Who is Victimized by Fraud? Evidence from Consumer Protection Cases*

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Abstract

I use data on victims from twenty-three consumer protection law enforcement actions to examine how victimization rates varies across communities. In addition, I separately examine victimization in Payday Loan, Student Debt Relief, Health Care, and Business Opportunity cases. For these cases, I find higher victim rates in more heavily black, higher income, older, and more urban communities and lower victim rates in more heavily Hispanic, higher household size, higher credit score, and more college educated communities.

Keywords: victimization, fraud, demographics, consumer protection

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1 Introduction

Fraud is a persistent feature of the commercial landscape. The Federal Trade Commission (FTC) has found that about 16% of Americans are victimized yearly in its latest survey (Anderson, 2019), with similar rates of victimization internationally (Dijk et al., 2007). In order to combat fraud, consumer protection authorities would like to identify which types of consumers are more likely to be victimized by different types of fraud. Such information can assist consumer education efforts by targeting information on fraud to likely victims. It can also assist law enforcement to target enforcement efforts.

However, regulators are typically unaware of the demographics of consumers in any given legal case, or type of fraud, are, and how they differ from the US average. For example, the FTC in a recent report to Congress stated that:

> [T]he FTC has not generally collected demographic information about the victims in its enforcement actions. Therefore, as part of its Every Community Initiative, the FTC is undertaking new research to help the agency assess how its law enforcement actions and its work to remediate harm protects these communities.

In particular, the FTC was interested in racial and ethnic demographics, as it promised to "[p]erform additional research to help the FTC identify and target frauds affecting African American and Latino communities" (Federal Trade Commission, 2016).

One way to examine how demographics affect victimization from fraud is through surveys, which the FTC and other organizations conduct regularly (Anderson, 2013, 2019). The main advantage of such surveys is that they examine a nationally representative sample of the overall population. However, sample sizes are often small – for example, Anderson (2019) had 3,700 respondents, and so significantly less than 1,000 fraud victims – which can make it difficult to examine the demographics of specific types of fraudulent activities.

Another approach is to examine consumer complaints; the FTC and partner organizations receive millions of consumer complaints per year (Raval, 2019a), and so consumer complaints provide a useful source of information on victimization. As Raval (2019b) points out, though, consumer complaints reflect both victimization and the propensity to complain, which also varies across demographic groups, and so complaint statistics have to be adjusted in order to reflect victimization. In addition, consumers may not know to complain about credence goods, and so few consumer complaints concern herbal supplements, psychic scams, or pyramid schemes relative to the degree of victimization from these frauds.

In this paper, I take a third approach to examining how demographics affect victimization by exploiting datasets of victims of different frauds that complements information from complaints and victimization surveys. Because these datasets contain the addresses of affected consumers, I can match victims to demographics at the zip code level derived from American Community Survey (ACS) data. Doing so allows me to examine much larger numbers of victims than in most studies; the largest case, Ideal Financial, has more than two million victims.

Because the demographic information is at the zip code level, any inferences on demographics are best thought of as reflecting differences between different American communities. This focus on differences across communities matches policymakers' own focus; the report above is part of the FTC's "Every Community Initiative" and specifically references African American and Latino communities.

In total, I examine twenty-three such cases across different types of fraudulent activity. Of these cases, two involve payday loan applications, two involve student debt relief, six involve health care (mostly weight loss supplements), and seven involve either business opportunity or work from home scams. Finally, six cases involve other frauds, including a mortgage relief case, spyware case, extended auto warranty case, a free gas for life book sold via a negative option, a case related to money transfer for imposter scams, and a Spanish language vacation prize scam. This diversity allows me to examine whether the demographics of specific types of fraud.

Most research examining the demographics of fraud victims has examined the responses of surveys of the general population (Anderson, 2007, 2013, 2019; Dijk et al., 2007; Schoepfer and Piquero, 2009; Van Wyk and Benson, 1997). In addition, some research has focused on specific frauds by conducting surveys of fraud victims from particular cases (Pak and Shadel, 2011). These studies have focused on different frauds than examined in this paper; as the Stanford Center for Longevity states: "Little work has been done to profile victims of scams other than lottery and investment fraud."[1] For example, Deliema et al. (2020) profile victims of investment fraud.

In addition, two recent papers (Bosley and Knorr, 2018; Bäckman and Hanspal, 2019) examine the demographics of multi-level marketing or pyramid schemes through the Fortune Hi-Tech Marketing and Herbalife cases, respectively, using location information, as in this paper. Those papers thus examine a somewhat different type of economic activity than the cases that I examine in this paper.

The paper proceeds as follows. Section 2 examines the overall FTC case distribution and

[1]See http://longevity.stanford.edu/profiling/.

describes the victim datasets used in this study. Section 3 describes my research hypotheses and then details the demographic characteristics I examine. Section 4 examines the demographic determinants of victimization using data from consumer protection cases. Section 5 then provides a discussion of the findings and concludes.

2 Legal Cases

2.1 FTC Case Distribution

Before I discuss the cases that I use in my analysis, I first examine the overall distribution of consumer protection actions brought by the FTC. I use two data sources to compile a distribution of FTC actions. The first data source, the FTC's Protecting Older Consumers Reports, detail the full set of new enforcement actions brought between between October 1, 2017 and September 30, 2019 (i.e. fiscal years 2018 and 2019) in appendices.[2] The second data source, the FTC's refund reports, detail all cases for which refunds to consumers were distributed between July 2016 and April 2020.[3]

The types of cases in the new case dataset and refund case dataset may differ for several reasons. First, because it takes time for enforcement actions to go through the litigation

[2]See https://www.ftc.gov/system/files/documents/reports/protecting-older-consumers-2017-2018-report-congress-federal-trade-commission/protecting_older_consumers_-_ftc_report_10-18-18.pdf for the 2017-2018 report and https://www.ftc.gov/system/files/documents/reports/protecting-older-consumers-2018-2019-report-federal-trade-commission/p144401_protecting_older_consumers_2019_1.pdf for the 2018-2019 report. While labeled as "Older Consumers" reports, in practice they include all consumer protection cases barring one case which I also include in Table I.

[3]See https://www.ftc.gov/reports/bureau-consumer-protection-consumer-refunds-program-consumer-refunds-effected-july-2016 and https://www.ftc.gov/reports/2018-annual-report-refunds-consumers for the first two redress reports. In addition, refund case data is now posted on the FTC's Tableau page at https://public.tableau.com/profile/federal.trade.commission#!/vizhome/Refunds_15797958402020/RefundsbyCase, which include cases with newer refund distributions.

process, and the refund case data starts in 2016, the refund case data will include many cases that began earlier than in the new case data. The types of cases that the FTC brings may vary over time. Second, the FTC often undertakes "sweeps" in which it brings several actions on one type of consumer protection problem at the same time in order to send a message to the marketplace.[4] Such sweeps will mean certain years may have a much higher number of cases of a particular type than others. Third, the number of cases may not reflect either the scale of the fraud or the amount of FTC effort required to bring the case; for example, consumer refunds obtained in the Volkswagen diesel defeat device cases are several billions of dollars. Finally, the refund case data only includes cases for which the FTC distributed refunds, and so will not include cases without monetary relief (for example, cases with only injunctive relief).

For each dataset, I classify each consumer protection action into topics based upon the case description; the topic categories I use are, for the most part, based upon the categories used to classify Consumer Sentinel complaints.[5] I allow cases to be included in multiple topics if warranted. I also exclude privacy cases.

Table I contains a summary of the distribution of the FTC's consumer protection cases. The first column is a given topic, the second and third columns the number and percentage of cases from each topic from the set of new cases between October 2017 and September 2019, and the fourth and fifth columns the number and percentage of cases from each topic from the set of cases with refunds between July 2016 and April 2020. Perhaps the most striking lesson from this table is the diversity in the types of consumer protection actions

[4] See, for example, "Operation Ruse Control" against deceptive auto dealers, detailed in https://www.consumer.ftc.gov/blog/2015/03/operation-ruse-control.

[5] See, for example, Appendix B in https://www.ftc.gov/system/files/documents/reports/consumer-sentinel-network-data-book-2019/consumer_sentinel_network_data_book_2019.pdf.

brought by the FTC, with 28 topics in total. Moreover, 21 topics have at least one case in the new case data, out of 106 cases total, and 24 topics have at least one case in the refund case data, out of 104 cases total.

In order to focus on the most common topics, I bold all topics that comprise at least 5% of the cases. Nine topics comprise at least 5% of cases in one dataset; only four comprise more than 5% in both of the datasets. The most common topic is Health Care, there are 16 Health Care cases (15.1%) in the new case data and 22 Health Care cases (21.2%) in the refund case data. Business and Job Opportunity cases are the second most common type of case, with 12 (11.3%) cases in the new case data and 15 (14.4%) cases in the refund case data. Debt Relief is tied for second most common topic in the new case data and is the fourth most common in the refund case data, with 12 (11.3%) cases in the new case data and 9 (8.7%) cases in the refund case data. Finally, there are 9 (8.5%) Negative Option cases in the new case data and 8 (7.7%) Negative Option cases in the refund case data. However, Negative Option cases, which involve signing up consumers for a recurring subscription for which the burden is on the consumer to cancel, often occur in the context of dietary supplement cases in Health Care – five of the Negative Option cases in each dataset are also classified as Health Care. In addition, Other Advertising issues, Debt Collection, Internet Services or Technical Support, Online Shopping and Reviews, and Payday Lending are all topics that are at least 5% of cases in one of the datasets.

