Hassle Costs and Consumer Voice: Evidence from a Website Redesign*

Michel Grosz
Federal Trade Commission
mgrosz@ftc.gov

Devesh Raval
Federal Trade Commission
draval@ftc.gov

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Abstract

We examine how reducing hassle costs affects consumer voice using a website redesign in which the Federal Trade Commission (FTC) made consumer complaints easier to file. Reducing hassle costs could increase complaints from vulnerable consumers, or lead to complaints about less severe problems. Using a regression discontinuity approach, we find that complaints to the FTC jumped by 40%, driven by increases in complaint completion rates, and that consumers submitted more detailed information. Complaints increased the most for older consumers, a group at risk for fraud; complaints after the redesign were also shorter and easier to read, which may indicate the redesign induced less sophisticated consumers to complain. On the other hand, complaints induced by the redesign were less likely to report monetary losses, and were more likely to report telemarketing and imposter scams, categories where consumers are less likely to report losing money.

Keywords: fraud, complaints, consumer protection, public good, hassle costs

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1 Introduction

Consumer voice plays an important role in markets (Hirschman, 1972). Consumers post product reviews online and contact firms for redress when they are dissatisfied with a product. By doing so, they help firms improve their products and consumers choose what to buy. Defrauded consumers report their experiences to consumer protection agencies – with more than 5 million consumers reporting having lost almost $9 billion in 2022 (Federal Trade Commission, 2023). Policymakers use this information to detect problems in the marketplace, to warn consumers of these problems, and as evidence to initiate enforcement actions.

Whether consumers decide to exercise their voice, however, can depend upon the degree of "hassle costs" for doing so (Akerlof, 1978; Nichols and Zeckhauser, 1982). For example, firms may design their Customer Response Management (CRM) systems to reduce costs by making it difficult for consumers to complain or obtain redress (Dukes and Zhu, 2019). Hassle costs create two countervailing effects. By screening out low value participants, hassle costs could target resources to individuals with the most to benefit from them, such as consumers with legitimate complaints. On the other hand, it may be difficult for disadvantaged consumers to express their voice when hassle costs are large.

In this article, we study how hassle costs affect consumers' voice in the context of an important public good – consumer reports on fraud. Only 5% of consumers affected by fraud say they complained to a government agency or the Better Business Bureau (Anderson, 2021). The private benefits to consumers from complaining are small, especially if a consumer did not fall for the scam or if reporting fraud may not lead to recovered losses. On the other hand, filing a report requires significant time costs, including learning about which agency accepts reports and submitting all the appropriate information. Thus, reporting fraud relies on the costs being less than benefits from altruism and the low expected private value of recovering one's losses.

We examine a major website redesign that substantially reduced the hassle costs of complaining to the FTC.[1] In October 2020, the FTC redesigned its online interface for reporting scams and

[1] We refer to consumers' voluntary submission of information about fraud and other scams interchangeably as "reports" and "complaints" throughout this article. Although the FTC and other institutions long described this information as "complaints," the FTC now describes this information as "reports", in order to emphasize the problems that consumers may observe as opposed to whether the consumers were directly affected or lost money as a result.

fraud to make the process substantially easier to complete. This change was unanticipated by consumers. By reducing the hassle costs required to complain, the redesign allows us to examine the demographics of consumers deterred by hassle costs and the types of problems such consumers report. We provide more details on the website redesign, and our data on complaints, in Section 2 and Section 3.

Using a regression discontinuity approach detailed in Section 4, we first show in Section 5 that the FTC's redesign led to a substantial rise in reporting. In the month following the redesign, the number of completed online complaints increased by 40 percent. This jump in complaints comes exclusively from the completion margin, rather than more consumers seeking to complain. We do not find any change in the number of users arriving to the FTC's desktop or mobile complaint sites, increases in Google searches leading to the FTC's website, or significant increases in complaining to alternatives, such as calling the FTC to report fraud or complaining to other government agencies or the BBB.

The quality of the complaint records also improved after the redesign. Most data fields are optional when lodging a complaint even though they provide valuable information to policymakers. We find 10 percentage point increases in the share of complaints that voluntarily included consumer geographic information, age, and the name of the company involved.

We then assess how hassle costs affect the demographics of complaining consumers, and find some support that vulnerable consumers are more likely to complain after the redesign, in Section 6. Policymakers are especially interested in protecting older adults from fraud (Federal Trade Commission, 2022*a*). While the number of consumers in all age categories increased, the largest increases were for consumers aged 70 to 79, at 63%, and over 80, at 77%, compared to about 50% for younger consumers.[2]

In addition, after the redesign consumers write complaints that are 35% shorter than before and also easier to read. These changes are consistent with less sophisticated consumers induced to complain by the redesign. We also examine measures of the probability that fraud victims complain based on zip code demographics calculated in Raval (2020*b*), and find that the redesign induced more complaints from communities less likely to complain pre-change.

[2]The share of consumers that do not report age declines substantially, so the increase by age group is larger than the 40% overall increase in complaints. However, we find in Appendix B.1 that the median age of the names of complaining consumers also rises after the redesign; consumers almost always report their name.

On the other hand, the redesign did not close the large disparities in complaining between white and non-white consumers found in Raval (2020*b*).[3] We impute consumers' race and ethnicity using the first name and surname that all consumers report and find similar increases for complaints from white and Black consumers after the redesign, and slightly lower increases for complaints from Latino consumers. These findings are consistent with Raval (2020*b*)'s argument that racial disparities in complaining are due to feelings of social alienation rather than information or hassle costs.

In Section 7, however, we find evidence that the reduction in hassle costs induced complaints about less severe problems than before the redesign. First, the share of consumers reporting a monetary loss decreased by 2.6 percentage points, so the easier complaint process brought in consumers for whom the monetary harm was likely smaller. In addition, consumers were less likely to use words related to an online purchase in their complaint after the redesign, which is also consistent with smaller losses.

We take two machine learning text based approaches to examine how the issues that consumers complain about change with the redesign. First, since the categorization of the issues itself changed with the redesign we cannot measure the effect on the categories directly. Instead, we fine tune a large language model to predict these categories using data on complaint text post-redesign. We then predict the probabilities of each category before and after the redesign. We find the largest increases in complaints to be about telemarketing and imposter scams; these issues tend to have lots of consumers exposed to the scam (i.e., receiving a phone call) but only a few lose money. Such issues are exactly the topics for which complaints are primarily based on altruism – to warn other consumers – rather than increasing the likelihood of recovering losses, and so may be deterred by hassle costs.

Second, we use a topic modeling approach to assign complaints to a large set of topics, and then examine how these topics change with the redesign. Consistent with the predicted categories, we find several imposter related topics increase after the redesign, compared to only one topic related to online shopping. However, we also find increases in several topics related to identity theft, which should have been filed on the specialized *identitytheft.gov* FTC website. Here, the reduction in

[3] Using data on consumers affected by nine consumer protection law enforcement actions, Raval (2020*b*) found that residents of heavily Black and Latino areas who lost money in the cases were about half as likely to complain as residents of heavily White areas.

hassle costs likely meant that some consumers substituted to the website that became easier to use.

We sum up our analysis in Section 8 by using a LATE framework to compare how the complaints from compliers induced by the reduction in hassle costs compare to those of always-takers who would have complained regardless of the redesign. We find quite large differences between complier complaints and always taker complaints for many characteristics. For example, we find that 35% of complier complaints are about imposter scams, compared to 18% of taker complaints; complier complaints have text that is 400 characters shorter on average and more than 3 grade levels lower in sophistication.

This paper contributes to a literature on hassle costs and targeting that has largely focused on disadvantaged groups applying to government programs (Currie, 2006; Diamond and Sheshinski, 1995; Kleven and Kopczuk, 2011).[4] In marketing, Dukes and Zhu (2019) examines how firms can optimally design a CRM system through manipulating the degree of hassle costs. Hassle costs can also improve the internal decision making of firms by eliciting truthful information from agents (Laux, 2008; Simester and Zhang, 2014).

More broadly, consumer reports on fraud have all the hallmarks of an undersupplied public good; understanding who voluntarily contributes to public goods has long been a focus of research (Fischbacher and Gächter, 2010; Gächter et al., 2010; Bergstrom, Blume and Varian, 1986; Chan, Mestelman and Muller, 2008; Chaudhuri, 2011).

We also contribute to a literature examining how consumers voice their opinions in markets. We directly relate to consumer complaints about fraud. So far, this literature has focused on identifying the types of consumers affected by frauds and scams (Anderson, 2013, 2019; Deliema, Shadel and Pak, 2020; Raval, 2021), as well as those who choose to complain (Anderson, 2021; DeLiema and Witt, 2021; Gans, Goldfarb and Lederman, 2021; Raval, 2020*a*,*b*; Raval and Grosz, 2022). A broader literature examines consumer reviews online, including how demand responds to reviews (Luca, 2011; Lewis and Zervas, 2020), firms faking reviews (Anderson and Simester, 2014; He, Hollenbeck and Proserpio, 2022; Luca and Zervas, 2016; Mayzlin, Dover and Chevalier, 2014) and consumers selecting into reviewing (Nosko and Tadelis, 2015; Fradkin, Grewal and Holtz,

[4]Economists have examined the selection process for the Earned Income Tax Credit (Kopczuk and Pop-Eleches, 2007; Bhargava and Manoli, 2015; Chetty, Friedman and Saez, 2013), disability insurance (Foote, Grosz and Rennane, 2019; Parsons, 1991), unemployment insurance (Ebenstein and Stange, 2010), and public health insurance (Aizer, 2007).

2021; Fradkin and Holtz, 2023). Both complaints and reviews provide examples of how disclosing additional information about firms can affect markets (Jin and Leslie, 2003; Tadelis and Zettelmeyer, 2015).

Finally, a large literature in marketing and computer science has focused on how the design of web interfaces affects how users interact with a site. Much of this work focuses on "dark patterns", in which a website seeks to manipulate consumers to their detriment, such as making it difficult to cancel a recurring subscription (Luguri and Strahilevitz, 2021; Mathur et al., 2019). Here, in contrast, the FTC worked to make its complaint site easier to use for consumers. Our work is complementary to researchers seeking to improve disclosures of advertisements and convey useful information to consumers.

2 Background

Consumers hoping to report fraud or scams have several ways that they can complain to policymakers. Consumers can call 1-877-FTC-HELP or visit the FTC's website, originally called "Complaint Assistant" and available at `www.ftccomplaintassistant.gov`. The FTC added a mobile version of this website in 2014.[5]

Besides the FTC, consumers can complain to many government agencies or non-governmental organizations. In this paper, we use data from the two largest: the Better Business Bureau (BBB) and Consumer Financial Protection Bureau (CFPB). The CFPB accepts complaints about financial products, such as credit cards, debt collection, payday loans, prepaid cards, and money transfer services. The BBB is a non-profit organization that has accepted complaints about companies for decades. The Consumer Sentinel Network, a consortium run by the FTC, collects complaints from the FTC, BBB, CFPB, and many other sources.

On October 22nd, 2020, the FTC launched a new website to collect consumer complaints, renamed as `ReportFraud.ftc.gov`, and available in online and mobile versions. The new website replaced the old Complaint Assistant system.[6] The FTC cited increases in fraud reports relative to the previous year, as well as a focus on better reporting on the incidence of fraud and scams

[5] See `https://www.ftc.gov/news-events/news/press-releases/2014/05/file-consumer-complaint-ftc-your-mobile-device`.

[6] See `https://www.ftc.gov/news-events/news/press-releases/2020/10/ftc-announces-new-fraud-reporting-platform-consumers-reportfraudftcgov`.

across diverse communities, as reasons for the change (Federal Trade Commission, 2021*a*,*b*).

The `ReportFraud.ftc.gov` website specifically addressed several issues that users of the previous site had noted in usability studies. In particular, users mentioned that the previous website's categorization of fraud and scam types was confusing and unclear. Users also noted that the site was difficult to navigate, too "busy," and had formatting issues that overwhelmed users and made important links difficult to find.

The redesigned website addressed these issues in many ways. First, the URL is shorter and easier, and explicitly brands consumers as "reporting" rather than "complaining". Consumers might see reporting as more neutral than complaining, and so less psychologically costly, as well as not requiring monetary losses from fraud. The landing page and flow of the new website was also designed to be more user friendly. Figure 1 and Figure 2 show the landing pages and flow of the new website and the one it replaced. One the new website, clicking on the "Report Now" button leads consumers on a series of customized steps to report their fraud. The new version of the website also requires fewer steps to submit a complaint to encourage completion. When consumers complete their report, the new website also gives them specific next steps on how to resolve their specific problem.

Another important feature of the new website is that it prompts consumers for different questions depending on their answers to previous questions, making the submission process more streamlined and efficient. For example, consumers reporting a scam related to an impersonator will be asked about which government agency or entity the scammer pretended to be, while consumers who reported an issue related to online shopping will not be asked those questions. Instead, these consumers might be asked about whether and how much they paid for a product, whether and when they received it, and whether they received a refund. Consumers who report having paid some amount as part of their complaint will be prompted with further questions about the timing, amount, and other details of the payment itself.

