate and the complaint rate:

$$r_i^V = r_i^C \frac{r_i^V}{r_i^C} \tag{2}$$

Information on per capita complaint rates from aggregate Consumer Sentinel data gives us r_i^C. I then estimate $\frac{r_i^V}{r_i^C}$, the inverse of the complaint to victim ratio, using estimates of equation (1). The coefficients on demographics β_s^j allow me to predict a zip code's complaint rate or victim rate solely based on its demographics. Since β_s^V indicates how a given demographic variable D_{is} affects the victim rate, and β_s^C how a given demographic variable affects the complaint rate, the difference between the two tells us how the victim to complaint ratio changes with demographics. Formally, the predicted victim to complaint ratio for zip code i using the estimates of demographic factors from the regression specification in equation (1) is:

$$\frac{r_i^V}{r_i^C} = \frac{\exp(\sum_s(\beta_s^V D_{is}))}{\exp(\sum_s(\beta_s^C D_{is}))} = \exp(\sum_s(\beta_s^V - \beta_s^C)D_{is}). \tag{3}$$

I use the expression in equation (3) to create weights, normalizing these weights by



(a) All Zip Codes (b) Majority Black Zip Codes

Figure 9 Distribution of Weights

Note: The graph depicts the distribution of weights calculated using equation (3) with the estimates of equation (1) using all 9 cases. Weights are normalized so that the median zip code has a weight of 1.

dividing by the weight for the median zip code. Figure 9 depicts these weights both for all zip codes, and for majority black zip codes. For all zip codes, 50% of zip codes have a weight between 0.86 and 1.19. However, the weights have a long right tail of large weights; the 90th percentile weight is 1.51, 95th percentile weight is 1.82, and 99th percentile weight is 2.41. The median weight for majority black zip codes is about double the median weight for all zip codes at 1.97, with 90% of weights for majority black zip codes between 1.45 and 2.54. Thus, complaints from majority black areas would receive much greater weight under this weighting scheme.

Figure 10 depicts a heat map of these weights for the Los Angeles area. Areas near the coast, such as Malibu, Santa Monica, and Venice Beach, are weighted less than one, so zip codes like these complain at higher rates than their rate of victimization relative to the

