Who is Victimized in Consumer Protection Cases?*

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Abstract

I use data on victims from nineteen consumer protection law enforcement actions to examine how per-capita victimization rates vary across communities, as well as how who is victimized varies across Payday Loan, Health Care, and Business Opportunity 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, 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 11% of Americans are victimized yearly (Anderson, 2013), 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. For example, the FTC in a recent report to Congress stated that it would "[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). 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 (2013) had 3,600 respondents, and so less than 500 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, 2018). As Raval (2019) 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. 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.

In total, I examine nineteen such cases, which allows me to examine how demographics affect victimization across different types of fraudulent activity. Of these cases, two involve payday loan applications, six involve health care (mostly weight loss supplements), and six involve either business opportunity or work from home scams. Finally, five cases involve other frauds, including a mortgage relief case, spyware case, extended auto warranty case, a free gas for life book, and a case related to imposter scams.

The most consistent finding across cases is that victimization rates are much higher in heavily black areas. I find higher victimization rates in heavily black areas for Payday Loan, Health Care, Business Opportunity, and the Other Fraud cases separately, with positive and significant effects for the percentage of black residents on victimization in 11 of 19 cases. In contrast, victimization tends to be lower in more Asian areas. The effects for the percentage of Hispanic residents appear to be nonlinear with the highest rates of victimization in moderately Hispanic areas and the lowest rates in the most Hispanic areas.

Socioeconomic status also matters; in particular, victimization in these cases tends to be substantially lower in heavily college educated areas. I also find higher rates of victimization in older, richer and more urban areas, and lower rates of victimization in areas with larger households.

Most research examining the demographics of fraud victims has examined the responses of surveys of the general population (Anderson, 2007, 2013; 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]

In addition, two recent papers (Bosley and McKeage, 2015; Bäckman and Hanspal, 2018) 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 different type of economic activity than the cases that I examine in this paper.

The paper proceeds as follows. Section 2 describes the demographic data and victim datasets used in this study. Section 3 examines the demographic determinants of victimization using data from consumer protection cases. Section 4 then provides a discussion of the findings and concludes.

2 Data

This paper relies on data from a set of legal cases for which I have data on affected consumers from consumer databases of the company. I match victims from these cases to area

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

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 proxy for cultural and economic factors that could affect whether a consumer is victimized. First, many of the fraudulent activities are related to business opportunities or financing, such as payday loan applications. I thus include several variables related to household income, including the median household income and unemployment rate of the zip code. Since larger households may require more income for the same standard of living, I also include median household size.

Previous research has focused on "disadvantaged" consumers as those of highest risk for victimization; for example, Andreasen (1975) argues that poor, old, uneducated, and minority consumers are more likely to be disadvantaged. Using victimization surveys, Anderson (2007) and Anderson (2013) find varying victimization rates by demographics, with higher victimization rates for minority consumers and the most educated consumers and lower victimization rates for the elderly. How demographics affect victimization likely depends on context; for example, the elderly may be more vulnerable for tech support scams, the unemployed for "work at home" opportunities, etc.

I thus include several variables that may proxy for the level of disadvantage of consumers. First, I include variables to control for the race and ethnicity of the zip code, including the fraction of the zip code that is black, is Hispanic, and is Asian. I also include median age, the percentage of college educated residents in the zip code, and the percentage of urban residents in the zip code.

I then match the demographic variables listed above from the 2008-2012 American Community Survey (ACS) at the zip code level with victim data from different consumer protection cases. 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.[2] 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. In Appendix B, I examine how these demographics vary across zip codes.

2.2 Legal Cases

I match these zip code level demographics to data on victims from nineteen 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.[3] 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 nineteen 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 2.1.

[2]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.

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

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 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 nineteen cases concern different types of fraud; I divide them into four groups. Two cases – Ideal and Platinum – concern scams related to payday loan applications. Six cases – DoubleShot, Genesis Today, NourishLife, SimplePure, Solace, and Tommie Copper – are related to health care. 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. In addition, six cases – AdvStrategy, Guidance, IME, MobileMoney, MoneyNow, and TopShelf – are business opportunity or work from home related scams. Two of these six cases have relatively low dollar losses per consumer; the other four have losses per consumer in the thousands of dollars.