The new ReportFraud website was launched on October 22, 2020, after which users visiting the previous website were automatically redirected to the new site. The FTC did not promote its new website ahead of time, so consumers did not anticipate that the user interface would be different from one day to the next. The FTC did, however, promote the new website after the redesign, including with a press release the same day. In addition, the FTC has undertaken ongoing outreach

Figure 1: Landing Page and Flow of Complaint Assistant (Old Website)

(a) Landing Page

(b) Flow

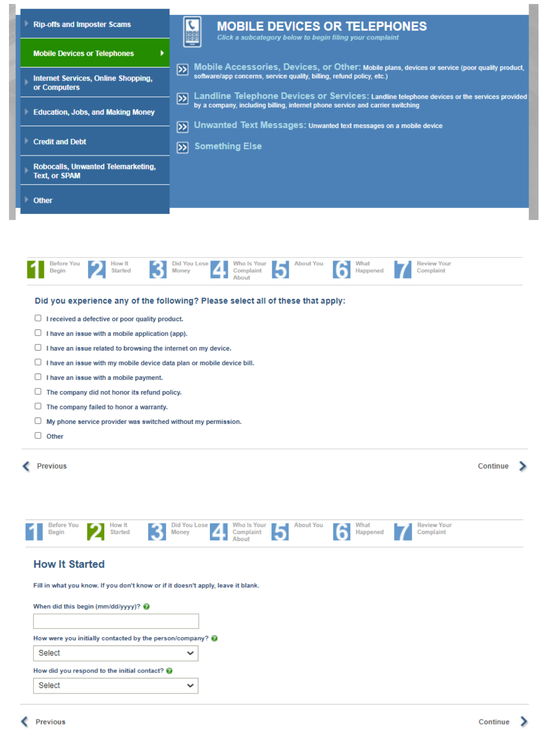
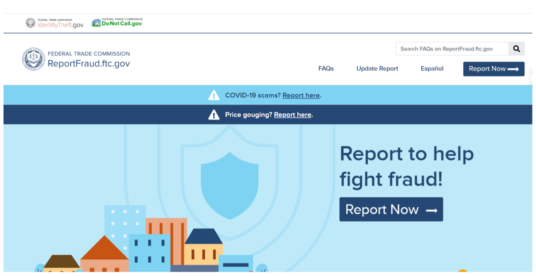
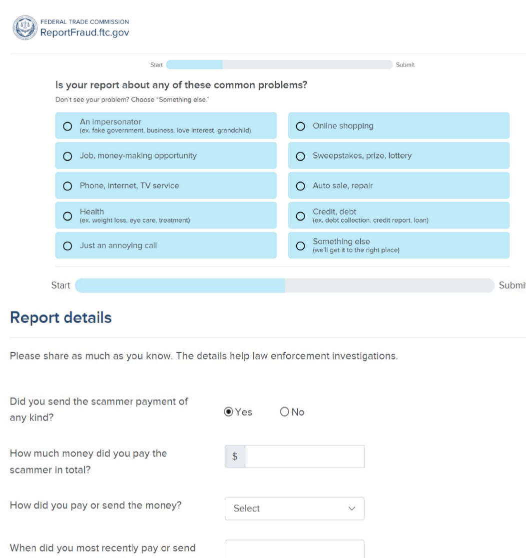


Figure 2: Landing Page and Flow of ReportFraud (New Website)

(a) Landing Page



(b) Flow



efforts to promote the new website, especially in communities with known under-reporting of fraud and high rates of fraud (Federal Trade Commission, 2021*b*). These efforts include online videos and blogs, social media posts, outreach to national and local partners, and paid ads. Later, in March 2021, the FTC began another effort to further increase reports from lower-income communities with the launch of its Community Advocate Center. This program provides specialized links to legal services providers and encourages reports from the providers and the people they serve (Kaufmann, 2021).

3 Data

We use data on complaints from the Federal Trade Commission, the Consumer Financial Protection Bureau, and the Better Business Bureau. These three sources account for approximately three quarters of all the complaints contained in the Consumer Sentinel Network consortium of complaints (Raval, 2020*a*).[7]

Each complaint in the Consumer Sentinel data includes information about the consumer and the content of the complaint. We observe the consumer's name, zip code, city, state, country, and broad age bands, if the consumer included this information. We also observe the date the complaint was filed, as well as broad categories of complaints and the text of the complaint itself. For FTC complaints, we are able to separately identify complaints filed on a laptop or desktop computer (which we refer to as "desktop"), on a mobile device, or over the phone.

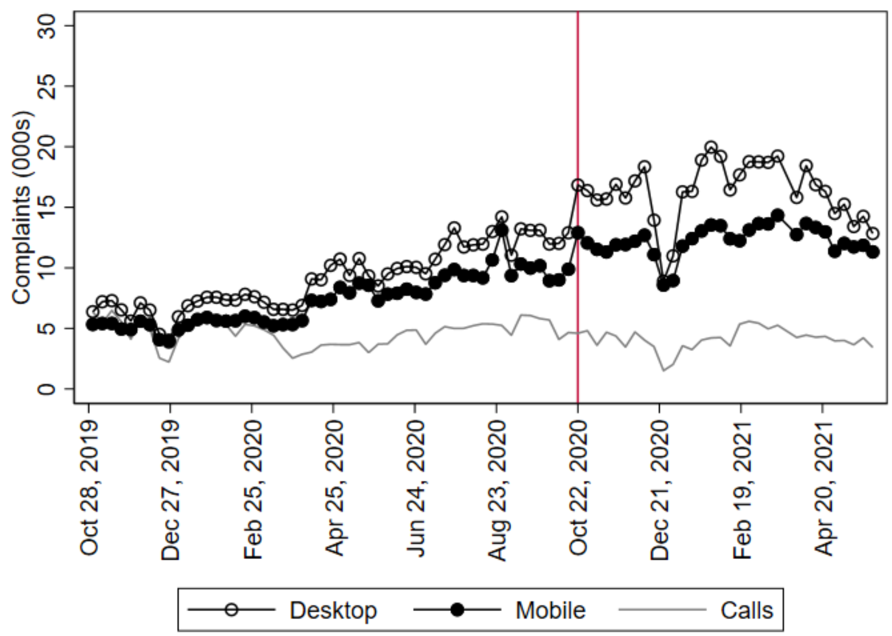
Figure 3 shows the weekly number of complaints to the FTC by channel between October 31, 2019 and June 6, 2021. In the first week of data shown in the figure, the FTC received approximately 12,000 complaints across its desktop and mobile platforms, and an additional 6,400 complaints over the phone. Over time, the desktop and mobile complaints rise in a parallel fashion compared to the complaints over the phone. In addition, we see a spike in complaints in the first week of April 2020, as the full effect of the coronavirus pandemic began to take hold, and a decline in complaints during the Christmas and New Year's holidays season.

The week of the FTC's redesign is marked by a red vertical line. Complaints for desktop and mobile sources jump significantly the week of the redesign. In contrast, there is no similar jump

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

in FTC phone complaints. Figure A1 depicts the same graph for the BBB and CFPB, for which there is no jump the week of the FTC's redesign either.

Figure 3: Complaints by Week to the FTC



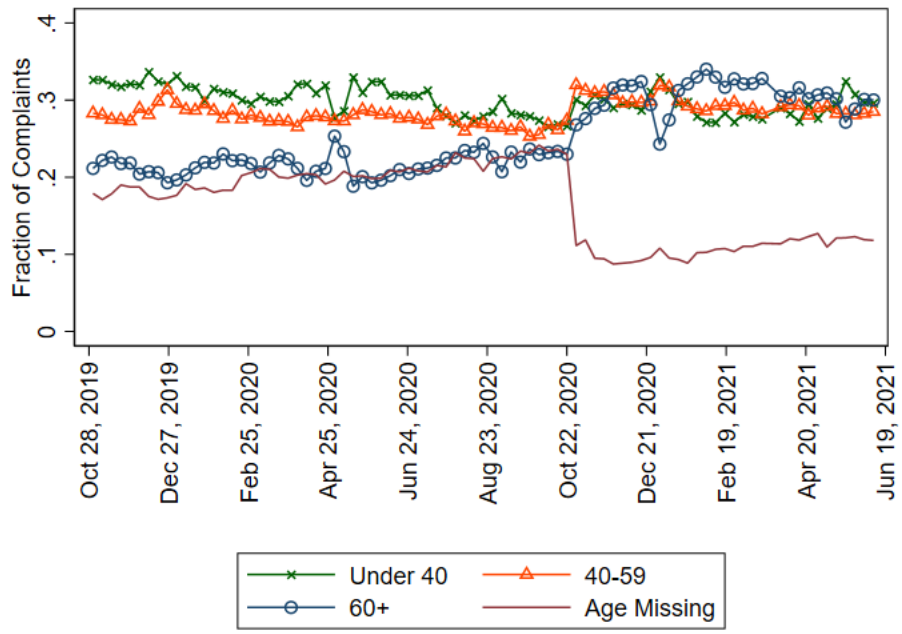
Notes: The figure shows the number of complaints, in thousands, logged each week between October 26, 2019 and June 19, 2021, across the three FTC sources. The weeks are defined as starting on Thursdays, since the website redesign was a Thursday. The vertical line shows the date of the website redesign.

The complaint data also include self-reported information about consumers' age. Figure 4 shows the distribution of self-reported consumer age for consumers who filed complaints with FTC desktop and mobile systems. First, complaints that do not report age drop suddenly after the redesign. Second, the distribution of age conditional on reporting also seems to have changed. In particular, the share of consumers aged 60 or older, who might be the ones with the most difficulty in completing online complaint forms, go from being the group with the lowest share of complaints to being the highest. This increase in share suggests that older consumers may be more likely to complain after the redesign, or that they were now more likely to report their age.

4 Empirical Strategy

To analyze the short-term effects of the website redesign, we estimate a regression discontinuity (RD) in time. RD designs with time as the running variable are a common empirical strategy in

Figure 4: FTC Online Complaints by Week and Age



Notes: The figure shows the fraction of total complaints logged each week between October 26, 2019 and June 19, 2021, across the three FTC sources and age bands. The weeks are defined as starting on Thursdays, since the website redesign was a Thursday.

marketing, where different user interfaces can be implemented quickly and unexpectedly (Hausman and Rapson, 2017).

Consumers did not anticipate that the ReportFraud website would change design overnight because the change in the website design was not advertised or announced ahead of time by the FTC. Thus, users wishing to log in a complaint on October 21 and October 22—the days before and after the redesign—would have unexpectedly experienced different user interfaces. We assume that rates of fraud and consumers' willingness to report fraud did not see similar dramatic breaks from one day to the next.

We estimate the following empirical specification:

$$y_t = \beta Post_t + f(Date_t) + g(DOW_t) + \epsilon_t, \tag{1}$$

where y_t is the number of complaints with a particular attribute on each day t. We use data on daily complaints for the 60 days before and after the date of the website change, from August 23, 2020, to December 21, 2020, and bin complaints by day. We do not extend past December 21 because the beginning of the holiday season introduces a dramatic trend break in complaints. The variable $Post_t$ indicates whether the date is after the website change, and β is the coefficient of interest. The term $f(Date_t)$ is a polynomial in the date: we use third-degree polynomials in our preferred specification. To account for differences in complaint rates over the course of a week, we also control for day-of-the-week effects through $g(DOW_t)$.

5 Do Complaints Increase After the Redesign?

A primary goal of the FTC's website redesign was to increase the number of complaints submitted. We find substantial increases in the quantity and quality of complaints. These increases are because consumers are more likely to finish complaining, rather than more consumers seeking to complain.

5.1 Quantity of Complaints

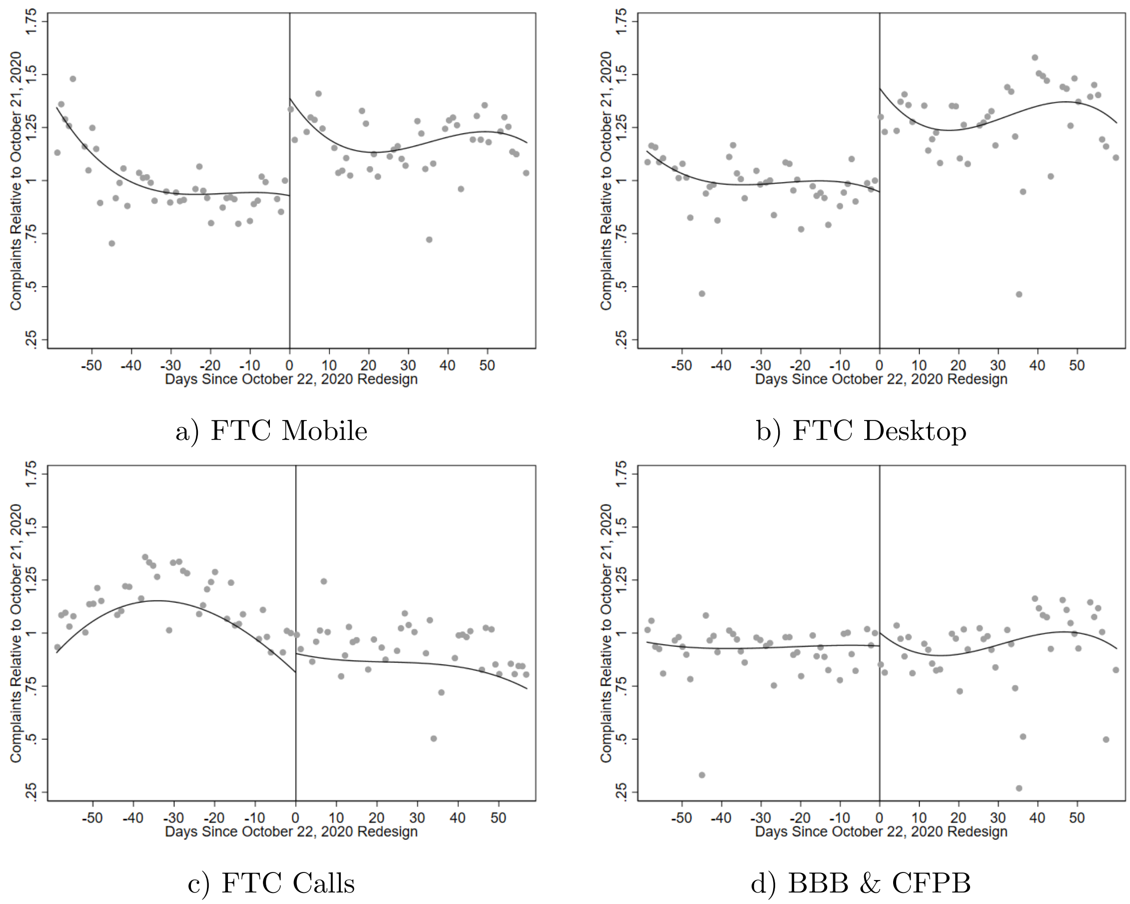
We examine data on complaints filed to the FTC through three sources—desktop, mobile, and phone—as well as complaints filed to the BBB and CFPB. FTC desktop and mobile complaints were directly affected by the redesign, while FTC phone complaints and BBB and CFPB complaints were not.