Table I FTC Consumer Protection Case Distribution

Topic	New Cases Number	New Cases Percent	Refund Cases Number	Refund Cases Percent
Advertising (Other)	**6**	**5.7%**	2	1.9%
Auto Related	4	3.8%	5	4.8%
Banks and Lenders	2	1.9%	0	0%
Business and Job Opportunities	**12**	**11.3%**	**15**	**14.4%**
Charitable Solicitations	5	4.7%	0	0%
Cramming	0	0%	4	2.9%
Credit Card	0	0%	1	1.0%
Credit Reports	1	0.9%	1	1.0%
Debt Collection	4	3.8%	**6**	**5.8%**
Debt Relief	**12**	**11.3%**	**9**	**8.7%**
Do Not Call	5	4.7%	2	1.9%
Education	0	0%	2	1.9%
Grants	2	1.9%	0	0%
Health Care	**16**	**15.1%**	**22**	**21.2%**
Imposter	3	2.8%	4	3.8%
Internet Services / Tech Support	5	4.7%	**11**	**10.6%**
Made in USA	5	4.7%	0	0%
Mobile Phone	0	0%	3	2.9%
Multi-Level Marketing	0	0%	3	2.9%
Negative Option	**9**	**8.5%**	**8**	**7.7%**
Office Supplies and Services	1	0.9%	5	4.8%
Online Shopping and Reviews	**7**	**6.6%**	2	1.9%
Other	4	3.8%	2	1.9%
Payday Lending	0	0.0%	**6**	**5.8%**
Payment Processing	4	3.8%	1	1.0%
Prizes and Sweepstakes	1	0.9%	1	1.0%
Shop At Home and Catalog Sales	0	0%	1	1.0%
Real Estate / Timeshare	1	0.9%	2	1.9%
Total	106	100%	104	100%

Note: Data on new cases based on the October 2017 to September 2019 period. Data on cases with refunds based on cases with refund distributions between July 2016 and April 2020.

2.2 Cases Used In Analysis

For analysis, I use data on victims from twenty-three legal cases. In order to obtain these cases, staff at the Federal Trade Commission undertook a search of recent cases involving violations of consumer protection laws.[6] In order to be included in the paper, a given case had to have data from a customer database. 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 twenty-three legal cases to use in the analysis. I only include victims which report a zip code that can be matched to the set of zip codes I detail in Section 3.

I summarize the differences across these cases in Table II. In Appendix A, I provide further details on the cases, including a short description and links to further information. In the second column of Table II, I display the number of victims for each case that can be matched to zip codes with full demographic data. 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.

All of the twenty-three cases concern different types of fraud. I divide these cases into groups based upon the topics in Table I if more than one case is on the same topic. Four groups comprise topics that were included in the nine topics highlighted in Table I as having more than 5% of cases in either the new case dataset or refund case dataset. Six cases – DoubleShot, Genesis Today, NourishLife, SimplePure, Solace, and Tommie Copper – are related to Health Care, the most common topic in both datasets of the FTC's case distri-

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

bution. Of the health care cases, only Tommie Copper is not a dietary supplement case, as it concerns compression clothing marketed for relief of severe and chronic pain. All the dietary supplement cases concern weight loss, at least in part, except for NourishLife which concerns supplements marketed to treat autism-related speech issues. The SimplePure case also involved a negative option program.

Seven cases are business opportunity or work from home related scams, the second most common topic in both datasets of the FTC's case distribution. Two of these seven cases – IME and MoneyCode – have relatively low dollar losses per consumer, while four cases – AdvStrategy, Guidance, MoneyNow, and TopShelf – have losses per consumer in the thousands of dollars. Finally, the last Business opportunity case, Digital Altitude, is unique as the median victim lost only $40, but the average loss was between $700 to $1,000 as a subset of victims suffered extremely large losses. For Digital Altitude, out of the 44,866 victims that I use, 37,782 have losses less than $500, most of which are close to $40, while 7,084 have losses greater than $500. In the empirical analysis, I thus divide Business Opportunity cases into two subgroups, and divide victims in the Digital Altitude case in two as well. The first subgroup, "BusOppLow", includes cases with low dollar losses for victims, including IME, MoneyCode, and victims in Digital Altitude with losses of less than $500. The second subgroup, "BusOppHigh", includes cases with high dollar losses for victims, including AdvStrategy, Guidance, MoneyNow, and TopShelf and victims in Digital Altitude with losses of greater than $500.

Two cases – EZDocs and SSS – are related to debt relief for student loans in particular; debt relief was tied for second most common topic in the new case data and was the fourth most common in the refund case data. Seven of the twelve debt relief cases in the new case data concerned student loan debt relief in specific, while two of the nine debt relief cases in the new case data concerned student loan debt relief. Two cases – Ideal and Platinum – concern scams related to payday loan applications. In the refund case data, 6 or 5.8% of cases are on Payday Lending, although surprisingly no cases in the new case dataset relate to Payday Lending.

Finally, six cases cannot be classified into one major group but concern fraudulent activity; I group these under "Other Fraud". The CD Capital case concerns a company claiming to provide mortgage debt relief, the Dolce case sales of extended auto warranties, Green Millionaire sales of a free "gas for life" book sold through a negative option program, the WinFixer case spyware and computer security scans, PHLG the money transfer element of imposter scams, and VGC a vacation prize scam targeted at Spanish speaking consumers.

As Table II demonstrates, these cases have a large amount of variation in the number of victims in the company's databases, and in the average consumer loss. While some cases have thousands of victims, the Ideal case has about 2 million victims. The average loss per consumer ranges from $30-$40, as in the Ideal case, to several thousands of dollars for many of the business opportunity scams.

3 Research Hypotheses and Demographics

My starting point in this research is the disadvantaged consumer hypothesis (Andreasen, 1975). Andreasen (1975) argued that poor, old, uneducated, and minority consumers are more likely to be disadvantaged, and so at higher risk of victimization. I state this formally below.

Table II Cases with Victim Lists

Case	No. Victims	Average Loss	Case Description
		Payday Loan Applications	
Ideal	2,008,356	≈ \$30-\$40	Payday Loan Apps
Platinum	69,499	≈ \$110	Deceptive Credit Cards
		Student Debt Relief	
EZDocs	38,810	≈ \$600 - \$700	Student Debt Relief
SSS	20,540	≈ \$700 - \$800	Student Debt Relief
		Health Care	
DoubleShot	15,910	≈ \$70	Weight Loss
Genesis Today	182,887	≈ \$50	Weight Loss
NourishLife	6,682	≈ \$500	Speech Disorder / Autism
SimplePure	680,377	≈ \$90	Deceptive Claims and Negative Option
Solace	1,528	≈ \$120 - \$150	Weight Loss
Tommie Copper	762,321	≈ \$70	Pain Relief
		Business Opportunity	
AdvStrategy	11,338	≈ \$2,200	Business Opportunity
DigitalAltitude	44,866	≈ \$700 - \$1,000 (mean), \$40 (median)	Business Coaching
Guidance	6,691	≈ \$1,600 -\$8,000	Business Coaching
IME	3,844	≈ \$250	Home Business
MoneyCode	42,597	≈ \$50	Online Business
MoneyNow	1,797	≈ \$2,800	Home Business
TopShelf	3,282	≈ \$5,000 -\$7,000	Online Business
		Other Fraud	
CD Capital	1,169	≈ \$1,400	Mortgage Relief
Dolce	5,712	≈ \$700	Extended Auto Warranty
Green Millionaire	65,350	≈ \$60	Free Gas for Life Book, Negative Option
PHLG	2,640	≈ \$500	Money Transfer for Imposter Scams
VGC	51,085	≈ 250	Spanish Language Vacation Prize
WinFixer	304,246	≈ \$60	Computer Security

Note: The average loss per victim and number of victims are approximate and based on available information from the FTC legal complaint, press releases, or redress information. The number of victims may differ from public information as it reflects all victims that can be matched to zip codes in Section 3, after duplicate entries were removed.

Hypothesis 1 *Communities with more disadvantaged consumers will have higher rates of victimization.*

I identify demographic characteristics related to disadvantage through the 5 digit zip codes of victims' addresses. Thus, the demographic characteristics I use reflect the characteristics of the community that victims live in rather than their individual characteristics.

My primary source for demographic information is the 2014-2018 American Community Survey (ACS). However, the ACS data contains hundreds of demographic variables. I thus apply the following criteria to narrow down the variables that I use. First, I include demographic variables that I believe provide indicators of disadvantage. Second, I only include characteristics that exhibit substantial heterogeneity across zip codes.[7] Third, I focus on characteristics that provide substantial independent variation from each other, in order to avoid both statistical multicollinearity problems as well as difficulties in interpreting effects. For example, the median age and the percentage of residents above 65 are quite correlated with each other, as are median household income and the share of residents in poverty and race/ethnicity variables and the share of residents that are foreign born.

First, I hypothesize that minority communities are more likely to be disadvantaged, and so victimized. Thus, I include several variables to control for the race and ethnicity of the zip code, including the fraction of residents in the zip code that are black, are Hispanic, and are Asian. Second, I hypothesize that more educated and more rich communities will be less disadvantaged and so less victimized. I thus include the share of the population that is college educated and the median household income of the zip code. Finally, I hypothesize that older

[7]For example, it would be interesting to examine the percentage of zip code residents that are female, but, given the average of the fraction of female zip codes across zip codes is 51%, the difference between the 90th and 10th percentiles is less than 6 percentage points.

consumers and consumers living alone (i.e. not in a family) will be more vulnerable to fraud. To include these characteristics, I include the median age and the median household size of the zip code.

I also include the percent of the zip code population that is urbanized; there is a lot of current policy interest in how victimization varies between rural and urban residents. Because I do not have strong priors on whether urban or rural residents are more disadvantaged, I do not put forth a hypothesis on the relationship between the share of urban residents and victimization.

I also examined other sources of demographic information beyond the US Census Bureau. Here again, my goal was to obtain information on demographic characteristics with independent variation from those in the ACS. I focus on attributes of residents of the zip code, not of the zip code itself. For example, the FDIC has data on bank branches and deposits at the zip code level, but banking markets are likely larger than a single zip code.