All three of these categories are common consumer protection fraud cases brought by the FTC. For example, of the 61 unique cases mentioned in the FTC's 2017 and 2018 redress reports, four cases are related to payday lending, seven cases to business opportunity or work from home scams, and twelve cases to health related claims.[4]

[4]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 redress reports.

In addition, five 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 relief, the Dolce case sales of extended auto warranties, Green Millionaire sales of a free "gas for life" book, the WinFixer case spyware and computer security scans, and PHLG the money transfer element of imposter scams.

As Table I 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 several of the business opportunity scams.

3 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.[5] 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 2.1 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 local unemployment rate, the percentage of college graduates, the median age, median household income, and median household size. In addition, I weight zip codes by their 2010 population, so more populous zip codes receive greater weight.

I first estimate equation (1) for all of the 19 cases pooled; I report these estimates in the Table II. However, because the effects of demographics likely vary by the type of fraud conducted, I examine demographic effects for the Payday, Health Care, Business Opportunity, and Other Fraud cases separately. Finally, because even within category cases can be quite different from each other, I report estimates for each case separately in Table III to Table VI.

Because I estimate effects for demographic factors using splines, I only report the effect 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, 0% for the unemployment rate, and 25 for median age.[6] I report the effects for intermediate values of the demographic variables for the main case group specifications as well in Table A-2.

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

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

3.1 Race and Ethnicity

The most striking finding is that heavily black communities have substantially higher rates of victimization across all of the case groups. In the results pooling all of the cases, communities with a 100% black population have a 189% higher victim rate than those with a 0% black population, holding all other variables fixed. The largest effect is for the Payday Loan cases. On average, communities with a 100% black population have a 413% higher rate of victimization than 0% black communities in Payday Loan cases, with increases above 400% for both of the Payday Loan cases separately. Victimization is 41% 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.

On average, victimization for 100% black communities is 68% higher than in 0% black communities in Business Opportunity cases. However, when looking at each case separately, I only find large positive effects of percentage black on victimization for the two low dollar loss (IME and MoneyCode) cases. For the other four cases, with average losses in the thousands of dollars, the effect of percentage black on victimization is negative; it is statistically significantly negative for one of these.

Finally, victimization is 91% higher for 100% black communities compared to 0% black communities for the Other Fraud cases. I find significant, positive effects of percentage black on victimization across all of the cases, with a 264% increase for the mortgage relief case (CD Capital), a 426% increase for the auto warranty case (Dolce), a 353% increase for the imposter money transfer case (PHLG), a 61% increase for the Green Millionaire free gas for life book case, and a 89% increase for the spyware case (WinFixer).

On average, I find a decline in victimization in heavily Hispanic areas. Using data from all of the cases, the victim rate is 19% lower in 100% Hispanic areas compared to 0% Hispanic areas. I find a substantial decline for Health Care cases (-36%) and Business Opportunity cases (-41%), compared to almost no change for Payday Loan and Other Fraud cases (3%). I find a statistically significant decline in victimization for 100% Hispanic areas compared to 0% Hispanic areas in 9 of the cases, compared to only one with a statistically significant positive effect.

However, the effect of the fraction Hispanic residents on victimization appears to be nonlinear, inverse U shape, with the highest victimization rates in moderately Hispanic communities. For example, on average, the victimization rate is 11% higher for 25% Hispanic communities compared to 0% Hispanic communities; this effect is 10% for Payday Loan cases, 3% for Health Care cases, 37% for Business Opportunity cases, and 48% for Other Fraud cases.

I also find a decline in victimization in more Asian areas. On average across all the cases, the victimization rate is 17% lower in 25% Asian areas compared to 0% Asian areas; this decline is 19% for Payday Loan cases, 16% for Health Care cases, 6% for Business Opportunity cases, and 2% for Other Fraud cases. I find statistically significant declines in 10 out of 19 cases; the only case to have a statistically significant *positive* effect is the NourishLife case, which involved dietary supplements for autism related speech therapy.