The FTC phone complaints provide a comparison for consumers with complaints that would be appropriate to file with the FTC. The complaints filed with the BBB are broadly similar to the FTC in terms of the types of industries and scams (Raval, 2020*a*), although the BBB is not a government agency. The CFPB is a sister federal agency, although its complaints are limited to financial topics and so overlap less with FTC complaints.

Figure 5 displays the number of daily complaints by source 60 days before and after the website change. In order to show the regression discontinuity, we also display estimates of a third degree polynomial with day of the week effects for the periods before and after the change. Each panel is adjusted to be expressed in shares relative to October 21, the date before the redesign, which is set to 1. For example, a marker at 1.25 means that there were 25% more complaints that day than on October 21.

The number of FTC mobile and desktop complaints clearly jump at the date of the website redesign. In contrast, the FTC's phone complaints are flat through the threshold, as are the BBB

Figure 5: RD Estimate of Website Redesign on Number of Complaints



Notes: The figure shows the daily number of complaints report to each of the three FTC sources and to the CFPB and BBB, from 60 days before and after the FTC's website redesign on October 22, 2020. For each panel, the number of complaints are expressed relative to the number of complaints on the day prior to the redesign, October 21, 2020, which are set to one. The vertical bar shows the date of the redesign. The fitted lines are an RD estimate that includes a third-degree polynomial and controls for the day of the week.

and CFPB complaints.[8]

Table 1 shows the coefficient estimates that correspond to the figure, where the number of complaints is expressed in logs. FTC online complaints–combining desktop and mobile complaints–increased by 40% due to the change in the user interface, with a similar jump for desktop (42%) and mobile (37%) complaints. The effect on FTC calls is positive at 8%, but not statistically significant. Similarly, the coefficients are smaller and not statistically significant for the BBB and CFPB. Table A1 shows similar results using a first order polynomial, with a smaller significant estimate for online complaints (28%) and a negative and not significant estimate for FTC phone calls (-9%).

[8] Figure A2 shows the total number of complaints, and Figure A3 disaggregates the BBB and CFPB.

Table 1: RD Estimate of Website Redesign on Number of Complaints

	(1) FTC Online	(2) FTC Mobile	(3) FTC Desktop	(4) FTC Calls	(5) CFPB	(6) BBB
RD Estimate	0.395***	0.374***	0.416***	0.0808	0.0467	0.160
	(0.0721)	(0.0634)	(0.0657)	(0.0531)	(0.0747)	(0.130)

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of daily complaints. The specification includes a third degree polynomial and controls for day of the week. FTC Online refers to the sum of FTC mobile and desktop complaints. The data include complaints from 60 days before and after the FTC's website redesign on October 22, 2020. Robust standard errors clustered at the daily level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

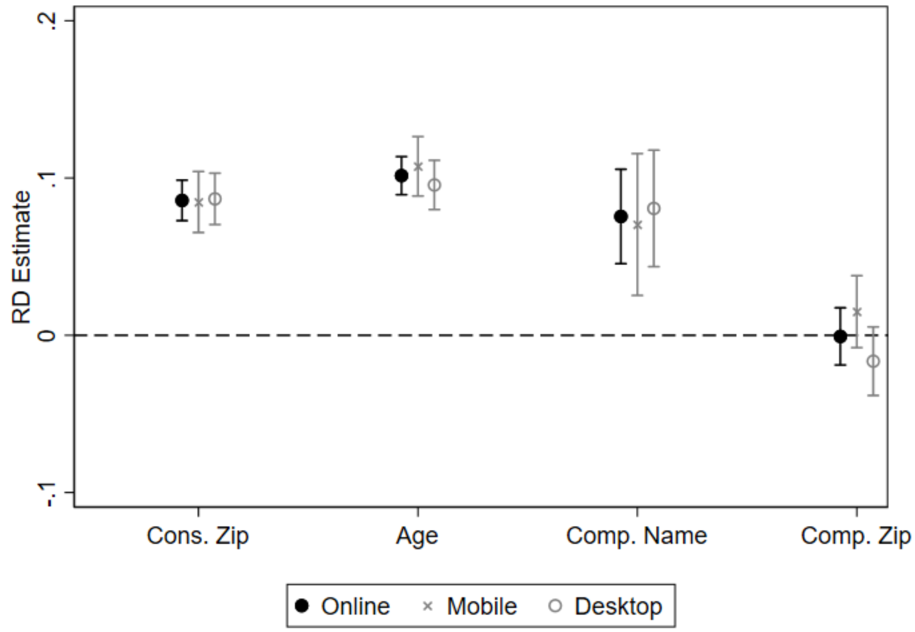
5.2 Quality of Complaints

We then investigate how the quality of complaints changed as a result of the website redesign, as a key goal of the redesign was to make it easier for consumers to provide information in complaints. Our proxy for complaint quality is whether consumers input optional personal information in complaints, including the location that the consumer lives in, their age, and details of the company that defrauded them.

This information is helpful for policymakers for several reasons. First, policymakers are interested in the demographics of complainants; age is an important such characteristic and consumer location allows one to impute race/ethnicity and examine local area demographics. Second, information on the companies or individuals defrauding consumers is necessary for enforcement against bad actors. Finally, policymakers may want to contact consumers to gain more information on their problems and submit evidence in court proceedings.

We find substantial increases in the quality of complaints after the website redesign. Figure 6 shows RD point estimates and 95% confidence intervals on the likelihood that the consumer provided different pieces of information in each completed complaint. After the website redesign, the share of consumers reporting their zip code rises by 9 percentage points and those reporting their age rises by 10 percentage points. Consumers were also almost 10 percentage points more likely to report the name of the company or individual who had defrauded them. The redesign had no effect on the share of consumers who provided information on the location of the offending company or individual.

Figure 6: RD Estimate of Website Redesign on FTC Complaint Quality



Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the fraction of daily complaints that included a zipcode, consumer's age, the defrauding company's name, or the defrauding company's zipcode. Robust standard errors clustered at the daily level. The corresponding table is Table A3.

5.3 Mechanisms for Increases in Complaints

The increase in complaints documented above could happen because existing users of the website were more likely to complete the process of filing a complaint, or because new users decided to visit the website and complain. We find evidence that consumers increased their rate of completion of complaints, and that the number of users of the website did not increase in the short run. This mechanism is consistent with hassle costs leading to some consumers starting, but never filing, complaints. It also supports the RD identifiying assumption that only the website itself changed at the threshold date.

First, we analyze data from Google Analytics on the number of users and new users per day on the FTC's website. Because we also know the total number of complaints per day, we estimate the completion rate as the number of complaints each day in the Consumer Sentinel data divided by the number of total users from Google Analytics. In Table 2, we report RD estimates from the website redesign of the change in log total users and new users (columns 1 and 2), and the completion rate (column 3). The number of total users or new users did not change after the redesign. However, the completion rate rose by 4 percentage points.

Table 2: RD Estimate of Website Redesign on FTC Users and Completions

	(1) Total Users (log)	(2) New Users (log)	(3) Completion Rate
RD Estimate	-0.000515	0.00591	0.0399*
	(0.0644)	(0.0759)	(0.0197)

Notes: The table shows estimates of equation (1). In columns 1 and 2 the dependent variable is the log number of total users and new users. In the final column the dependent variable is the fraction of started complaints that were completed. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Second, the press surrounding the redesign could have induced new users to visit the website and complain. We thus examine the effect of the FTC's next press release about the ReportFraud website after the redesign. On March 3, 2021, the FTC announced a new campaign to increase reporting of fraud in low-income communities.[9] Table A2 shows that, overall, there was an insignificant increase of 8% in FTC online complaints (12% for mobile and 5% for desktop). This exercise shows that the effect of the overall redesign was much larger than the short run effect of the announcement of a promotional campaign to increase reporting.

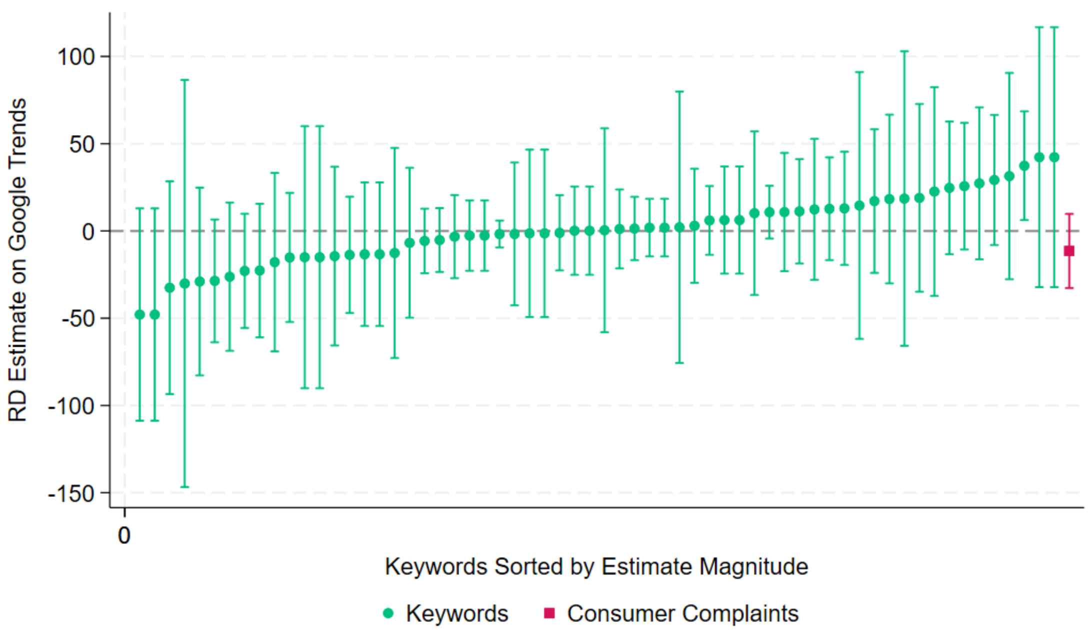
Third, we examine Google Analytics data on web searches that lead consumers to the FTC's complaint website. We have data on the keywords on Google that consumer use to reach the FTC's website as of November 2023. We can match these keywords to weekly data on Google trends, and so examine how "demand" for complaints changed at the time of the website redesign. We look at all keywords with a minimum volume of at least 50 searches, and for which the FTC's complaint website is the top ranked organic link on Google. The top 5 keywords are "ftc complaint", "scam report", "report scam", "report scammer", and "report fraud". Since the keywords for which the FTC's complaint website is the top link could have changed with the redesign, we also examine Google trends for the category of "Consumer complaints" in the US.

Figure 7 shows the RD estimate for each of the keywords, as well as for the "consumer complaint" category, along with a 95% confidence interval with a Bonferroni correction for multiple hypothesis testing. The estimates use nine weeks of weekly data before and after the redesign, along with a

[9] See https://www.ftc.gov/news-events/news/press-releases/2021/03/ftc-launches-initiative-encourage-lower-income-communities-report-fraud.

linear polynomial.[10] Almost none of the results are statistically significant, and most are small in magnitude. In fact, the average estimate is 0.30 for trend values that range from 0 to 100; the effect for the consumer complaint category is *negative*, at -26.9, and not statistically significant. Together, these results provide further evidence that the effect of the redesign comes primarily through increases in completion rates among consumers who would have already navigated to the FTC's website.

Figure 7: RD Estimate of Website Redesign on Google Keyword Searches



Notes: The figure shows point estimates and 95% confidence intervals for RD estimates of how the Google Trends popularity for 65 different keywords changed in the 10 weeks before and after the website redesign. Data are at the weekly level, and the specification includes a third degree polynomial. Coefficients are sorted by their magnitude. The confidence intervals include a Bonferroni correction for multiple hypothesis testing. The effect for the Consumer Complaints Category is in red as the last confidence interval in the figure.

6 How do the Demographics of Complaining Consumers Change with the Redesign?

The hassle costs literature predicts that disadvantaged consumers may be less likely to complain when hassle costs increase. Not surprisingly, a major goal of the website redesign was to improve complaint rates among groups that are less likely to complain. In this section, we find larger

[10] Results with a longer or shorter time window and polynomials of different orders yield similar results.

increases in complaints from older adults, as well as a decline in the sophistication of the writing style of complainants and increases from zip codes less likely to complain before the redesign. However, we do not find major differences in complaint rates between Black and white consumers, smaller increases for Latino consumers, as well as larger increases in complaints from areas with better Internet access. Thus, we find some qualified support for the hypothesis that hassle costs reduce complaints from disadvantaged consumers.

6.1 Age

We first study the age of consumers who complain, the only demographic characteristic that the FTC explicitly asks for in its complaint submission process. Some scammers explicitly target older adults (Mclean, 2020); one reason may be older adults are at or past their lifecycle peak for wealth accumulation (DeLiema et al., 2020). In response, Congress passed the "Stop Senior Scams Act" in 2022 in order to prevent scams targeting seniors, and the FTC regularly publishes reports to Congress about efforts dedicated to protecting older adults (Federal Trade Commission, 2022*b*).