I thus include data on the 2016 average credit score of a zip code provided by the Federal Reserve Board. I examine credit scores for two reasons. First, poor credit may lead consumers to use financial instruments such as payday loans or seek debt relief. Second, economists have viewed credit scores as a measure of social capital (Bricker and Li, 2017), in which low credit scores would be another sign of disadvantage through the low social capital of a community.[8]

I formalize these specific hypotheses below:

Hypothesis 1a *Communities with a greater share of black or Hispanic residents will have*

[8]This data is available at https://www.federalreserve.gov/econres/feds/files/feds2017008_data.zip. The average credit score is missing from 1,203 of the 27,937 zip codes I use for analysis; I thus include a indicator for missing credit score in my empirical analyses.

higher rates of victimization.

Hypothesis 1b *Communities with more college educated residents will have lower rates of victimization.*

Hypothesis 1c *Communities with a greater household median size will have lower rates of victimization.*

Hypothesis 1d *Communities with a higher median age will have higher rates of victimization.*

Hypothesis 1e *Communities with a higher average credit score will have lower rates of victimization.*

Which consumers are disadvantaged, and so have greater victimization, likely depends on context and so may vary across different types of fraud. For example, more educated consumers with more computer use may be more vulnerable for tech support scams, and consumers with poor credit for payday loan and student debt relief scams. While I do not define specific hypotheses related to specific types of fraud, I will examine how demographics affect victimization for different frauds in the next section.

I then combine the demographic variables detailed above with the victim data. I also 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.[9] I

[9]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.

Table III Summary Statistics

Variable	Mean	SD	10th Percentile	90th Percentile
Population (thousands)	31.7	20.8	6.2	59.4
Percent Black	12.3	17.8	0.5	34.7
Percent Hispanic	17.8	20.9	1.8	49.6
Percent College Educated	31.3	17.1	12.7	56.3
Median Household Income (thousands)	65.5	26.8	37.8	102
Median Age	38.5	6.2	31.2	45.8
Percent Urban	81.6	30	31.7	100
Average Credit Score	699.4	35.1	652.1	743.3
Median HH Size	2.7	0.4	2.2	3.2
Percent Asian	5.4	8.6	0.2	13.5

Note: All statistics estimated after weighting each zipcode by its population.

also exclude zip codes missing the ACS demographic variables described above. This process leaves a set of 27,937 zip codes that I use for my main analyses.

Table III provides summary statistics for the demographic variables that I include across the zip codes weighted by their population. There is substantial heterogeneity in all of these demographics across zip codes. For the 10th percentile zip code, blacks are 0.5% of the zip code population, compared to 35% for the 90th percentile zip code. Similarly, the 10th percentile zip code is 1.8% Hispanic, while the 90th percentile zip code is 50% Hispanic. The difference between the 90th and 10th percentile zip code is 40 percentage points for the share of residents that are college educated, over $60,000 in median household income, about 15 years in median age, about one extra person for median household size, almost 70 percentage points for percentage urban, and about 90 points for the average credit score. Thus, as the standard deviation and quantiles reported make clear, there are heavily white and heavily minority, rich and poor, and urban and rural zip codes. In Appendix B, I provide further statistics in how quantiles of different demographic variables vary across zip codes.

4 Results

In order to disentangle the effects of different demographic factors, I estimate the following fractional logit model (Papke and Wooldridge, 1996):

$$E[y_{ik}|D_i, \gamma_k] = G(\beta D_i + \gamma_k), \tag{1}$$

where i is the zipcode and k the company. The dependent variable y_{ik} is the per-capita victim rate for company k in zipcode i. In a fractional logit model, the conditional expectation of the dependent variable is modeled as a logistic function G of linear covariates. I use a fractional logit specification for the victim rate so that all estimates of the demographic effects β can easily be translated into percent changes compared to the baseline group, holding all other variables fixed.[10] Examining the percent change is important because I examine specifications for different types of scams, which have different base rates of victimization.

I include all the demographic variables mentioned in Section 3 in D_{is}. Because demographic effects are likely non-linear, I model the effects of these demographic characteristics flexibly through linear B-splines. 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 average credit score, the percentage of college graduates, the median age, median household income, and median household size. In addition, I weight zip codes by their population, so more populous zip codes receive greater weight.

Because I estimate effects for demographic factors using splines, I only report the effect

[10] A fractional logit model is used to model a dependent variable that ranges between 0 and 1, which the per-capita victim rate satisfies.

for selected values relative to an omitted category. The baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age.[11] Because my estimates of demographics are at the zip code level, I cluster standard errors at the zip code level in all specifications. Thus, my estimates of standard errors are robust to unobserved shocks to the victimization at the zip code level that are common across cases (for example, due to unobserved demographic factors at the zip code level).

I first estimate equation (1) for all of the 23 cases pooled together. However, because the effects of demographics likely vary by the type of fraud conducted, I examine demographic effects for the Payday, Health Care, Student Debt Relief, and Business Opportunity cases separately. I separate the Business Opportunity cases into those with low total dollar losses and those with high total dollar losses. I report these estimates in Table IV for selected values of each demographic variable. I report the effects for intermediate values of the demographic variables for the main case group specifications as well in Table C-1 in the Web Appendix. Finally, because even within category cases can be quite different from each other, I report estimates for each case separately in Table A-2 to Table A-7.

In addition, to depict the potential nonlinear effects of each demographic variable on the victimization rate, I also plot the entire path of the estimated effect of each demographic variable relative to the omitted category in Figure 1 to Figure 4. For example, the left figure of Figure 1 examines how the victimization rate varies with the percentage of black

[11] In all of the specifications I run, the number of observations is the number of zip codes times the number of cases.

zip code residents, while the right figure of Figure 1 examines the relationship between the victimization rate and the percentage of Hispanic zip code residents. In each figure, the red dashed line depicts the Pooled estimates, the blue solid line estimates for Health Care cases, the green solid line estimates for low dollar Business Opportunity cases, the purple solid line estimates for high dollar Business Opportunity cases, the orange solid line estimates for Payday Loan cases, and the yellow solid line estimates for Student Debt Relief cases.

Finally, to show the distribution in effects across cases, Figure 5 depicts boxplots of the percent effect, in the left figure, and the t-statistic, in the right figure, of effects across cases. The left edge of the box is the 25th percentile, the middle bar the median, and right edge of the box the 75th percentile; the whiskers reflect the lowest and highest points whose distance from the edge of the box is at most 1.5 times the interquartile range.

4.1 Race and Ethnicity

The most striking finding is that heavily black communities have substantially higher rates of victimization across almost all of the case groups. In the results pooling all of the cases, communities with a 100% black population have a 116% higher victim rate than those with a 0% black population, holding all other variables fixed. The largest effects are for the Payday Loan and Student Debt Relief cases. On average, communities with a 100% black population have a 209% higher rate of victimization than 0% black communities in Payday Loan cases, with increases of 207% and 277% for each Payday Loan case separately. Similarly, on average, communities with a 100% black population have a 190% higher rate of victimization than 0% black communities in Student Debt Relief cases, with increases of 99% and 409% for each Student Debt Relief case separately.

I find smaller and less consistent effects for Health Care cases. Victimization is 31% higher for 100% black communities than 0% black communities in Health Care cases on average; I find a significant positive effect for two cases, a significant negative effect for one, and insignificant effects for three cases.

For Business Opportunity cases, I find higher rates of victimization in heavily black communities for low dollar cases, and lower rates in high dollar cases. On average, victimization for 100% black communities is 131% higher than in 0% black communities in low dollar Business Opportunity cases, with increases between 100% and 167% for all three low dollar cases. However, for high dollar business opportunity cases, I find a 30% decline in victimization for 100% black communities compared to 0% black communities. For four of the five high dollar business opportunity cases, the effect of percentage black on victimization is negative; it is statistically significantly negative for one of these. For the high dollar loss consumers in the Digital Altitude case, I estimate a statistically insignificant 21% increase in victimization for 100% black communities compared to 0% black communities, while for the low dollar loss consumers in the same case I estimate a 167% increase.

Finally, victimization increases with the percentage of black residents in the zip code for all of the Other Fraud cases separately. I find large positive effects of percentage black on victimization across all of the cases, with a 150% increase for the mortgage relief case (CD Capital), a 273% increase for the auto warranty case (Dolce), a 181% increase for the imposter money transfer case (PHLG), a 53% increase for the Green Millionaire free gas for life book case, a 391% increase for the Spanish language vacation prize scam (VGC), and a 74% increase for the spyware case (WinFixer).

On average, I find a non-linear, inverse U shape effect for the percentage of Hispanic residents in the zip code. Victimization rates are typically slightly higher in moderately Hispanic communities compared to non-Hispanic communities. For example, on average, the victimization rate is 9% higher for 25% Hispanic communities compared to 0% Hispanic communities; this effect is 4% for Payday Loan cases, 28% for Student Debt Relief cases, 0% for Health Care cases, 60% for low dollar Business Opportunity cases, and 14% for high dollar Business Opportunity cases.

However, I find significant declines in victimization going from a 0% Hispanic area to a 100% Hispanic area.Using data from all of the cases, the victim rate is 14% lower in 100% Hispanic areas compared to 0% Hispanic areas. I find a substantial decline for Health Care cases (-42%) and high dollar Business Opportunity cases (-62%), modest declines for Payday Loan (-23%) and low dollar Business Opportunity cases (-25%), and no decline for Student Debt Relief cases (-3%). I find a statistically significant decline in victimization for 100% Hispanic areas compared to 0% Hispanic areas in 13 of the cases, compared to only three with a statistically significant positive effect.