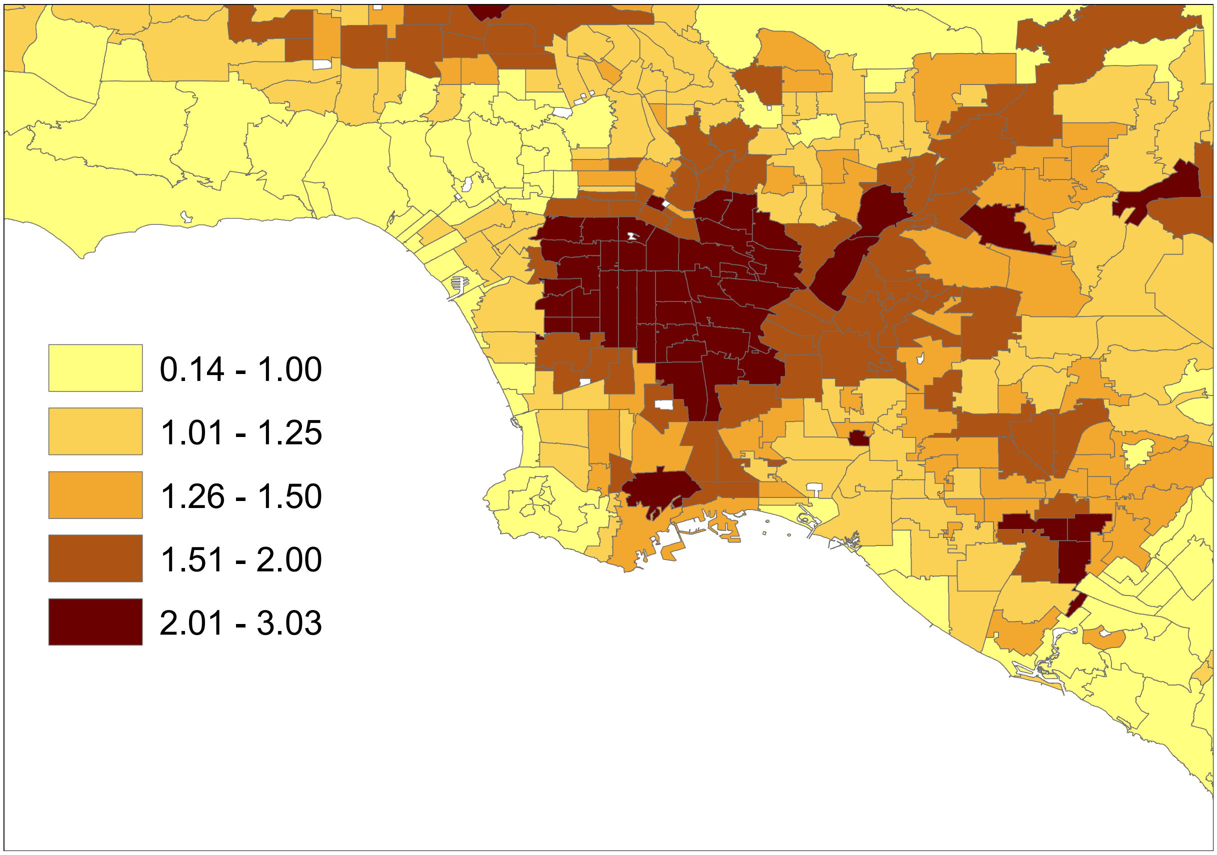


Figure 10 Map of Weights for Los Angeles Area

Note: The graph depicts a heat map of weights calculated using equation (3) with the estimates of equation (1) using all 9 cases. Weights are normalized so that the median zip code has a weight of 1.

median zip code. By contrast, South Central and East LA have weights more than double the median zip code based on their demographics; complaints from areas such as these are much less common relative to their rate of victimization. Thus, the weighting strategy magnifies the voice of residents of South Central and East LA compared to those in Santa Monica and Malibu in order to better reflect victimization rates.

I then multiply the zip code complaint rates in Figure 8 by these weights in order to construct an implied victimization rate based on all 2015 fraud complaints. The resulting implied victimization rate has a very different relationship with racial demographics than the