3.2 Socioeconomic Status

I find substantial evidence that victimization declines with the degree of college educated residents. On average across the cases, the victimization rate is 63% lower in 100% college educated areas compared to 0% college educated areas. This effect remains large for Payday Loan (-79%), Health Care (-45%), and Business Opportunity (-41%) cases. The only exception is Other Fraud cases (5%). However, the effect of the fraction of college educated residents is negative and statistically significant for 4 of the 5 Other Fraud cases. Across cases, I find statistically significant, negative effects of the share of college educated residents on victimization in 12 cases. For only two cases, the autism related speech therapy case NourishLife, and the spyware case WinFixer, do I find statistically significant increases in victimization with the fraction of 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 46% higher in communities with a median household income of $130,000 compared to communities with a median income of $20,000; victimization is 108% higher for the Health Care cases, 62% higher in the Business Opportunity cases, and 20% higher in the Other Fraud cases. Only for Payday Loan cases do I find a slight decline of 14% in the victimization rate in communities with a median income of $130,000 compared to those with a median income of $20,000. I find statistically significant positive effects of median income on victimization for eight cases. The effect of the unemployment rate on victimization is generally quite small, and insignificant statistically.

Older communities have higher victimization rates on average. On average across all of the cases, the victimization rate is 26% 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 70% higher victimization rate on Health Care cases compared to communities with a median age of 25, a 53% higher victimization rate on Business Opportunity cases, and a 65% higher victimization rate on Other Fraud cases. For Payday Loan cases, I find a 23% lower rate of victimization for communities with a median age of 55. Across cases, eight cases exhibit a positive, statistically significant relationship between median age and victimization, while three cases have a statistically significant, negative relationship.

I find slightly higher rates of victimization in urban areas. Communities that are 100% urban have a 19% higher rate of victimization in the Pooled results than areas that are 0% Urban; this effect is 19% for Payday Loan cases, 16% for Health Care cases, 2% for Business Opportunity cases, and 14% for Other Fraud cases. However, in the individual case results, I find five cases with statistically significant higher rates of victimization in urban areas, and five cases with statisically significant lower rates of victimization.

Finally, 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 34% 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 all four case groups, with a decline of 42% for Payday Loan cases, 24% for Health Care cases, 29% for Business Opportunity cases, and 35% for Other Fraud cases. I find statistically significant declines of victimization with household size for 14 of the 19 cases individually.

4 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 heavily college educated areas. However, everything else equal, richer areas appear to have higher victimization rates for many cases, and the most Hispanic areas have lower victimization rates. In addition, it remains unclear why victimization rates are lower in areas with larger households.

Second, this 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. Such agencies routinely receive data on the victims of a given scam 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 as part of the investigatory 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 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 cases. However, even cases unrelated to debt or income, such as Health Care cases, have significantly higher rates of victimization from heavily black areas.

In this study, I examined the demographic patterns of several consumer protection cases, all of which 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. In general, more work needs to be done to examine victims from several different types of cases in order to have a fuller understanding of the demographics of victimization.

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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.

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).[7]

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.[8]

A.2 Health Care

In the third 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 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.[9]

In the fourth 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.[10]

In the fifth case, FTC vs. NourishLife, LLC, et al. ("NourishLife"), the FTC alleged that NourishLife deceptively marketed dietary supplements for speech disorders, including autism-related

[7] 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.

[8] 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.

[9] 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.

[10] 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.

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.[11]

In the sixth 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.[12]

In the seventh 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.[13]

In the eighth 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 infomercials hosted by on the Montel Williams show, as well as print media and social media. The FTC sued the company and its principalies and individuals involved, and the case was settled for a partially suspended judgment of $86.8 million.[14]

A.3 Business Opportunity

In the ninth 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.[15]

In the tenth 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

[11] 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.

[12] 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.

[13] 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.

[14] 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.

[15] 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.

consumers business coaching services. The FTC settled these cases for between $10 million and $30 million for each set of companies involved.[16]

In the eleventh 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.[17]

In the twelvth case, the FTC vs. Ronnie Montano, et al. ("Mobile Money"), 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.[18]

In the thirteenth 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 almost $7.4 million.[19]

In the fourteenth 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.[20]

A.4 Other Fraud

The fifteenth case, FTC vs. CD Capital Investments, LLC, et al. ("CD Capital"), involved a company that 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.[21]

The sixteenth 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

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

[17] 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.

[18] 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.

[19] 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.