The Spanish language vacation prize (VGC) case provides a test of the model – almost all victims in this case were Hispanic as the scam was advertised in Spanish. Reassuringly, I see a massive rise of 1614% in the victimization rate for 100% Hispanic areas compared to 0% Hispanic areas.

I also find a decline in victimization in more Asian areas. On average across all the cases, the victimization rate is 11% lower in 25% Asian areas compared to 0% Asian areas; this decline is 12% for Payday Loan, Student Debt Relief, and Health Care cases, 0% for low dollar Business Opportunity cases, and 8% for high dollar Business Opportunity cases. I find statistically significant declines in 10 cases, compared to no statistically significant increases.

4.2 Other Measures of Disadvantage

I find substantial evidence that victimization declines with the degree of college educated residents. On average across all of the cases, the victimization rate is 58% lower in 100% college educated areas compared to 0% college educated areas. This effect remains large for Payday Loan (-73%), Student Debt Relief (-72%), Health Care (-47%), low dollar Business Opportunity (-67%), and high dollar Business Opportunity (-55%) cases. Like the share of Hispanic residentrs, the relationship between the share of college educated residents and victimization is somewhat nonlinear, however. Victimization rises moving from 0% college educated areas to about 20% college educated areas for many of the case groups, with an increase of about 20% for all of the cases overall, before sharply declining.

I find statistically significant declines in victimization moving from 0% college educated areas to 100% college educated areas for 15 cases. For only one case, the spyware case WinFixer, do I find statistically significant increases in victimization with the fraction of college educated residents. This increase may reflect greater computer use in communities with more college educated residents.

By contrast, on average victimization rises with the median income of the zip code. In the Pooled estimates, the victimization rate is 36% higher in communities with a median household income of $130,000 compared to communities with a median income of $20,000; victimization is 46% higher for the Health Care cases, 36% higher in the low dollar Business Opportunity cases, 24% higher in the high dollar Business Opportunity cases, 20% higher in the Payday Loan cases, and 50% higher in the Student Debt cases. I find statistically significant positive effects of median income on victimization for eleven cases, compared to statistically significant declines in only two cases.

Older communities have higher victimization rates on average. On average across all of the cases, the victimization rate is 43% higher in communities with a median age of 55, compared to communities with a median age of 25. Examining the case groups separately, I find that communities with a median age of 55 have a 52% higher victimization rate on Health Care cases compared to communities with a median age of 25, a 47% higher victimization rate on low dollar Business Opportunity cases, a 39% higher victimization rate in high dollar Business Opportunity cases, a 11% higher victimization rate in Payday Loan cases, and a 40% higher victimization rate on Student Debt Relief cases. Across cases, thirteen cases exhibit a positive, statistically significant relationship between median age and victimization, while only one case has a statistically significant, negative relationship.

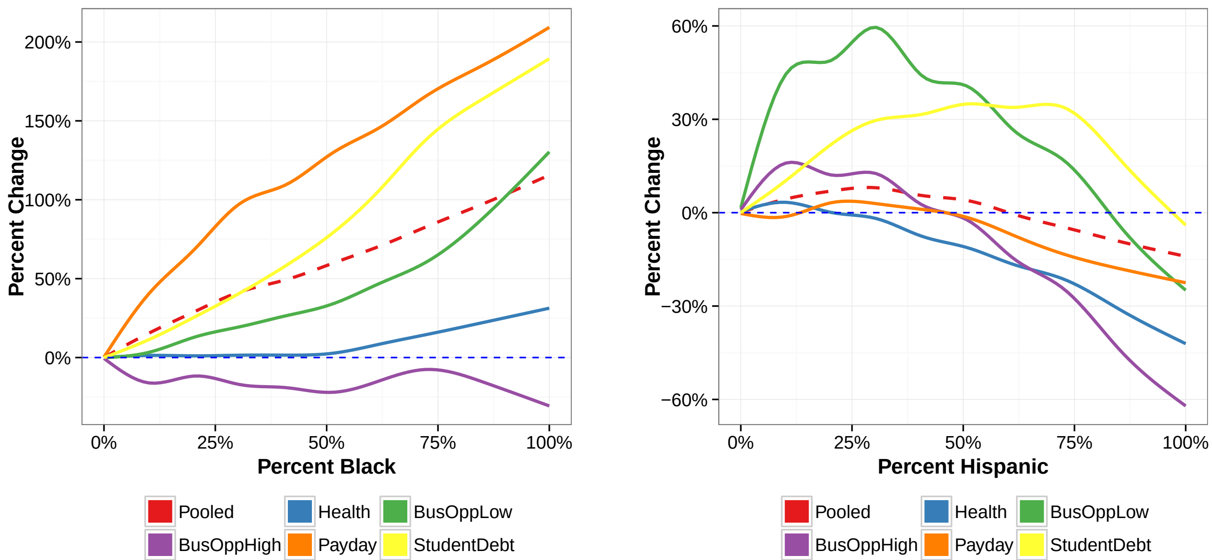
I find much lower rates of victimization in communities with larger households. Averaging across all cases, communities with a median household size of 4 have a 37% lower rate of victimization than communities with a median household size of 2. I find statistically significant negative declines of victimization with household size for Payday Loan cases with a decline of 48%, for Health Care cases with a decline of 29%, for low dollar Business Opportunity cases with a decline of 13%, and for high dollar Business Opportunity cases with a decline of 39%. For Student Debt Relief cases I find a null effect. I find statistically significant declines of victimization with household size for 15 cases individually, with an increase in victimization for only one case.[12]

[12] One explanation for these findings is that areas with larger households have a larger share of residents

Communities with higher credit scores have substantially lower victimization rates. Averaging across all cases, communities with an average credit score of 750 have a 42% lower victimization rate than an average credit score of 625. As hypothesized, I find larger declines with increasing credit scores for the debt related cases, with a 65% decline in Payday Loan cases and a 51% decline in Student Debt Relief cases. However, I also find a large decline for low dollar Business Opportunity cases (-42%), and smaller declines for Health Care cases (-15%), and high dollar Business Opportunity cases (-10%). I find statistically significant declines of victimization with average credit score for 14 cases individually, with declines above 50% for both Payday Loan cases, both Student Debt Relief cases, and the mortgage debt relief (CD Capital) case. In only one case, a weight loss supplement case (DoubleShot), do I find a statistically significant rise in victimization.

Of all the non-race related variables, the urbanicity of the zip code has perhaps the least effect on victimization. I find slightly higher rates of victimization in urban areas. Communities that are 100% urban have a 18% higher rate of victimization in the Pooled results than areas that are 0% Urban; this effect is 16% for Payday Loan cases, 17% for Health Care cases, 14% for low dollar Business Opportunity cases, -7% for high dollar Business Opportunity cases, and 26% for Student Debt Relief cases. In the individual case results, I find eleven cases with statistically significant higher rates of victimization in urban areas, and five cases with statisically significant lower rates of victimization.

who are children and so are not victimized in these scams. To examine this possibility, I reestimated the models using the victimization rate relative to the zip code population that was 18 years old or older, and continue to find negative effects of household size, although they are smaller. For example, in the results pooling across cases, communities with a median household size of 4 have a 25% lower victim rate than communities with a median household size of 2.

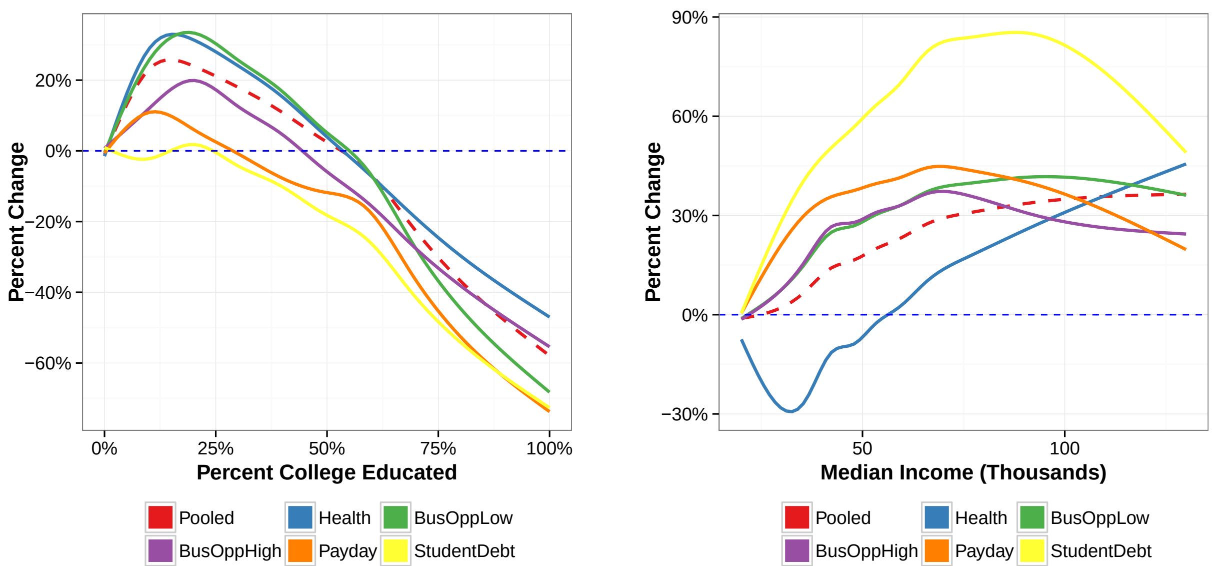


(a) Percent Black

(b) Percent Hispanic

Figure 1 Percent Change in Per Capita Victim Rate by Race and Ethnicity

Note: The graph depicts the percent change in the per capita victim rate for different demographic factors based on estimates of equation (1) for different types of fraud cases. All estimates are relative to a 0% percentage of zip code residents that are black and a 0% percentage of zip code residents that are Hispanic, respectively.