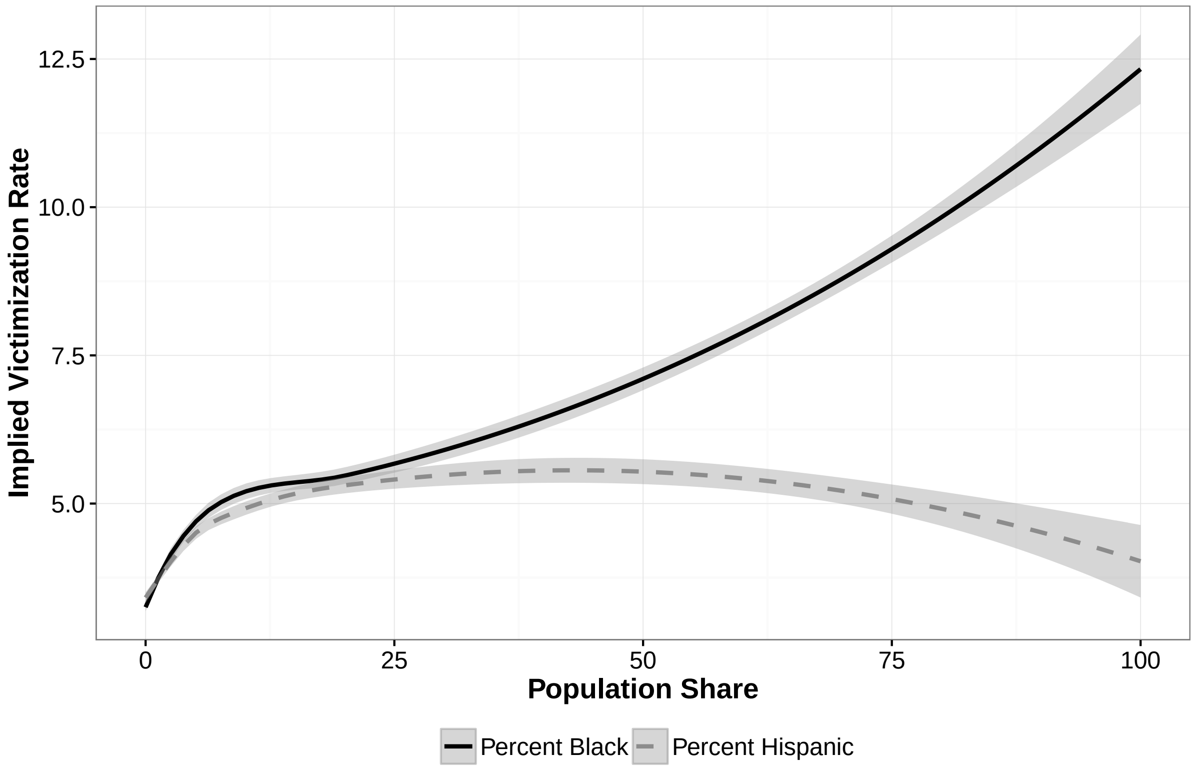


Figure 11 Implied Victimization Rates For Black and Hispanic Communities in 2015

Note: The graph depicts the nonparametric loess regression of the zip code per capita complaint rate multiplied by the weights derived above on the share of percent black or percent Hispanic in the zip code, based on all 2015 Fraud and Other complaints to Consumer Sentinel. Black solid lines reflect percent black, and grey dashed lines reflect percent Hispanic.

complaint rate. Figure 11 shows how the implied victimization rate varies across different demographic groups. The implied victimization rate is about 3.5 times as large for areas that are 100% black compared to areas that are 0% black. The victimization rate has an inverse U shape with the percent Hispanic of a zip code. Areas with a 25% share of Hispanic residents to a 50% share of Hispanic residents have close to a 50% higher victimization rate than areas that are 0% Hispanic, while areas with close to a 100% Hispanic population share have a 10% higher victimization rate than areas that are 0% Hispanic.

6 Conclusion

While consumers self-select into providing complaints, it is typically difficult to separate whether differences across groups in complaint behavior represent differences in the propensity to complain or the underlying rate of victimization. I have exploited a set of law enforcement actions for which I have access to databases of victims as well as complaints for each case, which has allowed me to examine how complaints compare to victimization. I have found that heavily black and heavily Hispanic communities have much fewer complaints than non-minority communities compared to their level of victimization.

While my results make clear that selection is a major issue in consumer complaints, it is far from clear how to account for such selection. A statistical approach to doing so would be to weight complaints based on how the complaint rate of their community compares to the degree of victimization; such weights would overweight communities with lower complaint rates and thus highlight their complaints. I have provided such an approach in this paper, and have shown how to both construct these weights and how such weights would alter relationships between complaint rates and the demographic composition of communities. This weighting strategy could be used to modify complaint data across many settings with data on both all users of a product and consumers that complain.[21]

An alternative, complementary approach to doing so would be convince more victims of fraud from minority communities to complain. However, I have found evidence in this paper

[21] For example, the CFPB may have information on where consumers of financial services live from consumer credit panels as well as zip codes of complaining consumers. Amazon.com and other online retailers have the shipping address of anyone who buys a product from them together with the same information on consumers that lodge complaints, as well as detailed information on their shopping patterns.

that the lower likelihood of complaining for victims from heavily minority areas is likely due to differences in social trust, rather than information on whether one was defrauded or who to complain to. Thus, advertising campaigns might increase the probability that victims complain, but not ameliorate the lower propensity to complain for victims from minority areas. Instead, government agencies could conduct outreach campaigns in communities whose residents are less likely to complain when victimized that aim to go beyond simply providing information on how to complain. Such outreach would have to convince residents of such areas that their input is valued and would help their communities, which might require greater engagement with local community organizations.

Finally, this paper has considered the issue of self-selection in the context of complaints to consumer protection authorities. Future work could examine whether patterns of self-selection on demographics are similar for online platforms such as Yelp or Amazon. Self-selection may differ on online platforms because consumers' alienation or lack of social trust affects for-profit private companies differently than public entities. In addition, for online platforms, market actors may influence whose voice we hear, either by promoting reviews through free products, such as through the Amazon Vine program, by filtering suspicious reviews, as Yelp does, or by suppressing negative reviews, a practice that Congress recently banned through the Consumer Review Fairness Act.