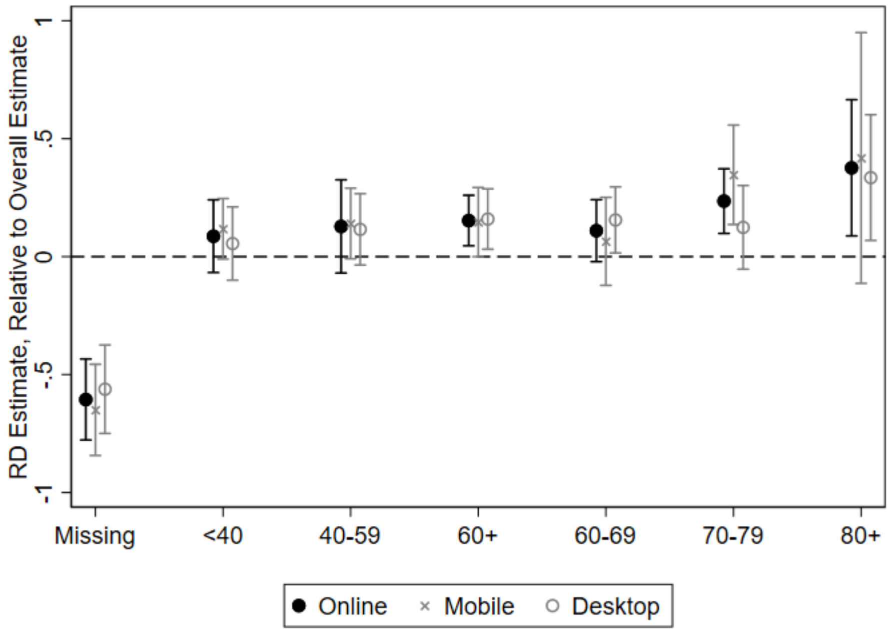
Figure 8 shows how the number of complaints in each reported age band changed after the redesign. We have expressed each estimate relative to the overall estimates reported in Table 1. All of the age bands grew at or faster than the 40% headline number because the share of consumers not reporting their age fell. For example, the under 40 band grew at 48%, which is only slightly higher, and not statistically significantly different from, the overall increase in complaints.

Nevertheless, we find substantially higher increases for older adults; complaints from consumers below 40 increased by 48%, and 40-59 by 52%, compared to 55% for consumers aged 60+. Of the population aged 60 and above, the increases were concentrated amongst the oldest adults. Complaints from consumers aged 70-79 went up by 63%, and 80+ by 77%, compared to 51% for 60-69. Thus, complaints from older adults increased the most after the redesign.

As shown previously, though, the redesign of the FTC's interface increased the proportion of consumers who recorded their age. This increase in age reporting makes it difficult to determine if the redesign brought in more consumers of a particular age, or that consumers of a particular age were more likely to report their age because of the easier consumer interface.

We thus supplement the analysis above by using the consumer's reported first name to impute age. We use the number of births each year since 1900 with a particular first name from the

Figure 8: RD Estimate of Website Redesign on FTC Consumer Reported Age Bands



Notes: The figure shows point estimates and 95% confidence intervals for RD estimates, where the dependent variable is the log number of daily complaints by consumers in each age band. The overall effect on total complaints is subtracted from each individual point estimate: 0.395 for online, 0.416 for desktop, and 0.374 for mobile. Consumer can also choose to not report their age. The age 60 and above is the sum of the other older age bands. Robust standard errors clustered at the daily level. Table A4 is the corresponding table.

Social Security Administration (SSA), as well as the likelihood of being alive in 2020 from the SSA actuarial tables. We combine these elements to calculate the median age for each name. This process makes the strong assumption that all names have the same expected life expectancy for a given birth year, and also does not account for immigration. These estimates, shown in Figure A4, also find the largest increases among older adults in the 70-79 and 80+ age bands, at 57% and 77% increases in complaints after the redesign, compared to increases of 39 to 42% for the age bands below 70. Thus, estimates using the median age of their name are broadly consistent with our findings from Figure 8.

6.2 Race/Ethnicity

We next look at the racial and ethnic composition of complaining consumers. Raval (2020*b*) found that consumers in both heavily Black and heavily Latino areas affected by fraud were less likely to complain than consumers in white areas, and posited that this difference in complaining was due to social alienation of non-white consumers rather than difference in information costs.[11] The website redesign allows us to test this prediction, as it sharply reduces one component of those information costs.

Because the Consumer Sentinel data do not explicitly ask for self-identified race or ethnicity, we impute race and ethnicity using consumer first and last names in a method analogous to the Bayesian Improved Surname Geocoding (BISG) (Consumer Financial Protection Bureau, 2014; Zhang, 2018). The availability of name data did not change before and after the redesign, because a non-missing name entry is required to complete the complaint. We match surnames to data from the Census on the distribution of race and ethnicity for more than 150,000 surnames. We also match first names to data from the Home Mortgage Disclosure Act (HMDA) on the distribution for more than 4,200 first names (Voicu, 2018).

For consumers with only first or last name matched to the Census or HMDA data, we calculated the probability that a consumer was a given race based upon the probability that their first or last name occurred in the population. For consumers with first and last name available, we used Bayes' Rule, with the probability an individual is of a particular race or ethnicity r given their first name f and last name s as:

$$Pr(r|f,s) = \frac{p(r|f) * q(s|r)}{\sum_{r \in R} (p * q)}, \tag{2}$$

where $p(r|f)$ is the share of individuals in the HMDA data with that first name who are of that race, and $q(s|r)$ is the share of that race who has the surname.[12] We convert the resulting probabilities to proxy race and ethnicity by assigning the consumer a race according to their highest probability (Zhang, 2018).

Figure 9 shows how the number of complaints in each imputed race and ethnicity changed with the redesign, expressed relative to the overall increase in complaints. We find substantial increases in complaints among all groups. We do not, however, find disproportionate increases amongst Black and Latino consumers; that is, the website redesign did not affect pre-existing *disparities* in complaining. For all online complaints, we find a 42% increase from white consumers, compared

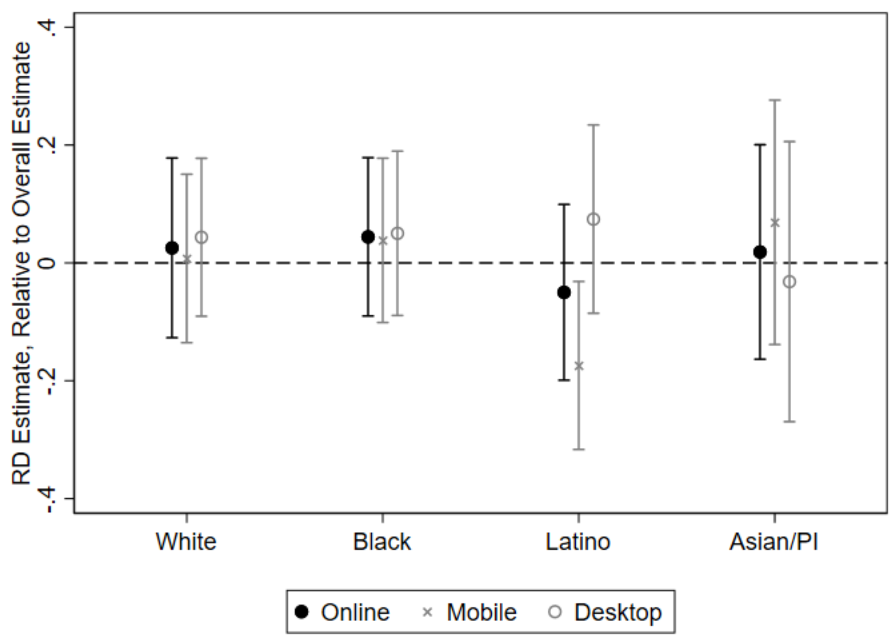
[11] Sweeting et al. (2020) provides a summary of this work.

[12] Overall, 20% of complaints did not match to the first name data, and 14% did not match to the surname data. Only 6% did not match to either.

to a 44% increase for Black consumers, 35% for Latino consumers, and 41% for Asian consumers. For mobile complaints, we find a much smaller increase for Latino consumers than other groups; mobile complaints from Latino consumers increase by only 20% after the redesign, compared to 38% for white consumers, 41% for Black consumers, and 44% for Asian consumers.

In Figure A5, we examine an analogous estimate where we also include the share of each race in the consumer's zip code in the 2010 Census to estimate the race imputation; complaints from white consumers rise by 43%, Black consumers by 37%, Latino consumers by 31%, and Asian consumers by 39%. These estimates are quite similar to those in Figure 9.

Figure 9: RD Estimate of Website Redesign on FTC Consumer Imputed Race and Ethnicity



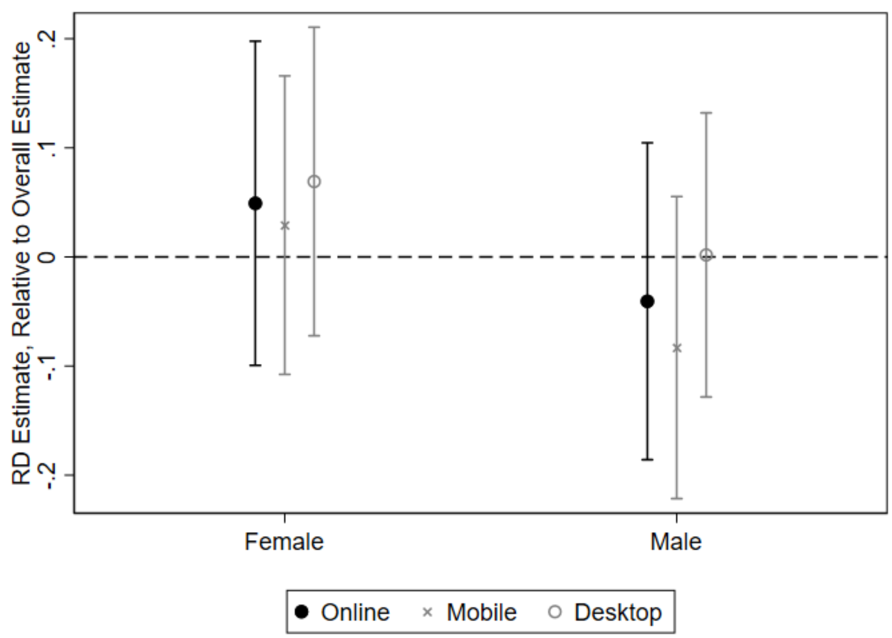
Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the log number of daily complaints by consumers in each imputed race or ethnicity category. The overall effect on total complaints is subtracted from each individual point estimate: 0.395 for online, 0.416 for desktop, and 0.374 for mobile. Race and ethnicity are imputed as the highest probability race or ethnicity group using posterior probabilities based on the consumer's first and last name. Robust standard errors clustered at the daily level. Table A5 is the corresponding table.

6.3 Sex

We also use an imputation technique to assess whether there were differential effects by sex. The SSA publishes counts of sex assigned at birth by name going back over 100 years for names with at least five occurrences in a state. We aggregate these counts to calculate the fraction of occurrences for each name assigned to male and female individuals. We then assign a name a sex if at least 80 percent of occurences are of that sex, which we can do for 97 percent of all names in the SSA data.

Figure 11 shows estimates of the effect of the website redesign on the complaints from consumers who were imputed to be male and female.[13] Complaints increase more after the redesign for female consumers (44%) than male consumers (35%). However, we cannot reject that the increase for both female and male consumers is the same as the overall 40% effect across all consumers.

Figure 10: RD Estimate of Website Redesign on FTC Consumer Imputed Sex



Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the log number of daily complaints by consumers in each imputed sex. The overall effect on total complaints is subtracted from each individual point estimate: 0.395 for online, 0.416 for desktop, and 0.374 for mobile. Sex is imputed using first name data from the SSA. Robust standard errors clustered at the daily level. Table A6 is the corresponding table.

6.4 Computer and Internet Access

Next, we examine whether the website redesign disproportionately affected consumers with better internet access. Here, we estimate a RD at the day-zipcode level and interact the "Post-Redesign" variable with either the share of consumers with broadband access or computer access at the zipcode level from the 2020 Census. In the median zipcode, 77% of consumers had access to broadband

[13]We report complaints for both sexes because sex is not possible to impute for a small minority of complaints, from consumers with rare names not listed in the SSA data, or names that we have not categorized as either male or female.

and 87% had access to computers. The corresponding shares for consumers were 67% and 81% in the 25th percentile zipcode, and 84% and 92% in the 75th percentile zipcode.

In Table 3, we show the estimates of the interaction term for both the broadband access specification and computer access specification, where the interaction effect would reflect a rise from a 0 to 100% share of consumers with broadband or computer access.

For desktop complaints, we find higher increases in complaints from areas with greater Internet access, with a 0.83 percentage point increase in the effect of the redesign for a 10 percentage point increase in broadband access, and a 1.1 percentage point increase for every 10 percentage point increase in computer access. However, mobile complaints increase more in areas with worse internet access, which may represent substitution between the mobile and desktop channel based on the degree of Internet access. Thus, all online complaints increase by only 0.3 to 0.4 percentage points for a 10 percentage point increase in broadband or computer access.

Table 3: RD Estimate of Website Redesign, by Zip Code Broadband and Computer Access

	(1) Online	(2) Mobile	(3) Desktop
Post x Broadband Access	0.0334	-0.0381	0.0828**
	(0.0175)	(0.0215)	(0.0266)
Post x Computer Access	0.0394	-0.0585	0.109**
	(0.0266)	(0.0321)	(0.0403)

Notes: The table shows RD estimates at the Zip code level. In the first row the dependent variable interacts the post-change dummy with a Zip code's average broadband access in the 2020 Census. Similarly, in the second row the interaction is with computer access. Robust standard errors clustered at the daily level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

6.5 Victim Likelihood of Complaining

The results above examined different demographic groups separately. Raval (2020*b*) examined how several zip code level demographic variables affected the likelihood of complaining by comparing complaints and victims for the same consumer protection case across several cases. Using these estimates, Raval (2020*b*) developed a set of weights designed to be the inverse of the predicted complaint to victim ratio based on those demographics in order to "correct" complaint data for differences in the likelihood of complaining across demographic groups. The median zip code was set to 1, with majority Black zip codes having an average weight of 2 as residents of those zip codes were about half as likely to complain as the median zip code.

In Table 4, we examine how these weights change with the redesign. The average weight increases by about 11% after the redesign, so the redesign led to disproportionately more complaints from areas with a lower predicted complaint to victim ratio, based on demographics, before the redesign.

Table 4: RD Estimates (Percentage Change), Victim Complaint Weights

	(1) Online	(2) Mobile	(3) Desktop
RD Estimate	0.115***	0.131***	0.0990***
	(0.0130)	(0.0215)	(0.0146)

Notes: The table shows estimates of equation (1). The dependent variable is the log of the mean daily victim complaint weights at the zipcode level from Raval (2020*b*). Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

6.6 Consumer Sophistication

Finally, we examine how the writing style of consumers changed using the open-ended text that consumers can fill to explain the details of their complaint. Before and after the change, consumers were prompted to fill in this text box, and the vast majority of them did so.