[20] See https://www.ftc.gov/enforcement/cases-proceedings/142-3228/top-shelf-marketing-corp for more details.

[21] 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.

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.[22]

The seventeenth case, FTC vs. Green Millionaire, LLC, et al. ("Green Millionaire"), involved a company that marketed a "Green Millionaire Book" with ads that 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.[23]

The eighteenth 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 ninteenth 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.[25]

B Demographics

Table A-1 provides summary statistics for the complaints from all Sentinel contributors, as well as the demographic variables that I include, across the zip codes weighted by their 2010 Census population. The average zip code has 30,000 residents, but the 90th percentile zip code has about 50,000 more residents. For the average zip code, 12% of residents are black, 16% Hispanic, 5% Asian, 30% college educated, and 81% urban. The median household income of the average zip code is $57,000 dollars, the median age 38, the unemployment rate 6%, and the median household size 2.7. However, as the standard deviation and quantiles reported make clear, there is a lot of heterogeneity in all of these demographics across zip codes: there are heavily white and heavily minority, rich and poor, and urban and rural zip codes.[26]

[22]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.

[23]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.

[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]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.

[26]I do not include any demographic factors that do not have substantial heterogeneity across zip codes. 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.

Table A-2 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.[27]

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 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.

[27]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 I Cases with Victim Lists

Case	Number of Victims	Average Loss	Case Description
	Payday Loan Applications		
Ideal	2,010,169	≈ \$30-\$40	Payday Loan Apps
Platinum	69,576	≈ \$110	Deceptive Credit Cards
	Health Care		
DoubleShot	15,294	≈ \$70	Weight Loss
Genesis Today	183,042	≈ \$50	Weight Loss
NourishLife	6,697	≈ \$500	Speech Disorder / Autism
SimplePure	681,124	≈ \$90	Deceptive Claims and Negative Option
Solace	1,548	≈ \$120 - \$150	Weight Loss
Tommie Copper	762,917	≈ \$70	Pain Relief
	Business Opportunity		
AdvStrategy	11,361	≈ \$2,200	Business Opportunity
Guidance	6,696	≈ \$1,600 -\$8,000	Business Coaching
IME	3,848	≈ \$250	Home Business
MobileMoney	42,628	≈ \$50	Online Business
MoneyNow	1,801	≈ \$2,800	Home Business
TopShelf	3,283	≈ \$5,000 -\$7,000	Online Business
	Other Fraud		
CD Capital	1,171	≈ \$1,400	Mortgage Relief
Dolce	5,726	≈ \$700	Extended Auto Warranty
Green Millionaire	65,443	≈ \$60	Free Gas for Life Book
WinFixer	304,493	≈ \$60	Computer Security
PHLG	2,641	≈ \$500	Money Transfer for Imposter Scams

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 2.1, after duplicate entries were removed.

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

	(1) Pooled	(2) Payday	(3) Health	(4) BusOpp	(5) OtherFraud
Pct Black = 100%	1.89	4.13	0.41	0.68	0.91
	(0.11)	(0.28)	(0.05)	(0.10)	(0.10)
Pct Hispanic = 100%	-0.19	0.03	-0.36	-0.41	0.03
	(0.04)	(0.07)	(0.03)	(0.05)	(0.08)
Pct College = 100%	-0.63	-0.79	-0.45	-0.72	0.05
	(0.03)	(0.02)	(0.04)	(0.04)	(0.11)
Median Income = 130k	0.46	-0.14	1.08	0.62	0.20
	(0.06)	(0.06)	(0.11)	(0.13)	(0.08)
Median Age = 55	0.26	-0.23	0.70	0.53	0.65
	(0.04)	(0.04)	(0.07)	(0.10)	(0.09)
Pct Urban = 100%	0.19	0.19	0.16	0.02	0.14
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Unemp Rate = 10%	0.02	0.05	-0.01	-0.05	-0.03
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Median HH Size = 4	-0.34	-0.42	-0.24	-0.29	-0.35
	(0.03)	(0.04)	(0.03)	(0.06)	(0.05)
Pct Asian = 25%	-0.17	-0.19	-0.16	-0.06	-0.02
	(0.02)	(0.03)	(0.02)	(0.04)	(0.04)
Observations	543476	57208	171624	171624	143020