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A Cases

Below, I provide details on the nine cases that I use for my main analysis, including the official case title, a short name that I use in the paper, as well as a short description of the case and links to further details.

I call the first case "Case B", as I am unable to disclose the company's name or details on its industry. However, I can say that it has been sued by a government agency for consumer protection violations and that its industry is different than those of the other cases.

The second case, FTC vs. Ideal Financial Solutions Inc., et al. ("Ideal"), involved a company that bought consumer payday loan applications and then used the bank account details in the applications to withdraw money from the consumers' bank accounts without their consent. The FTC sued Ideal Financial and won summary judgment, with a $43 million judgment against the defendants (two additional defendants settled for a $25 million judgment).[22]

The third case, the FTC vs. Apogee One Enterprises LLC, et al. ("Platinum"), also involved payday loan applications as well as telemarketing. The company allegedly called online payday loan applicants and offered them credit cards with heavily deceptive terms; for example, the cards could only be used at the defendant's online store, rather than at any store accepting Visa, Mastercard, or American Express as promised. The FTC sued Platinum Trust and eventually settled the charges, with a judgment of over $7.4 million that was returned to consumers via refunds.[23]

The fourth case, the FTC vs. Innovative Marketing Inc., et al. ("WinFixer"), involved a company that the FTC alleged falsely claimed that security scans had discovered malware on consumers' computers. The company then sold computer security software that would "fix" the problems identified. The FTC sued the companies and individuals involved in the scam; most settled with multi-million dollar judgments, while the defendant that went to trial was found liable for more than $163 million.[24]

In the fifth case, FTC vs. Health Formulas, LLC ("SimplePure"), the FTC alleged in part that SimplePure, and its related companies and individuals, misrepresented the health benefits of two dietary supplements, and enrolled consumers in a negative option program involving several more products in which they were billed automatically without their consent. The FTC sued the companies and individuals involved, and the case was settled for a partially suspended judgment of $105 million.[25]

In the sixth case, the FTC vs. Advertising Strategies LLC, et al. ("AdvStrategy"), the FTC

[22] See https://www.ftc.gov/enforcement/cases-proceedings/1123211-x130044/ideal-financial-solutions-inc-et-al and https://www.consumer.ftc.gov/blog/ftc-takes-down-ideal-financials-fraud-network for additional details on this case.

[23] See https://www.ftc.gov/enforcement/cases-proceedings/1123212/apogee-one-enterprises-llc-also-dba-apogee-enterprises-llc and https://www.ftc.gov/news-events/press-releases/2013/01/ftc-sends-74-million-refunds-consumers-harmed-scheme-sold for more details.

[24] See https://www.ftc.gov/enforcement/cases-proceedings/072-3137/innovative-marketing-inc-et-al and https://www.ftc.gov/news-events/blogs/business-blog/2014/02/court-appeals-upholds-win-consumers-winfixer-case for more details.

[25] Additional allegations include that (1) defendants induced consumers to order dietary supplements and other products by touting purported free trials, and then charged consumers for the free products unless consumers complied with their onerous refund policy, (2) defendants failed to disclose the terms and conditions of their onerous refund policy to consumers, and (3) defendants called consumers on the Do Not Call list, without their consent. See https://www.ftc.gov/enforcement/cases-proceedings/132-3159-x150015/health-formulas-llc-doing-business-simple-pure and https://www.ftc.gov/news-events/press-releases/2016/05/marketers-simple-pure-supplements-settle-ftc-court-action for more details.

alleged that a company used telemarketing to sell consumers fake business or investment opportunities, using various different purported online investment businesses. The FTC settled the case for a monetary judgment of $25 million.[26]

In the seventh case, the FTC vs. Lift International LLC, et al. and the FTC vs. Thrive Learning LLC ("Guidance"), the FTC alleged that a set of companies used deceptive telemarketing to sell consumers business coaching services. The FTC settled these cases for between $10 million and $30 million for each set of companies involved.[27]

In the eighth case, the FTC vs. Money Now Funding LLC ("MoneyNow"), the FTC alleged that a company falsely promised consumers a business opportunity in which they could run a business from their home referring local businesses to the defendants' money lending service. The FTC either won judgments or settled with defendants for monetary judgments of varying amounts up to $7.2 million.[28]