(a) Percent College Educated

(b) Median Household Income

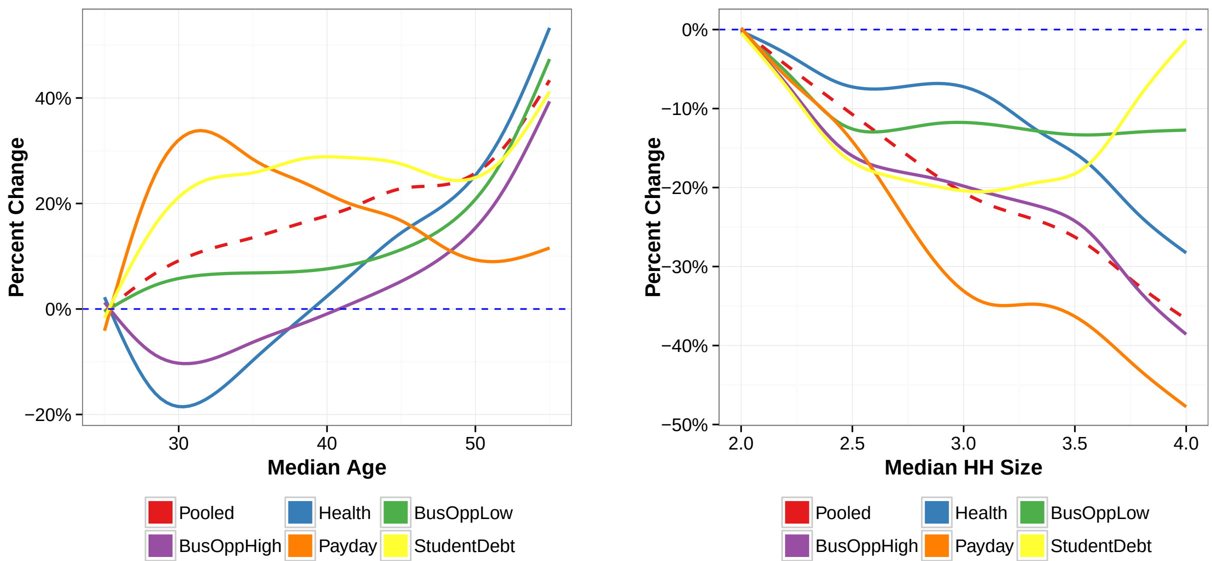
Figure 2 Percent Change in Per Capita Victim Rate by Education and Income

Note: The graph depicts the percent change in the per capita victim rate for different demographic factors based on estimates of equation (1) for different types of fraud cases. All estimates are relative to a 0% percentage of 25 years and older zip code residents that are college educated and a median household income of $20,000, respectively.

Table IV Percent Change in Per Capita Victim Rate by Demographic Factors, by Fraud Type

	(1) Pooled	(2) Payday	(3) StudentDebt	(4) Health	(5) BusOppLow	(6) BusOppHigh
Pct Black = 100%	1.16	2.09	1.90	0.31	1.31	-0.30
	(0.10)	(0.21)	(0.24)	(0.05)	(0.14)	(0.08)
Pct Hispanic = 100%	-0.14	-0.23	-0.04	-0.42	-0.25	-0.62
	(0.05)	(0.05)	(0.08)	(0.03)	(0.05)	(0.04)
Pct College = 100%	-0.58	-0.73	-0.72	-0.47	-0.67	-0.55
	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)	(0.08)
Median Income = 130k	0.36	0.20	0.50	0.46	0.36	0.24
	(0.04)	(0.07)	(0.12)	(0.05)	(0.08)	(0.11)
Median Age = 55	0.43	0.11	0.40	0.52	0.47	0.39
	(0.04)	(0.05)	(0.10)	(0.05)	(0.08)	(0.11)
Pct Urban = 100%	0.18	0.16	0.26	0.17	0.14	-0.07
	(0.01)	(0.02)	(0.04)	(0.01)	(0.02)	(0.03)
Avg Credit Score = 750	-0.42	-0.65	-0.51	-0.15	-0.42	-0.10
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.06)
Median HH Size = 4	-0.37	-0.48	-0.01	-0.29	-0.13	-0.39
	(0.02)	(0.03)	(0.06)	(0.03)	(0.06)	(0.06)
Pct Asian = 25%	-0.11	-0.12	-0.12	-0.12	-0.00	-0.08
	(0.02)	(0.03)	(0.04)	(0.02)	(0.04)	(0.05)
Observations	670488	55874	55874	167622	83811	139685

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its population. Standard errors clustered at the zip code level are in parentheses. The estimates of demographic effects are reported at selected values relative to an omitted group; the baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. The first column uses estimates for all cases ("Pooled"), the second column for Payday Loan cases, the third column for Student Debt Relief cases, the fourth column for Health Care cases, the fifth column for low dollar Business Opportunity cases, and the sixth column for high dollar Business Opportunity cases. Table C-1 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.



(a) Median Age

(b) Median Household Size

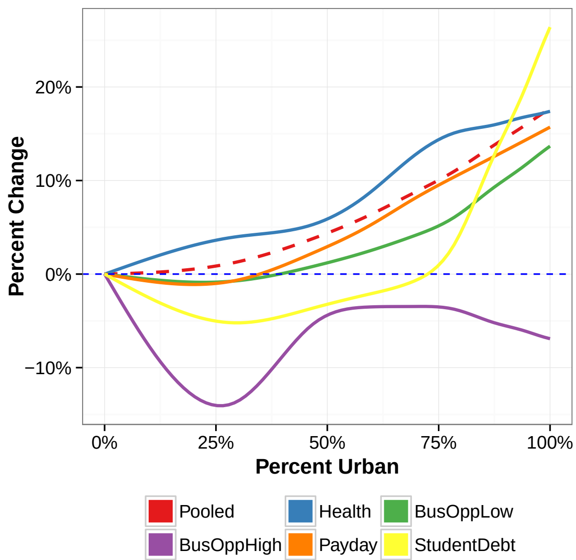
Figure 3 Percent Change in Per Capita Victim Rate by Age and Household Size

Note: The graph depicts the percent change in the per capita victim rate for different demographic factors based on estimates of equation (1) for different types of fraud cases. All estimates are relative to a median age of 25 and a median household size of 2, respectively.

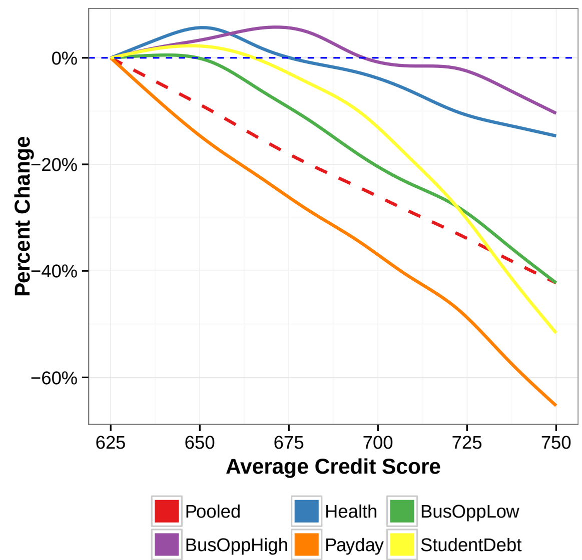
5 Discussion and Conclusion

In this paper, I have examined how demographics affect victimization using data from several FTC consumer protection cases. First, I find qualified support for the "disadvantaged consumer" (Andreasen, 1975) hypothesis. In particular, I find higher rates of victimization for heavily black areas and older areas and lower rates of victimization from areas with more college educated residents, higher credit scores, and larger households. However, everything else equal, richer areas appear to have higher victimization rates for many cases, and the most Hispanic areas have lower victimization rates.

Second, the approach taken in this paper can provide a simple way for enforcement agencies to learn about the demographics of the victims in cases that they bring. For



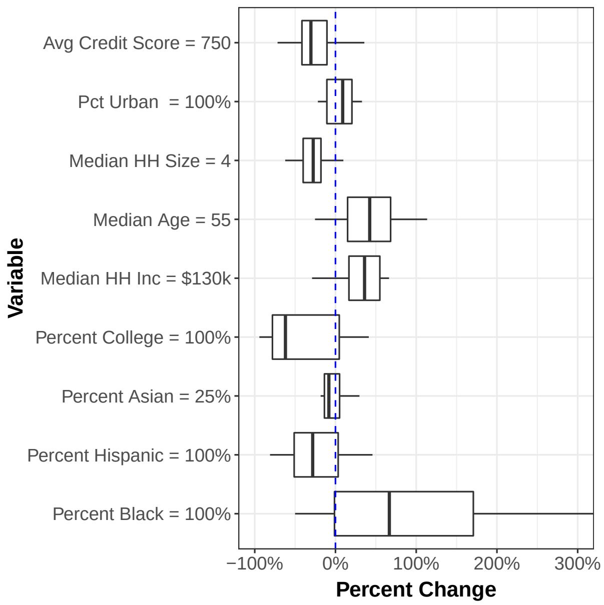
(a) Percent Urban



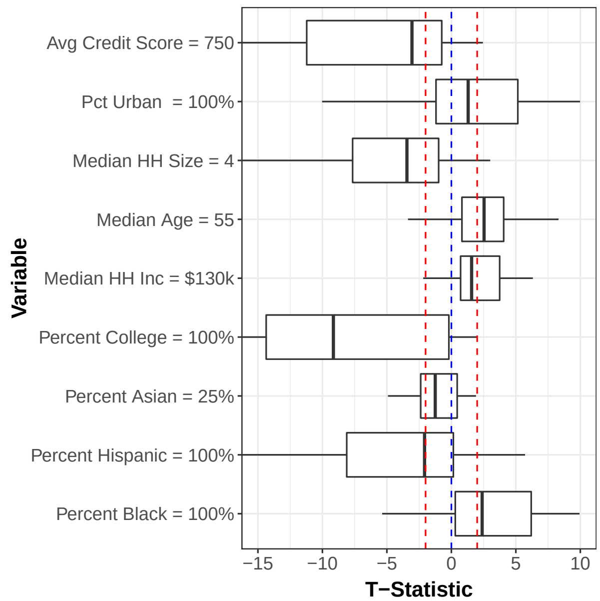
(b) Average Credit Score

Figure 4 Percent Change in Per Capita Victim Rate by Percent Urban and Average Credit Score

Note: The graph depicts the percent change in the per capita victim rate for different demographic factors based on estimates of equation (1) for different types of fraud cases. All estimates are relative to a 0% percentage of urban residents and an average credit score of 625, respectively.