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, 0% for the unemployment rate, 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 Health cases, the fourth column for Business Opportunity cases, and the fifth column for Other Fraud cases. Table A-2 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table III Percent Change in Per Capita Victim Rate by Demographic Factors: Payday Loan Cases

	(1) Ideal	(2) Platinum
Pct Black = 100%	4.07	5.85
	(0.28)	(0.58)
Pct Hispanic = 100%	0.04	-0.26
	(0.07)	(0.08)
Pct College = 100%	-0.79	-0.87
	(0.02)	(0.03)
Median Income = 130k	-0.15	0.15
	(0.06)	(0.14)
Median Age = 55	-0.22	-0.53
	(0.04)	(0.06)
Pct Urban = 100%	0.20	-0.10
	(0.02)	(0.03)
Unemp Rate = 10%	0.05	0.11
	(0.03)	(0.06)
Median HH Size = 4	-0.41	-0.51
	(0.04)	(0.05)
Pct Asian = 25%	-0.20	-0.13
	(0.03)	(0.05)
Observations	28604	28604

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its 2010 population. Robust standard errors 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, 0% for the unemployment rate, and 25 for median age. The first column uses estimates for all Payday Loan cases, while the remaining columns represent individual cases. Table A-3 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table IV Percent Change in Per Capita Victim Rate by Demographic Factors: Health Care Cases

	(1) Double Shot	(2) Genesis Today	(3) Simple Pure	(4) Nourish Life	(5) Solace	(6) Tommie Copper
Pct Black = 100%	-0.45	-0.03	0.33	0.08	-0.34	0.63
	(0.08)	(0.09)	(0.06)	(0.42)	(0.45)	(0.07)
Pct Hispanic = 100%	-0.80	-0.42	-0.21	1.70	2.72	-0.50
	(0.04)	(0.04)	(0.03)	(0.69)	(2.72)	(0.03)
Pct College = 100%	-0.73	0.07	-0.59	49.36	26.01	-0.43
	(0.08)	(0.11)	(0.03)	(20.90)	(25.12)	(0.05)
Median Income = 130k	0.97	1.29	0.67	0.25	0.83	1.34
	(0.31)	(0.19)	(0.08)	(0.17)	(0.51)	(0.15)
Median Age = 55	0.21	1.09	0.27	0.24	1.54	1.08
	(0.14)	(0.13)	(0.04)	(0.34)	(0.81)	(0.13)
Pct Urban = 100%	-0.11	0.15	0.02	-0.06	0.26	0.31
	(0.03)	(0.02)	(0.01)	(0.08)	(0.19)	(0.02)
Unemp Rate = 10%	-0.20	0.06	-0.04	0.15	-0.13	-0.00
	(0.05)	(0.04)	(0.02)	(0.18)	(0.22)	(0.02)
Median HH Size = 4	-0.27	-0.28	-0.19	-0.07	-0.60	-0.30
	(0.11)	(0.05)	(0.03)	(0.20)	(0.18)	(0.04)
Pct Asian = 25%	-0.12	-0.13	-0.22	0.28	-0.31	-0.13
	(0.07)	(0.03)	(0.02)	(0.13)	(0.13)	(0.02)
Observations	28604	28604	28604	28604	28604	28604

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its 2010 population. Robust standard errors 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, 0% for the unemployment rate, and 25 for median age. The first column uses estimates for all Health Care cases, while the remaining columns represent individual cases. Table A-4 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table V Percent Change in Per Capita Victim Rate by Demographic Factors: Business Opportunity Cases