In the first column of Table 5, we examine the effect of the website redesign on the size of the comment field text and find sharp declines in the amount that consumers wrote. The length of all online complaints fell by 35% after the redesign, with a 20% fall in the length of mobile complaints and a 50% fall in the length of desktop complaints.

Several factors could explain this decline. First, consumers induced by the redesign might have a simpler writing style and so write less. On the other hand, they could have less to complain about, or the redesign may have meant that consumers provided the site more information by the time they are asked for the open ended description and so have less information left to provide.

Thus, in the next columns of the table, we examine the Flesch-Kincaid grade level, which measures the level of reading comprehension required for a particular text based upon the ratio of words to sentences and syllables to words in the text.[14] We find substantial declines in the

[14] The Flesch-Kincaid grade level measure is defined as

$$0.39\left(\frac{words}{sentences}\right) + 11.8\left(\frac{syllables}{words}\right) - 15.59. \tag{3}$$

sophistication of the writing after the redesign.

On average, the grade level of the text in online complaints falls by about a grade level after the website redesign, the share of complaints with text at least an 8th grade level falls by 11 percentage points and with a college level falls by 8 percentage points. We find larger effects for mobile complaints than desktop complaints, as mobile complaints fell by 1.5 grade levels and desktop complaints fell by 0.4 grade levels. Overall, we find that the marginal consumer induced into complaining by the redesign wrote with a simpler writing style, with much larger changes for the mobile site.

Table 5: RD Estimate of Website Redesign on FTC Complaint Length and Grade Level

	(1)	(2)	(3)	(4)
		Flesch-Kincaid Grade Level		
	Length (Pct Change)	Median	>8th grade	>College
A. FTC Online				
RD Estimate	-34.93***	-0.938***	-0.107***	-0.0813**
	(6.623)	(0.213)	(0.0172)	(0.0257)
B. FTC Mobile				
RD Estimate	-20.33***	-1.479***	-0.157***	-0.136***
	(4.524)	(0.179)	(0.0145)	(0.0166)
C. FTC Desktop				
RD Estimate	-49.53***	-0.398**	-0.0581***	-0.0261*
	(8.274)	(0.131)	(0.0135)	(0.0121)

Notes: In column 1 the dependent variable is the log length of the median complaint's open-ended text field, at the daily level. In the second column the dependent variable is the median Flesch-Kincaid Grade Level, and the final two columns are the fraction of complaints above 8th grade or college according to the Flesch-Kincaid Grade Level. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

7 How do the Topics that Consumers Complain About Change with the Redesign?

In this section, we examine how the issues that consumers complain about change after the redesign. We take three different approaches based using the text of complaints. First, we use a large language model to predict the categories of complaints, and find larger increases in complaints about imposter scams and telemarketing, scams in which most affected consumers do not lose money. Second, we

Section B.3 shows analogous results using the Flesch Reading Ease score.

apply topic modeling to the text of complaints and find the largest increases for topics related to imposter scams, as well as identity theft complaints. Finally, we examine how the words used themselves changed, and find reductions in complaint words related to orders and purchasing, as well as reductions in the share of consumers reporting a monetary loss.

This evidence is consistent with more complaints about issues in which consumers encounter a scam but do not lose money. In such situations, complaints are likely driven by altruistic motives alone as there are no losses for consumers to recover; such complaints may be more likely to be deterred by hassle costs.

7.1 Categories

The complaints in Consumer Sentinel include the self-reported category of problem that the consumer is complaining about. Unfortunately, the categorization of frauds itself changed with the website redesign, so these categories are not directly comparable between the two time periods. We thus predict categories using the open-ended text fields and then examine how the predicted categories change after the redesign.

To implement this approach, we take advantage of the recent advances in text mining approaches and "fine tune" the *distilbert-base-uncased* Large Language Model to predict categories in the post redesign period, building on work that has previously used natural language processing to assess the sentiment of complaints (DeLiema and Witt, 2023).[15] Fine tuning a Large Language Model estimates the last layer of the neural network for the given objective (here, to predict categories using the complaint data), but keeps all other layers of the neural network estimated on much larger text datasets. We apply this model to online complaints using the 60 days after the website change and hold out 10% of the sample to test the accuracy of the model.

For our main estimates, we condense the categories into 5 groups based on the largest categories in the data: "Telemarketing," "Unsolicited Text/Email," "Imposter Scams," "Online Shopping/Reviews," and "All Other/Misc" as a catch all category; Appendix B.4 provides more details on this process. We then train the model to predict these 5 categories. If we assign each complaint to the category with the highest probability, we correctly predict 61% of the complaints in the held

[15] We use the Huggingface *transformers* library in Python.

out test dataset.[16]

We then estimate the RD using data on the sum of predicted probabilities of each category by day; Figure 11 depicts the RD results for the imputed categories relative to the baseline of the overall increase in complaints. While reports in all imputed categories increased, the telemarketing and imposter scam categories have much larger increases than the baseline rise in complaints. Complaints about telemarketing and imposter scams increase by 88% and 64%, respectively.

For both telemarketing and imposter scams, a lot of consumers are exposed to the scam but only a minority lose money. For example, in the case of telemarketing, consumers often report having received unwanted calls. Thus, for most consumers, reporting these scams relies solely on altruistic motives, rather than the prospect of recovering their losses.

We also examine an alternative, more detailed categorization with 13 categories instead of 5 in Figure A6 in Appendix B.4.[17] We find fairly consistent results to our main approach. The more detailed categories show that the disproportionate increase in imposter scams is driven by government imposters (81% increase) rather than business imposters (52%). Telemarketing is again the category with the largest increase at an 89% overall increase, although we also find larger increases for Tech Support and Unsolicited Email categories which each have a 62% increase. The smallest increase is for Unsolicited Text, for which we see only a 15% increase in complaints post redesign.

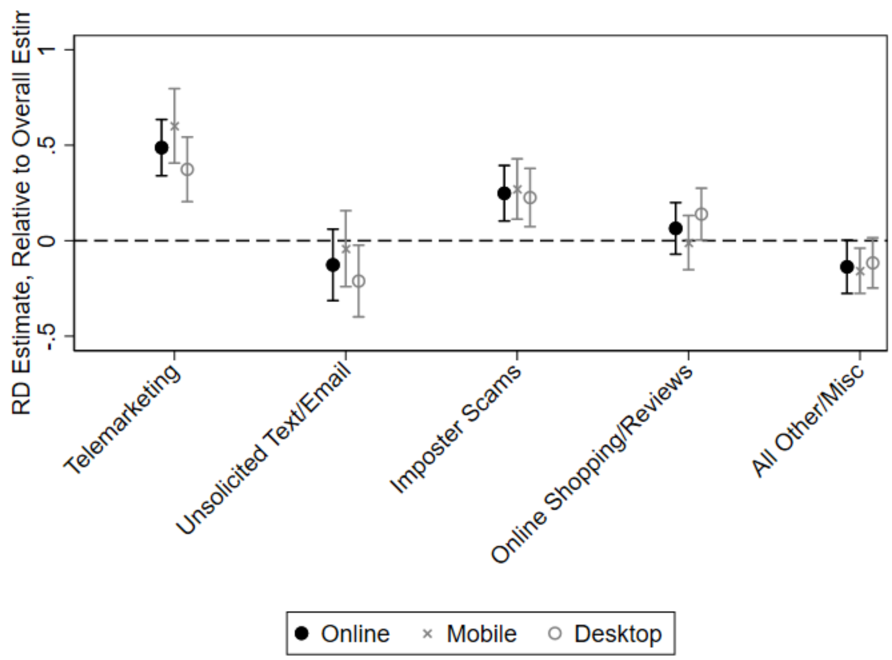
7.2 Topic Modeling

A weakness of the approach above is that it relies on the complaint categories that already exist in Consumer Sentinel. These categories are quite broad, and so may not convey some of the nuance of consumers' problems. They rely on consumers accurately entering the category that their problem concerns. Finally, some issues are not well captured by these categories. For example, a common consumer protection problem is "negative option" schemes where consumers sign up for a free trial, unaware that they are enrolling into a subscription program unless they affirmatively cancel. While negative option subscriptions all exhibit the same consumer protection problem, they would be

[16] We provide a "confusion matrix" comparing predicted to actual categories in Appendix B.4. In some cases, a complaint is assigned to multiple category codes. In these cases, we include the same complaint text for each category.

[17] These categories are Unwanted Telemarketing; Unsolicited Text; Business Imposter; Online Shopping; Govt Imposter; Unsolicited Email; Tech Support; Job Scams; Prizes/ Sweepstakes; Romance Scams; Misc Investments; Diet Plans / Centers; and All Other.

Figure 11: RD Estimate of Website Redesign on Imputed Product Category



Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the log sum of the predicted probability of each category using the text of consumer complaints. The overall effect on total complaints is subtracted from each individual point estimate: 0.395 for online, 0.416 for desktop, and 0.374 for mobile. Robust standard errors clustered at the daily level. Table A7 is the corresponding table.

classified differently depending on the industry involved. For example, negative option complaints might be classified as Diet Plans if they involve diet pills, Telephone Services if they involve a telecom carrier, or Online Shopping if they involve an online platform.

We thus also apply a topic modeling approach to the text of consumer complaints using the *BERTopic* package in Python (Grootendorst, 2022). The topic modeling approach first converts the text of complaints to a high dimensional numerical representation. It then reduces the dimensionality of this representation and clusters the complaints into different clusters. Finally, the approach combines all complaints in a cluster into a single document, and uses a term frequency analysis and a fine tuned Large Language Model to represent each topic based on the words unique in that document. We provide more details of this approach in Appendix B.5.

We implement this topic modeling approach on complaints from the two months before and after the redesign. We set the cluster size to at least 120 complaints; that is, each cluster has to have one complaint per day on average. The topic modeling approach identifies 368 topics; in addition, about 35% of the complaints are characterized as "outliers" and so not assigned topics.

We then estimate RD regressions on the number of complaints per day in each topic. We restrict the topics analyzed to topics with non-zero complaints in at least half of the days, so that our analysis does not pick up changes due to "new topics" such as a new scam occuring in the two month period after the redesign. We depict the RD estimates in Figure 12, bolding all topics whose RD estimate is statistically significantly different from 0 after a Bonferroni correction for the number of statistical tests.

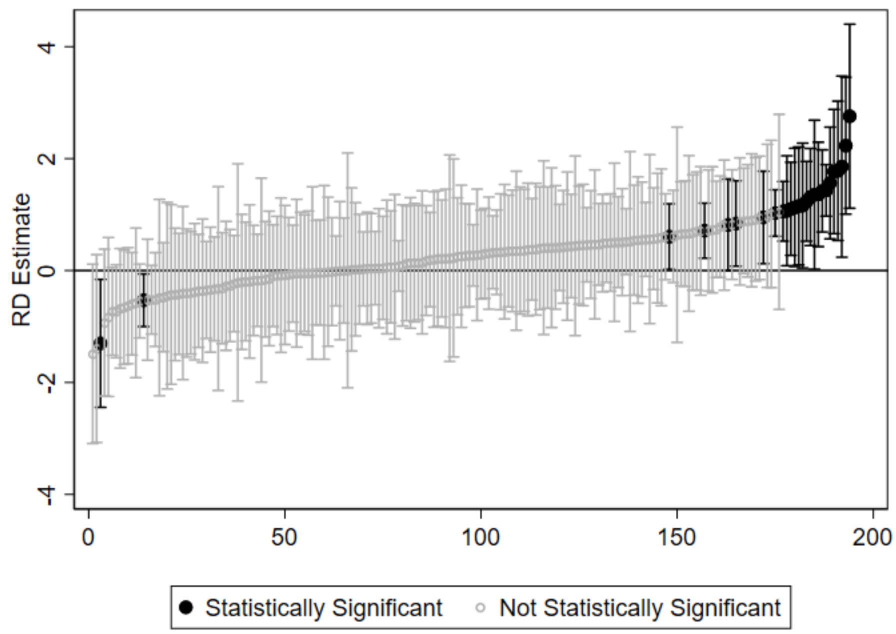
In total, we find significant increases for 23 topics and significant decreases for 2 topics. The topic modeling approach provides a representation for each topic based on a set of representative words and documents; we classify each topic into a broader category using these words and documents. Table 6 contains a list of all topics with statistically significant changes, including their keyword based representation, their RD estimate from the redesign, the number of complaints before and after the redesign, and the broader issue they are classified into.

Perhaps the most surprising finding is that five of the topics with a significant increase are about different identity theft scams, where scammers file for government loans or unemployment benefits in someone else's name. The FTC operates a separate website specifically for identity theft, *identitytheft.gov*, where these complaints should have been filed. The landing page for both the old and new complaint website displayed links to the identity theft website (see Figure 1 and Figure 2), although the screen real estate for the identity theft link is larger on the old website. The decrease in hassle costs may have made it easier for identity theft victims to file complaints at the fraud website, as opposed to giving up and eventually finding the identity theft website.

The remaining significant topics parallel our earlier category analysis. Of the remaining topics with a significant increase, the most common category, at six topics, is imposter scams, where the imposter may pretend to be government agencies like the SSA or police, businesses like Amazon or Apple, or friends/family/coworkers. This increase in complaints about imposter scam topics is consistent with the rise in the "Imposter Scam" category we documented in the category analysis. Three topics with an increase are email claims of a "hack" of consumers watching pornography on their computer. Only one topic with a significant increases is about online shopping, while the two topics with a significant decrease are about spam texts. These differences match the smaller increase in spam texts and online shopping complaints in the category analysis.

Finally, two topics are not about a specific type of scam. One topic clusters together Spanish language complaints, while another groups complaints that describe updates, presumably updating information from an earlier complaint. Increases in these two topics may mean that the website redesign made it easier to complain in Spanish, and encourage "repeat business" from consumers that had complained previously.