(a) Percent Effect



(b) T-Statistic

Figure 5 Boxplots of Distribution of Demographic Effects Across Cases

Note: The graph depicts the distribution of effects across all of the cases for the effects of different demographic factors relative to a baseline category based on estimates of equation (1). The left figure depicts the distribution of the percent effect and the right figure the distribution of the t-statistic. The left edge of the box is the 25th percentile, the middle bar the median, and right edge of the box the 7th percentile; the whiskers reflect the lowest and highest points whose distance from the edge of the box is at most 1.5 times the interquartile range. The baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. The blue vertical dashed line is at zero and the red vertical dashed lines are at t-statistics of 2 and -2.

many scams, such agencies receive data on the victims of a given scam either as part of the investigatory process or to provide consumer redress. In addition, unlike surveys of fraud victims, examining the demographics of victims using location data does not incur additional regulatory burden under the Paperwork Reduction Act or require additional expenses for surveying. Instead, regulators could automate studies of victim demographics after the conclusion of the legal process whenever they receive data on the victims of a given fraud. This approach complements using complaint data to infer demographic patterns, and may be particularly helpful for consumer protection cases for which complaint rates are likely to be low, such as those involving credence characteristics.

Finally, understanding who is victimized by different types of scams can help policymakers invest limited resources on consumer education and case selection. For education, consumer protection agencies could target outreach events and information campaigns to communities most heavily affected by different types of scams. It may help the effectiveness of this outreach to show members of these communities that they appear to be targeted at greater rates. In addition, enforcement agencies may desire to bring cases against companies targeting particular groups, as the FTC stated to Congress as one objective in Federal Trade Commission (2016):

> Bring more cases against entities that target or disproportionately affect African American and Latino consumers, such as those engaging in affinity frauds, income-related frauds, and debt-related frauds.

For example, this paper has shown that victims in many types of cases are disproportionately from heavily black areas, with the highest relative rates of victimization for Payday Loan and Student Debt Relief cases. However, even cases unrelated to debt or income, such as Health Care cases, have significantly higher rates of victimization from heavily black areas.

However, it remains unclear why victimization rates are so much higher in heavily black areas. One explanation could be that the FTC is more likely to bring cases with more black victims. However, I show in Raval (2019b) that victims of fraud in minority areas are much less likely to complain than victims living in other areas. Thus, investigations based upon consumer complaints are unlikely to result in cases that disproportionately affect black victims. In addition, my discussions with FTC staff indicate that policymakers were largely unaware of the demographic characteristics of victims prior to this research. Finally, after accounting for differences in the propensity to complain, evidence from consumer complaints also indicates higher victimization for fraud in heavily black areas (Raval, 2019a).

One explanation for higher victimization rates in heavily black areas for certain types of fraud, such as payday loan or student debt relief cases, is that residents in those areas are more likely to use payday loan services or have student debt. For example, Pew Charitable Trust (2012) find that blacks are about 100% more likely to use payday loans after controls, while Scott-Clayton and Li (2016) find that black students have about double the student debt of white students and Haughwout et al. (2019) find black-majority zip codes have about double the default rate on student loan debt of white majority zip codes.

A second explanation is targeting – fraudsters often purchase lists of victims from other scams, or lists of likely victims based on demographic or other characteristics. For example, both the payday loan cases involved companies that bought data on consumers applying for payday loans online. For anothr example, many of the cases may have lower victimization rates in heavily Hispanic areas – the opposite of the disadvantaged consumer prediction –

because the scam was marketed in English and residents in those areas felt less comfortable engaging with the scammers in English. Finally, residents of black communities could be more likely to fall victim to a scam conditional on being targeted. More research needs to be done to separate these explanations; for example, cases for which we have data on the set of consumers targeted as well as those who fall victim to a scam.

In conclusion, I wanted to mention two limitations of my analysis. First, this study is limited to consumer protection cases that involved activity that was allegedly complete "fraud." Every consumer who purchased the good or service is therefore treated as a victim. In cases where some, but not all, purchasers are harmed by a business practice, one cannot assume that all purchasers were victims. In those cases, one would need to compare those who were harmed (the victims) to consumers were not victimized.

Second, this study has only examined demographic information that could be linked to consumers through their address. It, thus, does not include information on factors such as psychological traits or evidence on financial literacy. In addition, demographics like median age may obscure non-linearities between age and victimization, as Americans are less segregated on age compared to race and ethnicity or education, and there are very few areas with say a median age above 75 or 80. Telephone surveys of a subset of the victims could provide information on non-demographic factors, as well as gather individual level demographic data, in order to obtain a fuller picture of victims of different types of scams.

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A Cases

Below, I provide details on the twenty-three 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.

A.1 Payday Loan Applications

The first 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).[13]

The second 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.[14]

A.2 Student Debt Loan Relief

The third case, the FTC vs. Alliance Document Preparation, LLC, et al. ("EZDocs"), the FTC alleged that the defendants targeted alumni of for-profit colleges struggling to repay student loans with promises of student loan debt forgiveness in return for illegal upfront fees. The FTC eventually settled the charges, with over $19 million in monetary judgments (partially suspended to over $5 million).[15]

The fourth case, the FTC vs. Strategic Student Solutions, LLC, et al. ("SSS"), the FTC alleged that the defendants falsely promised consumers that they would reduce or eliminate their student debt and offered them non-existent credit repair services. The FTC eventually settled the charges, with a monetary judgment of over $17 million (partially suspended to over $4 million).[16]

A.3 Health Care

In the fifth case, FTC vs. 734956 Canada Inc. ("DoubleShot"), the FTC alleged that a Canadian company, doing business as the Freedom Center Against Obesity, made deceptive claims in direct

[13] 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.

[14] 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.

[15] See https://www.ftc.gov/enforcement/cases-proceedings/172-3126/alliance-document-preparation-ez-docs-preps and https://www.ftc.gov/news-events/press-releases/2018/09/student-debt-relief-operators-agree-settle-ftc-charges for more details.

[16] See https://www.ftc.gov/enforcement/cases-proceedings/162-3239/strategic-student-solutions-llc and https://www.ftc.gov/news-events/press-releases/2017/05/ftc-stops-operators-unlawful-student-debt-relief-credit-repair for more details.

mail advertising to US consumers for its Double Shot weight loss pills, including claims that the pills caused permanent weight loss and that users could eat as much as they wanted of any food, do no exercise, and still lose 15 to 20 pounds weekly. The FTC filed a federal district court complaint against the company and an individual involved, and the case was settled for a judgment of $500,000.[17]

In the sixth case, FTC vs. Genesis Today, Inc., et al. ("Genesis Today"), the FTC alleged that Genesis Today made deceptive weight-loss claims in marketing its green coffee bean extract pills to US consumers through its representatives' appearances on TV shows such as The Dr. Oz Show and The View. The FTC sued the companies and individual involved; the case was settled for consumer redress of $9 million.[18]

In the seventh case, FTC vs. NourishLife, LLC, et al. ("NourishLife"), the FTC alleged that NourishLife deceptively marketed dietary supplements for speech disorders, including autism-related speech disorders, to US consumers through several marketing channels including different types of online advertising. The FTC sued the companies and individuals involved, and the case was settled for a partially suspended judgment of $3.68 million.[19]

In the eighth 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.[20]

In the ninth case, FTC vs. Solace International, Inc., et al. ("Solace"), the FTC alleged tthat Solace and a related company deceptively marketed dietary supplements for weight loss ("Lipidryl") to US consumers through advertisements online and on SkyMall. The FTC sued the companies and individuals involved, and the case was settled for a settlement amount of $400,000 and the proceeds of four houses. The total redress amount for Lipidryl purchasers was about $250,000.[21]

In the tenth case, FTC vs. Tommie Copper, Inc., et al. ("Tommie Copper"), the FTC alleged that Tommie Copper deceptively marketed copperinfused compression clothing to US consumers in order to as providing provide relief from chronic and severe pain and inflammation due to arthritis and other diseases. The product was advertised through several marketing channels including

[17] See https://www.ftc.gov/news-events/press-releases/2014/07/marketers-fat-burning-calorie-blocking-diet-pills-pay-500000 and https://www.ftc.gov/enforcement/cases-proceedings/132-3228/7734956-canada-inc-double-shot-weight-regulator for more details.

[18] See https://www.ftc.gov/news-events/press-releases/2015/01/marketer-who-promoted-green-coffee-bean-weight-loss-supplement and https://www.ftc.gov/enforcement/cases-proceedings/122-3283/genesis-today-pure-health-lindsey-duncan for more details.

[19] See https://www.ftc.gov/news-events/press-releases/2015/01/company-touted-products-ability-treat-childrens-speech-disorders and https://www.ftc.gov/enforcement/cases-proceedings/132-3152/nourishlife-llc for more details.

[20] 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.