Finally, in the ninth case, the FTC vs. PHLG Enterprises LLC ("PHLG"), the FTC alleged that a company served as a middleman to transfer money from consumers to Indian call centers using Western Union or MoneyGram cash transfers. The Indian call centers were conducting various different scams, such as imposter scams impersonating the IRS or government grant authorities. The FTC settled with defendants in this case for a suspended judgment of $1.5 million.[29]

B Demographics

Table A-1 contains the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentile quantiles of each variable across zip codes. The quantiles are estimated after weighting each zip code by its 2010 population. All of the ethnic demographics are heavily skewed – half of the American population lives in zip codes whose population is less than 5 percent black, less than 8 percent Hispanic, and less than 2 percent Asian. On the other hand, majority black and majority Hispanic zip codes each comprise more than 5 percent of population weighted zip codes. The measure of urbanization is similarly skewed; the median zip code is 98% urban, but more than 5% of zip codes are 0% urban.[30]

The other variables are somewhat less skewed. The median age for the median zip code is 37.5, with the bottom 5 percent of zip codes with a median age below 28 and the top 5 percent of zip codes with a median age above 47. The median household size is 2.6 for the median zip code, compared to below 2.1 for the bottom 5 percent of zip codes and above 3.5 for the top 5 percent of zip codes. The unemployment rate for the median zip code is 5.6 percent; the bottom 5 percent of zip codes have an unemployment rate below 2.7 percent while the top 5 percent of zip codes have an unemployment rate above 10.5 percent. For the median zip code, the median household income

[26] See https://www.ftc.gov/enforcement/cases-proceedings/162-3154/advertising-strategies-llc-et-al and https://www.ftc.gov/news-events/press-releases/2017/03/business-opportunity-scheme-operators-banned-telemarketing for more details.

[27] See https://www.ftc.gov/news-events/press-releases/2017/06/defendants-involved-selling-business-coaching-programs-settle-ftc for more details.

[28] See https://www.ftc.gov/enforcement/cases-proceedings/122-3216-x130063/money-now-funding-llc and https://www.ftc.gov/news-events/press-releases/2015/08/ftc-stops-elusive-business-opportunity-scheme for more details.

[29] See https://www.ftc.gov/enforcement/cases-proceedings/152-3245-x170019/phlg-enterprises-llc and https://www.ftc.gov/news-events/press-releases/2017/02/ftc-settlement-puts-stop-money-mule-who-profited-india-based-irs for more details.

[30] Because I exclude PO Boxes, I likely miss some of the population living in rural areas, who are more likely to use PO Boxes.

is 52 thousand dollars; the bottom 5 percent have a median income below 29 thousand dollars and the top 5 percent have a median income above 100 thousand dollars. Lastly, in the median zip code about 24 percent of the 25 year old and above population have completed college, compared to less than 8.6 percent for the bottom 5 percent of zip codes and above 61.2 percent for the top 5 percent of zip codes.

Table A-1 Quantiles of Demographic Variables

	Quantiles								
Variable	1%	5%	10%	25%	50%	75%	90%	95%	99%
Percent Black	0	0.1	0.4	1.4	4.7	14.5	34.9	54.6	87.6
Percent Hispanic	0	0.7	1.3	3	7.7	20.8	46.9	65.3	90.8
Percent Asian	0	0	0.1	0.6	2	5.2	12	19.1	43.7
Median Age	23.5	28.3	30.2	33.7	37.5	41.2	44.6	47.1	54.8
Household Size	1.8	2.1	2.2	2.4	2.6	2.9	3.2	3.5	4.1
Unemployment Rate	1.5	2.7	3.3	4.3	5.6	7.3	9.2	10.5	13.3
Percent Urban	0	0	28.1	74.3	98	100	100	100	100
Median Household Income (thousands)	23	29	33	41	52	68	88	101	130
Pct College Educated	5.1	8.6	10.9	15.8	24.1	37.4	52.4	61.2	75.5

Note: The 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentile quantiles of each variable across zip codes are included in the table, where the quantiles are estimated after weighting each zipcode by its 2010 population.