Figure 12: RD Estimate of Website Redesign on Imputed Topics



Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the log number of daily online complaints by consumers in each topic. Robust standard errors clustered at the daily level. We bold topics with a statistically significant change after a Bonferroni correction for the number of topics.

7.3 Likelihood of Losses

Above, we found the largest increases after the redesign were in complaint categories where many consumers with exposure to the scam may not have lost money. We now directly examine whether consumers lost money, because many consumers either report a zero loss or leave the question blank.

As Table 7 shows, consumers are less likely to report losing money after the redesign. The share of consumers reporting a loss falls by 2.6 percentage points, driven by mobile complaints for which the percentage of consumers reporting a loss falls by 5 percentage points. We find no decline for

Table 6: RD Estimate of Website Redesign on Selected Topics

Representation	Est.	(S.E.)	Total Complaints	Assigned Category
Positive and Significant				
49_unemployment claim_kansas dept_ks dept_unemployment benefit	2.76	(0.47)	1446	Identity Theft
47_esto_cuando_que el_como	2.23	(0.35)	1508	Spanish Language Cluster
187_data video_monitoring internet_uploaded trojan_letter video	1.86	(0.47)	485	Hack Claim
95_sba fraud_sba loan_loan sba_contacted sba	1.78	(0.36)	713	Identity Theft
48_unemployment claim_filed claim_fraudulent claim_filed fraudul	1.77	(0.32)	1451	Identity Theft
23_unemployment fraud_unemployment claim_filed claim_fraudulent claim	1.57	(0.29)	2552	Identity Theft
9_ifidonotreceivethebitcoin idefinitelywillsendoutyourvideorecordingto	1.43	(0.13)	3373	Hack Claim
1_icloud breach_saying icloud_icloud account_apple icloud	1.42	(0.21)	9218	Imposter
36_received voicemail_issue arrest_warrant arrest_left voicemail	1.36	(0.27)	1843	Imposter
112_regards outlook_outlook io_urgent task_email soon	1.36	(0.38)	600	Imposter
181_update help_update just_update ne_update problem	1.31	(0.25)	2730	Update on Previous Complaint
57_gift card_itunes gift_ebay gift_play gift	1.24	(0.21)	1308	Imposter
118_cashier check_receive check_payment_payment address	1.16	(0.32)	550	Advance Fee
60_phone robo_number robo_robo claim_robo tel	1.16	(0.30)	1189	Imposter
21_unemployment claim_illinois dept_filed claim_unemployment benefit	1.13	(0.30)	2624	Identity Theft
39_online interview_hiring manag_google hangout_interview	1.10	(0.24)	1729	Job Opportunity
121_stop robo_number robo_robo_calls robocal	1.07	(0.28)	547	Unwanted Calls
3_calls com_calls differ_caller_caller id	1.06	(0.15)	6612	Unwanted Calls
0_ss number_number suspend_ssa_ssn suspend	1.03	(0.12)	28618	Imposter
123_hacked taken_send video_video btc_traced hack	0.95	(0.24)	526	Hack Claim
75_ohio amazon_charge amazon_contacted amazon_called amazon	0.84	(0.22)	863	Imposter
281_shopper earn_shop earn_shopper work_mystery shopp	0.82	(0.23)	188	Job Opportunity
6_won million_scammer_prize money_told won	0.71	(0.14)	4068	Lottery/Prize
5_requested refund_asked refund_refund_received respons	0.61	(0.17)	4301	Online Shopping
Negative and Significant				
106_weight loss_losing weight_weightloss_loose weight	-1.30	(0.33)	635	Spam Text
2_spam text_unwanted text_received text_receiving text	-0.53	(0.14)	9213	Spam Text

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of complaints within each imputed topic area. For each topic, we include the representation of the topic, RD coefficient and standard error, the number of complaints in the two months before and after the redesign, and the category assigned by the authors to the topic. The representation of the topic includes a number (in order of size from 0 to 367) and representative words for the topic. The specification includes a third degree polynomial and controls for day of the week. Data includes complaints at the daily level across FTC desktop and mobile platforms. The data include complaints from 60 days before and after the FTC's website redesign on October 22, 2020. Robust standard errors clustered at the daily level.

desktop complaints. This decline in the fraction of consumers reporting a loss means that the mean per-consumer loss also declined, although these estimates are not statistically significant.

Table 7: RD Estimate of Website Redesign on FTC Complaints Reporting a Dollar Loss

	(1) Reported a Loss	(2) Mean Loss Amount (log)
A. FTC Online		
RD Estimate	-0.0258*	-0.199
	(0.0122)	(0.160)
B. FTC Mobile		
RD Estimate	-0.0501**	-0.207
	(0.0154)	(0.262)
C. FTC Desktop		
RD Estimate	-0.00155	-0.191
	(0.0163)	(0.202)

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of complaints that reported a dollar loss and the log of the mean value of the daily loss reported. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

This analysis relies on consumers' self-report on how much money they lost, but some consumers might leave this data field blank and only report losses in the text. Thus, we also make inferences about consumer experiences using the most distinctive words that appear in complaint texts. We start by identifying the most common words in the two months following the redesign.[18] Using equation (1), we estimate which of these words saw a statistically significant rise or decrease in use following the website redesign. To account for multiple hypothesis testing, we apply a Bonferroni correction to adjust the critical value for statistical significance.

Table 8 shows which of the 512 words we examined had a statistically significant rise or fall on both the mobile and desktop FTC complaint sites. Although 18% of words increased in relevance for desktop and 28% increased for mobile, very few had a statistically significant increase, and none had statistically significant increases in both sources. We can learn more from the terms that saw declines, however. One clear theme that emerges overlaps with the previous finding that consumers were less likely to report monetary losses. Terms related to payments, such as "check," "deposit," "money," "order," and "purchase" all saw declines in both interfaces.

[18] Specifically, we omit all numbers, punctuation, white space, and "stop words". We then stem the documents to their root, and limit the resulting terms to ones that occur in between 1% and 40% of complaint texts. The two months following the redesign are October 22 through December 21, 2020.

Table A8 shows the words that had statistically significant increases and decreases for just mobile or desktop interfaces. Within the mobile users interface, an additional theme that stands out is a decline in terms related to orders and refunds. Terms such as "refund," "paypal," "order," and "delay" all showed declines. For online interface users, an additional theme is that of computing itself. Terms like "comput," "onlin," "email," and "websit" decreased.

Thus, our analysis of the words used in complaints indicates that consumers were less likely to complain about issues related to payments, as well as orders, refunds, and computer related issues.

Table 8: Terms with Statistically Significant Declines

check, compani, contact, deposit, email, inform, money, never, offer, order, person, purchas, request, someon, state, though, websit

Notes: The table shows the terms that saw a statistically significant decline in use after the FTC's website redesign for both mobile and desktop complaints separately. The set of all possible terms do not common stop words or words that were included in fewer than 1 percent or over 40 percent of FTC complaints. All words were destemmed to create the most popular terms. Each resulting term was then used as a dependent variable in estimates of equation (1), with a Bonferroni correction to account for multiple hypothesis testing.

8 Consumers Induced to Complain By the Redesign

We now use our RD estimates to examine the characteristics of consumers induced to file a report due to the redesign. In the language of the Rubin causal model, we are interested in how the characteristics of the complier population compare to those of the always-taker consumers who were complaining even before the redesign. Although we cannot explicitly identify which consumers are in each group, we can use our results to study how their characteristics differ (Imbens and Rubin, 1997; Angrist and Pischke, 2009).

Since we observe mean characteristics before the redesign, which tell us about the mean of the always taker population, as well as the change in the number of complaints and characteristics with the redesign, we can obtain the mean characteristics of compliers. The mean of the baseline characteristic Y for compliers is:

$$E(Y_{complier}) = \Delta \frac{1+\gamma}{\gamma} + E(Y_{taker}), \tag{4}$$

where Δ is the RD (level) estimate for variable Y, γ is the RD (percentage) estimate for number of complaints, and $E(Y_{taker})$ is the mean of the characteristic for always takers–that is, the pre-redesign mean. We observe $E(Y_{taker})$ using data from before the redesign, and estimate γ in Section 5 and Δ in Section 6 and Section 7 for different characteristics. We derive equation (4) in Appendix C.[19]

This derivation requires two crucial assumptions. First, the population of defiers must be negligible; that is, consumers who would have submitted a complaint prior to the redesign would also have submitted one after. Since the redesign made the website much easier to use, we see this assumption as innocuous.

Second, all of the change from the redesign must be due to changes in composition; that is, the redesign did not affect the types of complaints from taker complainants. This assumption is trivially satisfied for a person's name: it is unlikely that the redesign caused takers to change their names. However, the assumption would fail for age bands because takers also increased their reporting of age conditional on submitting a complaint. In that case, we can still examine the average characteristics of compliers compared to takers under the additional assumption that missing characteristics are missing at random.

The first panel of Table 9 displays the mean for several demographic characteristics for taker and complier complainants, respectively. Compliers are more likely to be senior citizens than takers; the share 70-79 increases from 9% to 11%, and the share 80+ increases from 2% to 4%. They are also more likely to be female, at 59% compared to 50% for takers. We find small differences between compliers and takers on race and ethnicity, except that compliers are, on average, 3 percentage points less likely to be Latino.

Finally, compliers tend to live in zip codes in which victims complain less than the median zip code. Raval (2020*b*) estimates a demographic weight as the inverse of the predicted likelihood that a victim complains, normalized to one for the median zip code. This weight increases from 0.94 for taker complaints to 1.35 for complier complaints.

The second panel of the table examines characteristics of the text and whether consumers report a loss. Compliers use much less sophisticated language, with more than three grade levels

[19]For certain specifications, we estimate the RD estimate for variable Y in percentage terms rather than level terms. In that case, replace Δ in equation (4) with $(\delta + 1)E(Y_{taker})$, where $\delta + 1$ is the RD estimate in percentage terms. See Appendix C for more details.

less sophisticated text than takers. They also write much smaller complaints, with text about 500 characters shorter on average for compliers compared to takers. In addition, compliers are less likely to report a loss; on average, 23% of taker complainants report a loss, compared to 14% of complier complainants.

The last panel of the table examines the types of scams and schemes that consumers reported. For this analysis we use the complaint categories we imputed in Section 7.1. Compliers were more than twice as likely to report telemarketing and imposter scams than takers. However, they were just as likely to report issues with online shopping, and less likely to report text and email problems.[20]

Table 9: Differences between Takers and Compliers for FTC Online Complaints

	(1) Takers	(2) Compliers
Demographic Characteristics		
Age <40	0.36	0.33
Age 40-59	0.34	0.35
Age 60-69	0.18	0.18
Age 70-79	0.09	0.11
Age 80+	0.02	0.04
Asian/PI	0.05	0.05
Black	0.10	0.11
Latino	0.10	0.07
White	0.73	0.75
Female	0.50	0.59
Demographic Weight	0.94	1.35
Text and Losses		
Grade Level	9.16	5.85
Reported Loss	0.23	0.14
Length (Characters)	693	189
Imputed Product Category		
Telemarketing	0.07	0.20
Unsolicited Text or Email	0.25	0.13
Imposter Scams	0.18	0.35
Online Shopping and Reviews	0.10	0.11
All Other and Misc	0.40	0.20

Notes: The first column of the table, for takers, shows the mean characteristics for FTC complaints in the 30 days prior to the website redesign on October 22, 2020. The second column shows the imputed means for complier complainants. These means are calculated using the pre-redesign mean, the coefficient estimate from equation (1), and the coefficient estimate on the number of complaints, as in equation (4).

[20] Table A9 splits out this compliers analysis by the mobile and desktop complaints.

9 Conclusion

In this article, we have studied the effect of a major website redesign that made it much easier for consumers to complain about consumer protection problems to the government. Through the redesign, we can evaluate how hassle costs affect contributions to a public good in the context of consumer complaints. The release of the new website was unanticipated by the public and so allows us to use regression discontinuity techniques to evaluate the effect of the change. Online complaints to the FTC rose 40% overnight due to the change; we find no significant increase in complaints for calls to the FTC or complaints to the BBB or CFPB.

We find evidence for countervailing effects of hassle costs on complaining. On the one hand, the redesign leads to more complaints from older adults as well as reductions in the length and grade level of the text of the complaint. Hassle costs may thus keep less sophisticated or more vulnerable users from complaining. On the other hand, consumers are less likely to report having lost money, the complaint text is less likely to relate to purchases and payments, and complaints are more likely to concern imposter scams and telemarketing where most exposed consumers do not lose money. Thus, consumers induced to complain by the redesign may have experienced less severe consumer protection problems.

In our view, the changes in complaints from the reduction in hassle costs was beneficial to policymakers seeking to protect consumers. The FTC launched the "Every Community Initiative" to make sure that its efforts address the problems of the various communities in the United States (Federal Trade Commission, 2021*b*); thus, more complaints from older adults and communities less likely to complain before the redesign help the agency meet this goal. In addition, relying purely on altruistic motives for reporting may mean certain types of frauds where most affected consumers do not suffer financial losses are under-reported. More complaints on such issues help the agency learn about them and deter them, either through consumer education efforts or enforcement actions.

10 Funding and Competing Interests

We have no competing interests.

References

Aizer, Anna. 2007. "Public health insurance, program take-up, and child health." *The Review of Economics and Statistics*, 89(3): 400–415.

Akerlof, George A. 1978. "The economics of" tagging" as applied to the optimal income tax, welfare programs, and manpower planning." *The American economic review*, 68(1): 8–19.

Anderson, Eric T, and Duncan I Simester. 2014. "Reviews Without a Purchase: Low Ratings, Loyal Customers, and Deception." *Journal of Marketing Research*, 51(3): 249–269.

Anderson, Keith B. 2013. "Consumer fraud in the United States, 2011: The third FTC survey." *Washington, DC: Federal Trade Commission.*

Anderson, Keith B. 2019. "Mass-market consumer fraud in the United States: A 2017 update." *Federal Trade Commission. Washington, DC.*

Anderson, Keith B. 2021. "To Whom Do Victims of Mass-Market Consumer Fraud Complain?" *Available at SSRN 3852323.*

Angrist, Joshua D, and Jörn-Steffen Pischke. 2009. *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Bergstrom, Theodore, Lawrence Blume, and Hal Varian. 1986. "On the private provision of public goods." *Journal of public economics*, 29(1): 25–49.