[21] See https://www.ftc.gov/news-events/press-releases/2014/12/marketers-settle-ftc-charges-they-used-deceptive-ads-promoting and https://www.ftc.gov/enforcement/cases-proceedings/132-3117-x150010/solace-international-inc for more details.

infomercials hosted by on the Montel Williams show, as well as print media and social media. The FTC sued the company as well as individuals involved, and the case was settled for a partially suspended judgment of $86.8 million.[22]

A.4 Business Opportunity

In the eleventh case, the FTC vs. Advertising Strategies LLC, et al. ("AdvStrategy"), the FTC 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.[23]

In the twelfth case, the FTC vs. Digital Altitude LLC, et al. ("DigitalAltitude"), the FTC alleged that defendants misrepresented that they would teach consumers how to make substantial sums of money from an online business. The FTC obtained settlements with 7 defendants, with fully or partially suspended judgments in all of them. The FTC also obtained a default judgement against the remaining defendants, with a $54 million unsuspended judgment.[24]

In the thirteenth 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.[25]

In the fourteenth case, the FTC vs. Independent Marketing Exchange, Inc., et al. ("IME"), the FTC alleged that the companies made false earnings claims while selling several types of work at home schemes. The FTC settled this case for a partially suspended judgment of $919,000 for each of the companies and the individual involved.[26]

In the fifteenth case, the FTC vs. Ronnie Montano, et al. ("MoneyCode"), the FTC alleged that the company contacted consumers through spam emails, and falsely promised that consumers could earn hundreds to thousands of dollars per day using the company's Mobile Money products. The FTC settled this case for a partially suspended judgment of $7 million.[27]

In the sixteenth 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

[22] See https://www.ftc.gov/news-events/press-releases/2015/12/tommie-copper-pay-135-million-settle-ftc-deceptive-advertising and https://www.ftc.gov/enforcement/cases-proceedings/142-3194-x160007/tommie-copper for more details.

[23] 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.

[24] See https://www.ftc.gov/enforcement/cases-proceedings/172-3060/digital-altitude-llc and https://www.ftc.gov/news-events/press-releases/2018/02/ftc-obtains-court-order-halting-business-coaching-scheme for more details.

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

[26] See https://www.ftc.gov/news-events/press-releases/2011/05/ftc-recovers-properties-precious-metals-other-assets-case and https://www.ftc.gov/enforcement/cases-proceedings/independent-marketing-exchange-inc for more details.

[27] See https://www.ftc.gov/news-events/press-releases/2017/12/ftc-alleges-get-rich-quick-scheme-bilked-consumers-out-millions and https://www.ftc.gov/enforcement/cases-proceedings/142-3170/ronnie-montano for more details.

up to almost $7.4 million.[28]

In the seventeenth case, the FTC vs. Top Shelf Marketing Corp., et al. ("TopShelf"), the FTC alleged that the company falsely promised that the business development services they sold would assist consumers in starting a home-based Internet business. The FTC settled this case for a partially suspended judgment of $5.125 million.[29]

A.5 Other Fraud

The eighteenth case, FTC vs. CD Capital Investments, LLC, et al. ("CD Capital"), involved a company that the FTC alleged falsely claimed they could lower consumers mortgage payments and interest rates or prevent foreclosure, pretended to be affiliated with a government agency or consumers lenders or servicers, and illegally charged advance fees for these services. The FTC sued CD Capital and won summary judgment, default judgment, or settled (depending upon the defendants) with a judgment of $1.7 million, the amount of money consumers lost.[30]

The nineteenth case, FTC vs. Dolce Group Worldwide, The, LLC, et al. ("Dolce"), involved a company that allegedly marketed extended auto warranties through telemarketing with false claims that the consumers' warranty was about to expire, that they were calling on behalf of the car dealer or manufacturer, that they were offering extensions of consumers original auto warranties, and that the products sold provided complete and/or specified coverage for automobile repair. The FTC sued Dolce and settled with the defendants with a judgment of $4.2 million, the amount of money consumers lost.[31]

The twentieth case, FTC vs. Green Millionaire, LLC, et al. ("Green Millionaire"), involved a company that marketed a "Green Millionaire Book" with ads that the FTC alleged falsely claimed the book would give consumers free gas and electricity. The company also did not disclose that consumers would be enrolled in a subscription program, the cost of that program, and that consumers would have to cancel the program in order to avoid charges. The FTC sued Green Millionaire and settled with the defendants with a (partially) suspended judgment of $5.7 million.[32]

The twenty-first 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.[33]

[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/142-3228/top-shelf-marketing-corp for more details.

[30]See https://www.ftc.gov/news-events/press-releases/2016/09/ftc-action-court-bans-mortgage-relief-scammers-debt-relief and https://www.ftc.gov/enforcement/cases-proceedings/132-3289/cd-capital-investments-llc for additional details on this case.

[31]See https://www.ftc.gov/news-events/press-releases/2010/06/court-puts-brakes-company-deceptively-pitched-extended-auto and https://www.ftc.gov/enforcement/cases-proceedings/102-3173/dolce-group-worldwide-llc-fereidoun-fred-khalilian for additional details on this case.

[32]See https://www.ftc.gov/news-events/press-releases/2012/04/ftc-action-halts-alleged-scam-dangled-false-promise-free-gas-life and https://www.ftc.gov/enforcement/cases-proceedings/102-3204-x110055/green-millionaire-llc-et-al for additional details on this case.

[33]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-

In the twenty-second 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.[34]

In the twenty-third case, the FTC, et al. vs. VGC Corporation of America, et al. ("VGC"), the FTC alleged a company targeted Hispanic consumers by using Spanish language radio and TV ads and offered a vacation prize if consumers paid a fee; consumers never received the vacation package.[35] The FTC and Florida Attorney General's office settled with defendants in this case for a partially suspended judgment (given ability to pay) of more than $14 million, as well as injunctive provisions that prevented the defendants from marketing or selling vacation packages (among other provisions).

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 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 9 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.[36]

The other variables are somewhat less skewed. The median age for the median zip code is 38.2, with the bottom 5 percent of zip codes with a median age below 29 and the top 5 percent of zip codes with a median age above 49. 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 average credit score is 701.5 for the median zip code, but 5% of zip codes have an average credit score below 640 and 5% have an average credit score above 750. For the median zip code, the median household income is 59 thousand (2018) dollars; the bottom 5 percent have a median income below 34 thousand dollars and the top 5 percent have a median income above 117 thousand dollars. Lastly, in the median zip code about 27 percent of the 25 year old and above population have completed college, compared to less than 10 percent for the bottom 5 percent of zip codes and above 66 percent for the top 5 percent of zip codes.

C Case Specific Results

upholds-win-consumers-winfixer-case for more details.

[34]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.

[35]See https://www.ftc.gov/enforcement/cases-proceedings/102-3210/vgc-corporation-america-et-al and https://www.ftc.gov/news-events/press-releases/2011/05/ftc-stops-marketers-nationwide-free-vacationprize-scam-targeting for more details.

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

Table A-1 Quantiles of Demographic Variables

Variable	Quantiles 1%	5%	10%	25%	50%	75%	90%	95%	99%
Population (thousands)	1	3.2	6.2	15.9	29.2	43.4	59.4	70.3	94.5
Percent Black	0	0.2	0.5	1.6	5.1	14.8	34.7	53.8	85.7
Percent Hispanic	0	1.1	1.8	3.8	9.1	23.4	49.6	66.9	91.1
Percent College Educated	6	10	12.7	18	27.4	41.7	56.3	65.6	78.5
Median Household Income (thousands)	25.6	33.5	37.8	46.8	59.4	78.6	102	116.8	152.8
Median Age	23.9	29.3	31.2	34.6	38.2	42.2	45.8	48.8	57.6
Percent Urban	0	0	31.7	75.5	98.1	100	100	100	100
Average Credit Score	612.9	637	652.1	675.3	701.5	726.1	743.3	752.2	766.4
Median HH Size	1.8	2.1	2.2	2.4	2.6	2.9	3.2	3.5	4
Percent Asian	0	0	0.2	0.8	2.3	6	13.5	22.3	46.1

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 population.

Table A-2 Percent Change in Per Capita Victim Rate by Demographic Factors: Health Care Cases

	(1) Health	(2) DoubleShot	(3) GenesisToday	(4) NourishLife	(5) SimplePure	(6) Solace	(7) TommieCopper
Pct Black = 100%	0.31	-0.47	0.05	0.48	0.14	-0.28	0.59
	(0.05)	(0.09)	(0.10)	(0.59)	(0.05)	(0.60)	(0.09)
Pct Hispanic = 100%	-0.42	-0.79	-0.45	1.96	-0.35	1.65	-0.51
	(0.03)	(0.04)	(0.04)	(0.71)	(0.02)	(1.65)	(0.03)
Pct College = 100%	-0.47	-0.78	-0.04	26.16	-0.60	54.68	-0.41
	(0.03)	(0.06)	(0.10)	(12.07)	(0.02)	(50.96)	(0.04)
Median Income = 130k	0.46	0.19	0.41	-0.13	0.53	0.44	0.42
	(0.05)	(0.15)	(0.07)	(0.12)	(0.05)	(0.35)	(0.07)
Median Age = 55	0.52	0.05	0.82	0.37	0.28	1.14	0.68
	(0.05)	(0.10)	(0.10)	(0.30)	(0.03)	(0.65)	(0.09)
Pct Urban = 100%	0.17	-0.13	0.17	0.00	0.04	0.22	0.33
	(0.01)	(0.03)	(0.02)	(0.09)	(0.01)	(0.19)	(0.02)
Avg Credit Score = 750	-0.15	0.36	-0.04	0.01	-0.30	-0.13	-0.03
	(0.03)	(0.15)	(0.05)	(0.12)	(0.02)	(0.19)	(0.05)
Median HH Size = 4	-0.29	-0.34	-0.28	-0.11	-0.27	-0.28	-0.31
	(0.03)	(0.08)	(0.04)	(0.18)	(0.03)	(0.25)	(0.04)
Pct Asian = 25%	-0.12	-0.13	-0.06	0.09	-0.16	-0.18	-0.10
	(0.02)	(0.06)	(0.03)	(0.11)	(0.02)	(0.14)	(0.02)
Observations	167622	27937	27937	27937	27937	27937	27937