	(1) AdvStrategy	(2) Guidance	(3) IME	(4) MoneyCode	(5) MoneyNow	(6) TopShelf
Pct Black = 100%	-0.48	-0.20	0.98	1.50	-0.21	-0.37
	(0.08)	(0.18)	(0.39)	(0.18)	(0.28)	(0.23)
Pct Hispanic = 100%	-0.81	-0.62	-0.24	-0.15	-0.46	-0.57
	(0.04)	(0.12)	(0.24)	(0.08)	(0.24)	(0.17)
Pct College = 100%	-0.70	-0.41	-0.93	-0.76	0.58	-0.27
	(0.09)	(0.23)	(0.04)	(0.04)	(0.95)	(0.38)
Median Income = 130k	-0.04	1.44	1.05	0.64	0.48	1.12
	(0.18)	(0.57)	(0.60)	(0.16)	(0.59)	(0.69)
Median Age = 55	0.81	0.84	-0.38	0.47	0.14	0.32
	(0.24)	(0.29)	(0.19)	(0.11)	(0.39)	(0.32)
Pct Urban = 100%	-0.03	-0.19	0.00	0.13	-0.09	-0.21
	(0.04)	(0.05)	(0.08)	(0.03)	(0.10)	(0.07)
Unemp Rate = 10%	-0.02	-0.01	-0.14	-0.04	-0.23	-0.30
	(0.08)	(0.11)	(0.10)	(0.04)	(0.15)	(0.11)
Median HH Size = 4	-0.50	-0.19	-0.07	-0.26	-0.54	-0.24
	(0.08)	(0.14)	(0.21)	(0.07)	(0.18)	(0.20)
Pct Asian = 25%	-0.25	-0.15	0.10	-0.01	-0.30	-0.15
	(0.08)	(0.09)	(0.15)	(0.04)	(0.13)	(0.13)
Observations	28604	28604	28604	28604	28604	28604

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its 2010 population. Robust standard errors 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, 0% for the unemployment rate, and 25 for median age. The first column uses estimates for all Business Opportunity cases, while the remaining columns represent individual cases. Table A-5 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table VI Percent Change in Per Capita Victim Rate by Demographic Factors: Other Fraud Cases

	(1) CDCapital	(2) Dolce	(3) Green Millionaire	(4) PHLG	(5) WinFixer
Pct Black = 100%	2.64	4.26	0.61	3.53	0.89
	(1.03)	(0.76)	(0.13)	(0.99)	(0.11)
Pct Hispanic = 100%	0.04	-0.12	-0.58	0.30	0.18
	(0.46)	(0.17)	(0.04)	(0.36)	(0.10)
Pct College = 100%	-0.92	-0.82	-0.76	-0.88	0.37
	(0.15)	(0.07)	(0.04)	(0.10)	(0.16)
Median Income = 130k	-0.34	0.19	1.11	-0.29	0.11
	(0.53)	(0.25)	(0.19)	(0.32)	(0.08)
Median Age = 55	0.68	0.18	0.57	0.11	0.69
	(0.88)	(0.24)	(0.11)	(0.35)	(0.10)
Pct Urban = 100%	-0.07	-0.08	-0.21	0.19	0.27
	(0.13)	(0.06)	(0.02)	(0.13)	(0.03)
Unemp Rate = 10%	0.05	0.13	-0.07	0.14	-0.03
	(0.19)	(0.11)	(0.03)	(0.15)	(0.04)
Median HH Size = 4	-0.13	-0.44	-0.36	-0.43	-0.34
	(0.41)	(0.10)	(0.05)	(0.13)	(0.05)
Pct Asian = 25%	-0.69	0.12	-0.22	0.29	0.01
	(0.13)	(0.13)	(0.03)	(0.20)	(0.04)
Observations	28604	28604	28604	28604	28604

Note: Estimates are based upon equation (1) estimated after weighting each zipcode by its 2010 population. Robust standard errors 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, 0% for the unemployment rate, and 25 for median age. The first column uses estimates for all Other Fraud cases, while the remaining columns represent individual cases. Table A-6 reports estimates of the same specifications, but includes the effect of the demographic variables at several additional values.

Table A-1 Summary Statistics

Variable	Mean	SD	10th Percentile	90th Percentile
2010 Census Population (thousands)	29.5	19.4	5.8	54.9
Percent Black	12.2	18.3	0.4	34.9
Percent Hispanic	16.4	20.5	1.3	46.9
Percent College Educated	28.2	16.3	10.9	52.4
Median Household Income (thousands)	57.2	23	33.4	88.3
Median Age	37.6	6	30.2	44.6
Percent Urban	81	30.5	28	100
Unemployment Rate	6	2.4	3.3	9.2
Median HH Size	2.7	0.4	2.2	3.2
Percent Asian	4.8	8	0.1	12

Note: All statistics estimated after weighting each zipcode by its 2010 population.

Table A-2 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.