Bhargava, Saurabh, and Dayanand Manoli. 2015. "Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment." *American Economic Review*, 105(11): 3489–3529.

Chan, Kenneth S, Stuart Mestelman, and R Andrew Muller. 2008. "Voluntary provision of public goods." *Handbook of experimental economics results*, 1: 831–835.

Chaudhuri, Ananish. 2011. "Sustaining cooperation in laboratory public goods experiments: a selective survey of the literature." *Experimental economics*, 14: 47–83.

Chetty, Raj, John N Friedman, and Emmanuel Saez. 2013. "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings." *American Economic Review*, 103(7): 2683–2721.

Consumer Financial Protection Bureau. 2014. "Using publicly available information to proxy for unidentified race and ethnicity."

Currie, Janet. 2006. "The take-up of social benefits." *Public Policy and the Distribution of Income*, 80–148. Russell Sage Foundation.

DeLiema, Marguerite, and Paul Witt. 2021. "Mixed Methods Analysis of Consumer Fraud Reports of the Social Security Administration Impostor Scam."

DeLiema, Marguerite, and Paul Witt. 2023. "Profiling consumers who reported mass marketing scams: demographic characteristics and emotional sentiments associated with victimization." *Security Journal*, 1–44.

Deliema, Marguerite, Doug Shadel, and Karla Pak. 2020. "Profiling victims of investment fraud: Mindsets and risky behaviors." *Journal of Consumer Research*, 46(5): 904–914.

DeLiema, Marguerite, Martha Deevy, Annamaria Lusardi, and Olivia S Mitchell. 2020. "Financial fraud among older Americans: Evidence and implications." *The Journals of Gerontology: Series B*, 75(4): 861–868.

Diamond, Peter, and Eytan Sheshinski. 1995. "Economic aspects of optimal disability benefits." *Journal of Public economics*, 57(1): 1–23.

Dukes, Anthony, and Yi Zhu. 2019. "Why customer service frustrates consumers: Using a tiered organizational structure to exploit hassle costs." *Marketing Science*, 38(3): 500–515.

Ebenstein, Avraham, and Kevin Stange. 2010. "Does inconvenience explain low take-up? Evidence from unemployment insurance." *Journal of Policy Analysis and management*, 29(1): 111–136.

Federal Trade Commission. 2021*a*. "Curbing COVID Cons: Warning Consumers about Pandemic Frauds, Scams, and Swindles." Congressional Testimony.

Federal Trade Commission. 2021*b*. "Serving Communities of Color." Staff Report.

Federal Trade Commission. 2022*a*. "Protecting Older Consumers 2021–2022: A Report of the Federal Trade Commission."

Federal Trade Commission. 2022*b*. "Who experiences scams? A story for all ages." Consumer Protection Data Spotlight.

Federal Trade Commission. 2023. "New FTC Data Show Consumers Reported Losing Nearly $8.8 Billion to Scams in 2022." Staff Report.

Fischbacher, Urs, and Simon Gächter. 2010. "Social preferences, beliefs, and the dynamics of free riding in public goods experiments." *American economic review*, 100(1): 541–556.

Foote, Andrew, Michel Grosz, and Stephanie Rennane. 2019. "The Effect of Lower Transaction Costs on Social Security Disability Insurance Application Rates and Participation." *Journal of Policy Analysis and Management*, 38(1): 99–123.

Fradkin, Andrey, and David Holtz. 2023. "Do incentives to review help the market? evidence from a field experiment on airbnb." *Marketing Science*.

Fradkin, Andrey, Elena Grewal, and David Holtz. 2021. "Reciprocity and Unveiling in Two-sided Reputation Systems: Evidence from an Experiment on Airbnb." *Marketing Science*, 40(6).

Gächter, Simon, Daniele Nosenzo, Elke Renner, and Martin Sefton. 2010. "Sequential vs. simultaneous contributions to public goods: Experimental evidence." *Journal of Public Economics*, 94(7-8): 515–522.

Gans, Joshua S, Avi Goldfarb, and Mara Lederman. 2021. "Exit, tweets, and loyalty." *American Economic Journal: Microeconomics*, 13(2): 68–112.

Grootendorst, Maarten. 2022. "BERTopic: Neural topic modeling with a class-based TF-IDF procedure." *arXiv preprint arXiv:2203.05794*.

Hausman, Catherine, and David S Rapson. 2017. "Regression Discontinuity in Time: Considerations for Empirical Applications." National Bureau of Economic Research Working Paper 23602.

He, Sherry, Brett Hollenbeck, and Davide Proserpio. 2022. "The market for fake reviews." *Marketing Science*, 41(5): 896–921.

Hirschman, Albert O. 1972. *Exit, voice, and loyalty: Responses to decline in firms, organizations, and states.* Harvard university press.

Imbens, Guido W, and Donald B Rubin. 1997. "Estimating outcome distributions for compliers in instrumental variables models." *The Review of Economic Studies*, 64(4): 555–574.

Jin, Ginger Zhe, and Phillip Leslie. 2003. "The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards." *The Quarterly Journal of Economics*, 409–451.

Kaufmann, Daniel. 2021. "Community Advocate Center connects more people to the FTC." Federal Trade Commission press release.

Kleven, Henrik Jacobsen, and Wojciech Kopczuk. 2011. "Transfer program complexity and the take-up of social benefits." *American Economic Journal: Economic Policy*, 3(1): 54–90.

Kopczuk, Wojciech, and Cristian Pop-Eleches. 2007. "Electronic filing, tax preparers and participation in the Earned Income Tax Credit." *Journal of public Economics*, 91(7-8): 1351–1367.

Laux, Volker. 2008. "On the value of influence activities for capital budgeting." *Journal of Economic Behavior & Organization*, 65(3-4): 625–635.

Lewis, Gregory, and Georgios Zervas. 2020. "The Supply and Demand Effects of Review Platforms." *Unpublished manuscript.*

Luca, Michael. 2011. "Reviews, Reputation, and Revenue: The Case of Yelp. com."

Luca, Michael, and Georgios Zervas. 2016. "Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud." *Management Science*, 62(12): 3412–3427.

Luguri, Jamie, and Lior Jacob Strahilevitz. 2021. "Shining a light on dark patterns." *Journal of Legal Analysis*, 13(1): 43–109.

Mathur, Arunesh, Gunes Acar, Michael J Friedman, Eli Lucherini, Jonathan Mayer, Marshini Chetty, and Arvind Narayanan. 2019. "Dark patterns at scale: Findings from a crawl of 11K shopping websites." *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW): 1–32.

Mayzlin, Dina, Yaniv Dover, and Judith A. Chevalier. 2014. “Promotional Reviews: An Empirical Investigation of Online Review Manipulation.” *The American Economic Review*, 104(8): 2421–2455.

Mclean, Bethany. 2020. “IHow International Fraud Rings Operate and Target Older Americans.” *AARP.*

Nichols, Albert L, and Richard J Zeckhauser. 1982. “Targeting transfers through restrictions on recipients.” *The American Economic Review*, 72(2): 372–377.

Nosko, Chris, and Steven Tadelis. 2015. “The Limits of Reputation in Platform Markets: An Empirical Analysis and Field Experiment.” National Bureau of Economic Research.

Parsons, Donald O. 1991. “Self-screening in targeted public transfer programs.” *Journal of Political Economy*, 99(4): 859–876.

Raval, Devesh. 2020*a*. “Which Communities Complain to Policymakers? Evidence from Consumer Sentinel.” *Economic Inquiry*, 58: 1628–1642.

Raval, Devesh. 2020*b*. “Whose voice do we hear in the marketplace? Evidence from consumer complaining behavior.” *Marketing Science*, 39(1): 168–187.

Raval, Devesh. 2021. “Who is Victimized by Fraud? Evidence from Consumer Protection Cases.” *Journal of Consumer Policy*, 44: 43–72.

Raval, Devesh, and Michel Grosz. 2022. “Fraud Across Borders.” *Available at SSRN 4197797.*

Simester, Duncan, and Juanjuan Zhang. 2014. “Why do salespeople spend so much time lobbying for low prices?” *Marketing Science*, 33(6): 796–808.

Sweeting, Andrew, David J Balan, Nicholas Kreisle, Matthew T Panhans, and Devesh Raval. 2020. “Economics at the FTC: fertilizer, consumer complaints, and private label cereal.” *Review of Industrial Organization*, 57: 751–781.

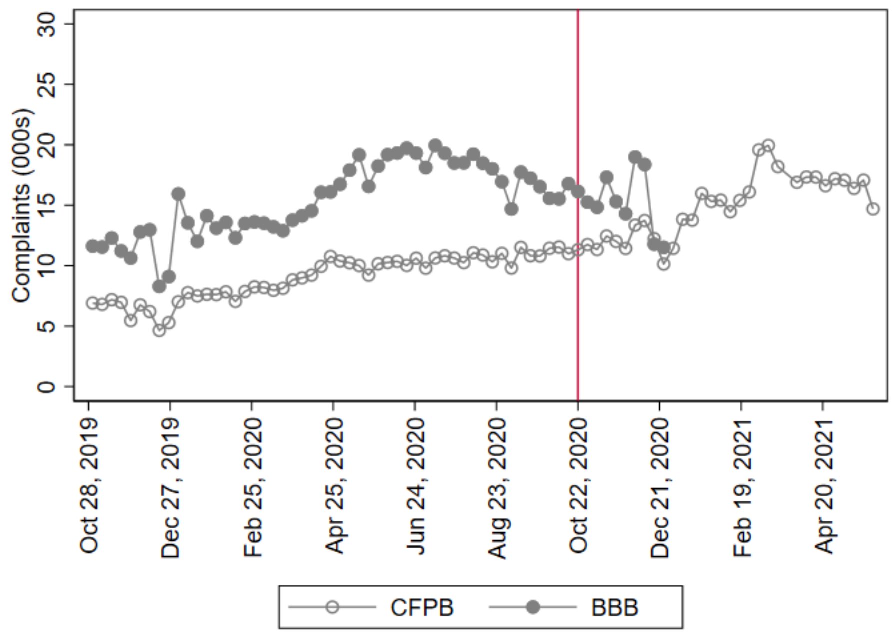
Tadelis, Steven, and Florian Zettelmeyer. 2015. “Information Disclosure as a Matching Mechanism: Theory and Evidence from a Field Experiment.” *American Economic Review*, 105(2): 886–905.

Voicu, Ioan. 2018. “Using first name information to improve race and ethnicity classification.” *Statistics and Public Policy*, 5(1): 1–13.

Zhang, Yan. 2018. “Assessing fair lending risks using race/ethnicity proxies.” *Management Science*, 64(1): 178–197.

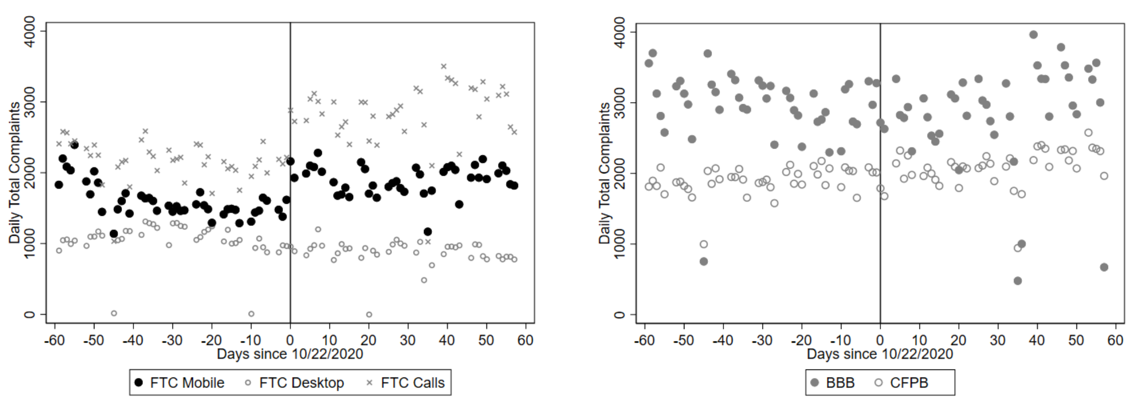
A Appendix Tables and Figures

Figure A1: Complaints by Week to the BBB and CFPB



Notes: The figure shows the number of complaints, in thousands, logged each week between October 26, 2019 and June 19, 2021, across the BBB and CFPB sources. The weeks are defined as starting on Thursdays, since the website redesign was a Thursday. BBB complaints are limited to before January 1, 2021. The vertical line shows the date of the website redesign.

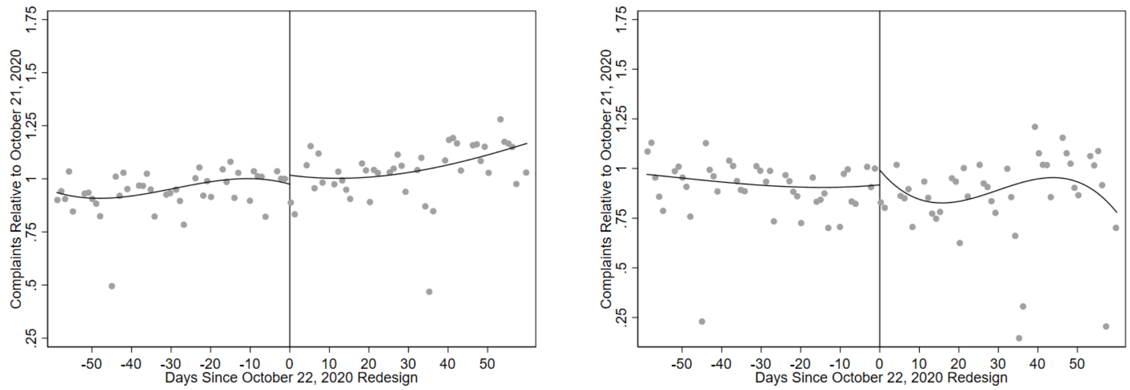
Figure A2: Complaints by Week, Raw Counts



a) FTC b) BBB/CFPB

Notes: The figure shows the number of complaints each day between from 60 days before and after October 22, 2020.