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its population. Standard errors clustered at the zip code level are in parentheses. The estimates of demographic effects are reported at selected values relative to an omitted group; the baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. The first column uses estimates for all Health Care cases, while the remaining columns represent individual cases. Table C-2 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table A-3 Percent Change in Per Capita Victim Rate by Demographic Factors: Business Opportunity (Low Dollar) Cases

	(1) BusOppLow	(2) DALow	(3) IME	(4) MoneyCode
Pct Black = 100%	1.31	1.67	1.00	1.06
	(0.14)	(0.20)	(0.44)	(0.17)
Pct Hispanic = 100%	-0.25	-0.11	-0.28	-0.37
	(0.05)	(0.08)	(0.23)	(0.06)
Pct College = 100%	-0.67	-0.65	-0.93	-0.64
	(0.04)	(0.06)	(0.04)	(0.05)
Median Income = 130k	0.36	0.19	0.57	0.50
	(0.08)	(0.10)	(0.37)	(0.11)
Median Age = 55	0.47	0.44	-0.03	0.53
	(0.08)	(0.12)	(0.23)	(0.11)
Pct Urban = 100%	0.14	0.13	0.05	0.15
	(0.02)	(0.03)	(0.09)	(0.03)
Avg Credit Score = 750	-0.42	-0.47	-0.40	-0.38
	(0.03)	(0.03)	(0.11)	(0.04)
Median HH Size = 4	-0.13	-0.07	-0.20	-0.17
	(0.06)	(0.07)	(0.16)	(0.07)
Pct Asian = 25%	-0.00	-0.01	0.07	0.01
	(0.04)	(0.05)	(0.14)	(0.04)
Observations	83811	27937	27937	27937

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its population. Standard errors clustered at the zip code level are in parentheses. The estimates of demographic effects are reported at selected values relative to an omitted group; the baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. The first column uses estimates for all Business Opportunity (Low Dollar) cases, while the remaining columns represent individual cases. Table C-3 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table A-4 Percent Change in Per Capita Victim Rate by Demographic Factors: Business Opportunity (High Dollar) Cases

	(1) BusOppHigh	(2) AdvStrategy	(3) DAHigh	(4) Guidance	(5) MoneyNow	(6) TopShelf
Pct Black = 100%	-0.30	-0.50	0.21	-0.30	-0.19	-0.43
	(0.08)	(0.09)	(0.24)	(0.17)	(0.32)	(0.23)
Pct Hispanic = 100%	-0.62	-0.81	0.04	-0.64	-0.52	-0.65
	(0.04)	(0.04)	(0.21)	(0.10)	(0.22)	(0.13)
Pct College = 100%	-0.55	-0.73	-0.51	-0.36	0.36	0.41
	(0.08)	(0.08)	(0.18)	(0.24)	(0.82)	(0.81)
Median Income = 130k	0.24	-0.17	0.54	0.31	1.70	0.11
	(0.11)	(0.12)	(0.26)	(0.24)	(0.93)	(0.28)
Median Age = 55	0.39	0.45	0.17	0.65	0.47	-0.13
	(0.11)	(0.17)	(0.19)	(0.22)	(0.41)	(0.18)
Pct Urban = 100%	-0.07	-0.03	0.22	-0.19	-0.11	-0.22
	(0.03)	(0.04)	(0.09)	(0.05)	(0.11)	(0.07)
Avg Credit Score = 750	-0.10	0.24	-0.35	-0.19	-0.35	-0.22
	(0.06)	(0.14)	(0.08)	(0.10)	(0.15)	(0.14)
Median HH Size = 4	-0.39	-0.62	-0.02	-0.25	-0.59	-0.25
	(0.06)	(0.06)	(0.16)	(0.12)	(0.16)	(0.19)
Pct Asian = 25%	-0.08	-0.18	0.04	-0.16	0.06	-0.14
	(0.05)	(0.08)	(0.10)	(0.08)	(0.18)	(0.12)
Observations	139685	27937	27937	27937	27937	27937

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its population. Standard errors clustered at the zip code level are in parentheses. The estimates of demographic effects are reported at selected values relative to an omitted group; the baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. The first column uses estimates for all Business Opportunity (High Dollar) cases, while the remaining columns represent individual cases. Table C-4 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table A-5 Percent Change in Per Capita Victim Rate by Demographic Factors: Payday Loan Cases

	(1) Payday	(2) Ideal	(3) Platinum
Pct Black = 100%	2.09	2.07	2.77
	(0.21)	(0.21)	(0.38)
Pct Hispanic = 100%	-0.23	-0.22	-0.44
	(0.05)	(0.05)	(0.06)
Pct College = 100%	-0.73	-0.73	-0.81
	(0.03)	(0.03)	(0.03)
Median Income = 130k	0.20	0.19	0.66
	(0.07)	(0.07)	(0.17)
Median Age = 55	0.11	0.12	-0.25
	(0.05)	(0.05)	(0.07)
Pct Urban = 100%	0.16	0.17	-0.11
	(0.02)	(0.02)	(0.03)
Avg Credit Score = 750	-0.65	-0.65	-0.72
	(0.02)	(0.02)	(0.02)
Median HH Size = 4	-0.48	-0.47	-0.60
	(0.03)	(0.03)	(0.03)
Pct Asian = 25%	-0.12	-0.12	-0.06
	(0.03)	(0.03)	(0.05)
Observations	55874	27937	27937

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its population. Standard errors clustered at the zip code level are in parentheses. The estimates of demographic effects are reported at selected values relative to an omitted group; the baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. The first column uses estimates for all Payday Loan cases, while the remaining columns represent individual cases. Table C-5 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table A-6 Percent Change in Per Capita Victim Rate by Demographic Factors: Student Debt Relief Cases

	(1) StudentDebt	(2) EZDocs	(3) SSS
Pct Black = 100%	1.90	0.99	4.09
	(0.24)	(0.26)	(0.45)
Pct Hispanic = 100%	-0.04	-0.19	0.46
	(0.08)	(0.09)	(0.16)
Pct College = 100%	-0.72	-0.79	-0.55
	(0.05)	(0.04)	(0.10)
Median Income = 130k	0.50	0.64	0.28
	(0.12)	(0.17)	(0.14)
Median Age = 55	0.40	0.40	0.41
	(0.10)	(0.13)	(0.16)
Pct Urban = 100%	0.26	0.33	0.16
	(0.04)	(0.05)	(0.05)
Avg Credit Score = 750	-0.51	-0.50	-0.52
	(0.03)	(0.04)	(0.04)
Median HH Size = 4	-0.01	0.10	-0.30
	(0.06)	(0.08)	(0.07)
Pct Asian = 25%	-0.12	-0.12	-0.12
	(0.04)	(0.05)	(0.05)
Observations	55874	27937	27937

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its population. Standard errors clustered at the zip code level are in parentheses. The estimates of demographic effects are reported at selected values relative to an omitted group; the baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. The first column uses estimates for all Student Debt Relief cases, while the remaining columns represent individual cases. Table C-6 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table A-7 Percent Change in Per Capita Victim Rate by Demographic Factors: Other Fraud Cases

	(1) CDCapital	(2) Dolce	(3) Green.Millionaire	(4) PHLG	(5) VGC	(6) WinFixer
Pct Black = 100%	1.50	2.73	0.53	1.81	3.91	0.74
	(0.80)	(0.63)	(0.14)	(0.68)	(1.78)	(0.12)
Pct Hispanic = 100%	-0.29	0.03	-0.65	-0.14	1614.26	0.07
	(0.29)	(0.21)	(0.03)	(0.23)	(276.36)	(0.09)
Pct College = 100%	-0.94	-0.82	-0.74	-0.90	8.56	0.30
	(0.10)	(0.06)	(0.03)	(0.06)	(4.72)	(0.15)
Median Income = 130k	1.29	-0.29	0.58	0.27	-0.54	0.09
	(1.34)	(0.13)	(0.11)	(0.40)	(0.11)	(0.07)
Median Age = 55	0.77	0.16	0.68	-0.04	8.75	0.73
	(0.73)	(0.20)	(0.10)	(0.30)	(2.29)	(0.10)
Pct Urban = 100%	-0.03	-0.12	-0.18	0.20	1.43	0.24
	(0.13)	(0.06)	(0.02)	(0.13)	(0.21)	(0.03)
Avg Credit Score = 750	-0.63	-0.21	-0.31	-0.39	0.30	-0.16
	(0.12)	(0.12)	(0.03)	(0.14)	(0.24)	(0.04)
Median HH Size = 4	-0.18	-0.57	-0.34	-0.43	1.02	-0.39
	(0.34)	(0.07)	(0.05)	(0.12)	(0.33)	(0.04)
Pct Asian = 25%	-0.56	0.30	-0.13	0.20	0.05	0.07
	(0.14)	(0.15)	(0.04)	(0.18)	(0.10)	(0.04)
Observations	27937	27937	27937	27937	27937	27937

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its 2010 population. Standard errors clustered at the zip code level are in parentheses. The estimates of demographic effects are reported at selected values relative to an omitted group; the baseline, omitted category is 0% for percentage black, percentage Hispanic, percentage Asian, percentage college educated, and percentage urban, 20,000 dollars for median household income, 2 people for median household size, 625 for the average credit score, and 25 for median age. All columns represent individual cases. Table C-7 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.