Figure A3: RD Estimate of Website Redesign on Number of Complaints, BBB and CFPB



a) CFPB

b) BBB

Notes: The figure shows the daily number of complaints report to the CFPB and BBB, from 60 days before and after the FTC's website redesign on October 22, 2020. For each panel, the number of complaints are expressed relative to the number of complaints on the day prior to the redesign, October 21, 2020, which are set to one. The vertical bar shows the date of the redesign. The fitted lines are an RD estimate the includes a third-degree polynomial and controls for the day of the week.

Table A1: RD Estimate of Website Redesign on Number of Complaints, First Degree Polynomial

	(1) FTC Online	(2) FTC Mobile	(3) FTC Desktop	(4) FTC Calls	(5) CFPB	(6) BBB
RD Estimate	0.282***	0.307***	0.256***	-0.0856	-0.00606	0.0255
	(0.0379)	(0.0395)	(0.0357)	(0.0456)	(0.0452)	(0.0677)

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of daily complaints. The specification includes a first degree polynomial and controls for day of the week. FTC Online refers to the sum of FTC mobile and desktop complaints. The data include complaints from 60 days before and after the FTC's website redesign on October 22, 2020. Robust standard errors clustered at the daily level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

B Additional Details on Empirical Approaches

B.1 Age Bands Using Vital Statistics Data

In our main analysis, we use the age bands that consumers can list when filling out the forms in the old and redesigned versions of the FTC website. However, we have shown that the rate at which consumers filled in the age bands themselves changed due to the redesign. As a robustness check we impute the age bands using consumer names, which were not subject to the same large swings in data quality due to the redesign.

We first compile the number of births in the US with each first name since 1900, available from the Social Security Administration (SSA). We then calculate the fraction of people born in each year with each name who would be alive in 2020, using the SSA actuarial life tables. These tables only calculate survival rates for birth years on the decade (e.g. 2010, 2000), so for births in other years we interpolate. Because we do not know the sex at birth of each consumer, we calculate the survival rates as the average of male and female survival rates. This exercise gives us the median birth year for each name, from which we can calculate the median age in 2020 for each name. We use the age bands from this imputed median age in the figure below. The key limitations of this approach are that we must assume that individuals with different names born in the same year have the same survival rates, and that there is no

Table A2: RD Estimate of March 3 2021 Press Release on Number of Complaints

	(1) FTC Online	(2) FTC Mobile	(3) FTC Desktop
Post	0.0805	0.115**	0.0462
	(0.0677)	(0.0422)	(0.0461)

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of daily complaints. The specification includes a third degree polynomial and controls for day of the week. FTC Online refers to the sum of FTC mobile and desktop complaints. The data include complaints from 60 days before and after the FTC's press release on March 3, 2021 about an initiative to encourage low-income communities to report fraud. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A3: RD Estimates, Quality of Data

	(1) Has Zip	(2) Has Age	(3) Company Name	(4) Company Zip
A. FTC Online				
RD Estimate	0.0857***	0.102***	0.0755***	-0.000729
	(0.00657)	(0.00617)	(0.0153)	(0.00927)
B. FTC Mobile				
RD Estimate	0.0847***	0.107***	0.0704**	0.0150
	(0.00991)	(0.00964)	(0.0230)	(0.0117)
C. FTC Desktop				
RD Estimate	0.0867***	0.0956***	0.0807***	-0.0165
	(0.00833)	(0.00798)	(0.0189)	(0.0111)

Notes: The table shows estimates of equation (1), where the dependent variable is the fraction of daily complaints that included a zipcode, included a consumer's age, included a defrauding company's name, or included a defrauding company's zipcode. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

immigration. Still, despite these limitations the results are similar to our main results that use the actual age bands from the FTC website.

B.2 Imputing Race and Ethnicity using Names and Zipcode

Our main race imputation uses consumer first and last names. However, race imputation using Bayesian techniques usually rely on geographic information as well (Voicu, 2018). We use the fraction of people with each first and last name who are of each race or ethnicity, as in the main results, but also include geographic data by zipcode from the 2010 Census. We calculate

$$p(r|s,f,g) = \frac{p(r|s)p(f|r)p(g|r)}{\sum_{r=1}^{6} p(r|s)p(f|r)p(g|r)}, \tag{5}$$

where $p(r|s,f,g)$ is the imputed probability of being of race or ethnicity r, given surname s, first name f, and geographic area g. For consumers who do not provide a zipcode, we use just the first and last name probabilities. The results are below and are quite similar to the main results.

Table A4: RD Estimates, Log Complaints in Each Age Range

	(1) <40	(2) 40-59	(3) 60+	(4) 60-69	(5) 70-79	(6) 80+
A. FTC Online						
RD Estimate	0.482***	0.523***	0.548***	0.505***	0.630***	0.771***
	(0.0787)	(0.101)	(0.0546)	(0.0670)	(0.0698)	(0.147)
B. FTC Mobile						
RD Estimate	0.492***	0.515***	0.520***	0.439***	0.721***	0.792**
	(0.0655)	(0.0764)	(0.0748)	(0.0951)	(0.108)	(0.271)
C. FTC Desktop						
RD Estimate	0.471***	0.531***	0.575***	0.572***	0.540***	0.751***
	(0.0794)	(0.0772)	(0.0654)	(0.0715)	(0.0905)	(0.136)

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of daily complaints by consumers in each age band. Consumer can also choose to not report their age. The age 60 and above is the sum of the other older age bands. Robust standard errors clustered at the daily level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A5: RD Estimates, Log Complaints in Each Imputed Race

	(1) White	(2) Black	(3) Latino	(4) Asian
A. FTC Online				
RD Estimate	0.421***	0.439***	0.345***	0.414***
	(0.0778)	(0.0686)	(0.0761)	(0.0928)
B. FTC Mobile				
RD Estimate	0.382***	0.412***	0.200**	0.443***
	(0.0729)	(0.0711)	(0.0727)	(0.106)
C. FTC Desktop				
RD Estimate	0.460***	0.466***	0.490***	0.384**
	(0.0684)	(0.0711)	(0.0815)	(0.121)

Notes: The table shows of equation (1), where the dependent variable is the fraction of daily complaints by consumers in each imputed race or ethnicity category. Race and ethnicity are imputed using a Maximum A Posteriori proxy based on the consumer's first and last name. Robust standard errors clustered at the daily level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

B.3 Flesch Reading Ease Score

The Flesch Reading Ease score assigns a text's readability a number between 1 (hardest) and 100 (easiest). The Flesch Reading Ease measure is defined as

$$206.835 - 1.015(\frac{words}{sentences}) - 84.6(\frac{syllables}{words}) \tag{6}$$

.

The scores can also be grouped into grade level difficulty, with lower than 70 being apt for 8th grade and above,

Table A6: RD Estimates, Log Complaints in Each Imputed Sex

	(1) Female	(2) Male
A. FTC Online		
RD Estimate	0.444***	0.354***
	(0.0758)	(0.0741)
B. FTC Mobile		
RD Estimate	0.403***	0.291***
	(0.0698)	(0.0706)
C. FTC Desktop		
RD Estimate	0.485***	0.418***
	(0.0721)	(0.0664)

Notes: The table shows of equation (1), where the dependent variable is the fraction of daily complaints by consumers in each imputed sex. Sex is imputed using name counts from the Social Security Administration. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A7: RD Estimates, Imputed Categories

	(1) Telemarket	(2) Text/Email	(3) Imposter	(4) Online Shopping	(5) Other/Misc
A. FTC Online					
RD Estimate	0.882***	0.269**	0.643***	0.459***	0.258***
	(0.0752)	(0.0954)	(0.0742)	(0.0689)	(0.0712)
A. FTC Mobile					
RD Estimate	0.975***	0.332**	0.645***	0.364***	0.216***
	(0.0995)	(0.101)	(0.0806)	(0.0723)	(0.0604)
B. FTC Desktop					
RD Estimate	0.789***	0.205*	0.642***	0.555***	0.300***
	(0.0864)	(0.0957)	(0.0777)	(0.0693)	(0.0672)

Notes: The outcomes are the log sum of predicted probabilities for each imputed category based on the text of complaints. The specification includes a third degree polynomial and controls for day of the week. Data includes complaints at the daily level across FTC desktop and mobile platforms. The data include complaints from 60 days before and after the FTC's website redesign on October 22, 2020. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

and below 50 being college-level. We report results for the RD analysis on all three measures based on the Flesch Reading Ease Score in Table A12.

Overall, median reading ease increased by 2.5 points, with the share of texts with at least an 8th grade or college reading ease declined by 5 to 6 percentage points. On the mobile site, median reading ease increased by 4 points, and the share of texts with at least an 8th grade or college reading ease declined by approximately 11 percentage points. There were no changes in the online site.

Table A8: Terms with Statistically Significant Changes

	(1) Positive	(2) Negative
FTC Mobile Only	unfortun	communic, continu, correct, covid, delay, facebook, paypal, peopl, pictur, point, refund, thought, transact, updat
FTC Desktop Only	hello, signatur, prevent, devic, unemploy	account, actual, address, answer, believ, cancel, chang, complaint, comput, convers, credit, direct, investig, number, obtain, onlin, phone, posit, proceed, provid, receiv, report, research, return, servic, taken, think, verifi, wasnt

Notes: The table shows the terms that saw a statistically significant decline or increase in use after the FTC's website redesign for only mobile or desktop complaints; terms with a significant decline for both types of complaints are included in Table 8. The set of all possible terms do not common stop words or words that were included in fewer than 1 percent or over 40 percent of FTC complaints. All words were destemmed to create the most popular terms. Each resulting term was then used as a dependent variable in estimates of equation (1), with a Bonferroni correction to account for multiple hypothesis testing. The specification includes a third degree polynomial and controls for day of the week. Data includes complaints at the daily level across FTC desktop and mobile platforms. The data include complaints from 60 days before and after the FTC's website redesign on October 22, 2020.

B.4 Imputed Product Categories

The Consumer Sentinel database classifies FTC complaints into 30 product categories, which are themselves divided into about 100 more detailed product codes. However, this categorization, as well as how consumers provide the category of their complaint, changes with the website redesign. Thus, we use the text fields to predict complaint categories and examine how the predicted probabilities of complaints change with the redesign.

We develop our baseline categorization of complaints by taking the categories with at least a 10% share of desktop and mobile complaints in the two months after the redesign. Only three categories satisfy this criterion: Imposter Scams, Online Shopping / Reviews, and Unspecified Reports. Since "Unspecified Reports" is the largest category, we break it up into its product codes to create two additional categories with a share above 10%: Unwanted Telemarketing and Unsolicited Text or Email (which combines the Unsolicited Text and Unsolicited Email product codes). Finally, complaints with the "Other Misc." product code and complaints from categories below the 10% share above are categorized into a catch all "Other" category.

In order to further examine the performance of our baseline LLM predictions, we report the "confusion matrix" of these predictions in Table A13 using data from the 10% test set not used for estimation. We assign each complaint to the category with the maximum probability, and then compare predicted categories (rows in the table) to actual categories (column in the table). In general, the most common actual category is the same as the predicted category. For example, 66% of complaints predicted to be about "Online Shopping" are actually categorized as "Online Shopping" in Sentinel. The main exception is Telemarketing, as a lot of the complaints that we categorize as Telemarketing based on the LLM predictions are actually characterized as Imposter Scams. These incorrect predictions may reflect that many imposter scams happen via telephone calls, and so share similarities with Unwanted Telemarketing Calls.

We also develop a broader alternative categorization of complaints into 13 categories. We develop these categories by using the detailed product codes and including all product codes with at least a 1% share of desktop and mobile complaints in the two months after the redesign. We then combine all categories that are not included, as well as the "Other Misc." product code, into an "All Other" category. This process results in the following 13 categories: Unwanted Telemarketing; Unsolicited Text; Business Imposter; Online Shopping; Govt Imposter; Unsolicited Email; Tech Support; Job Scams; Prizes/Sweepstakes; Romance Scams; Misc Investments; Diet Plans / Centers; and All Other. We then fine tune the Large Language Model to predict these categories using data from the two months after the redesign, and hold out 10% of the sample as a test set.

Figure A6 and Table A14 display the RD estimates from this broader categorization. The predictive model has a predictive accuracy of 58% on the test set. Given the number of categories, we do not display the full confusion matrix.

Table A9: Differences between Takers and Compliers, FTC Mobile and Desktop Complaints

	(1)	(2)	(3)	(4)
	Mobile		Desktop	
	Takers	Compliers	Takers	Compliers
Demographic Characteristics				
Age <40	0.45	0.43	0.28	0.23
Age 40-59	0.36	0.37	0.33	0.33
Age 60-69	0.13	0.10	0.22	0.25
Age 70-79	0.05	0.09	0.13	0.13
Age 80+	0.01	0.01	0.04	0.04
Asian/PI	0.05	0.06	0.05	0.04
Black	0.11	0.12	0.10	0.10
Latino	0.12	0.05	0.08	0.09
White	0.70	0.74	0.75	0.75
Female	0.53	0.59	0.47	0.58
Demographic Weight	0.95	1.43	0.94	1.27
Text				
Grade Level	9.64	4.21	8.68	7.32
Reported Loss	0.25	0.07	0.21	0.20
Length (Characters)	496	259	890	137
Imputed Product Category				
Telemarketing	0.06	0.21	0.08	0.19
Unsolicited Text or Email	0.25	0.18	0.25	0.08
Imposter Scams	0.18	0.36	0.19	0.35
Online Shopping and Reviews	0.11	0.09	0.09	0.14
All Other and Misc	0.40	0.16	0.39	0.25

Notes: The first column of the table shows the mean characteristics for FTC complaints in the 30 days prior to the website redesign on October 22, 2020. The second column shows the imputed means for complier complainants. These means are calculated using the pre-redesign mean, the coefficient estimate from equation (1), and the coefficient estimate on the number of complaints.

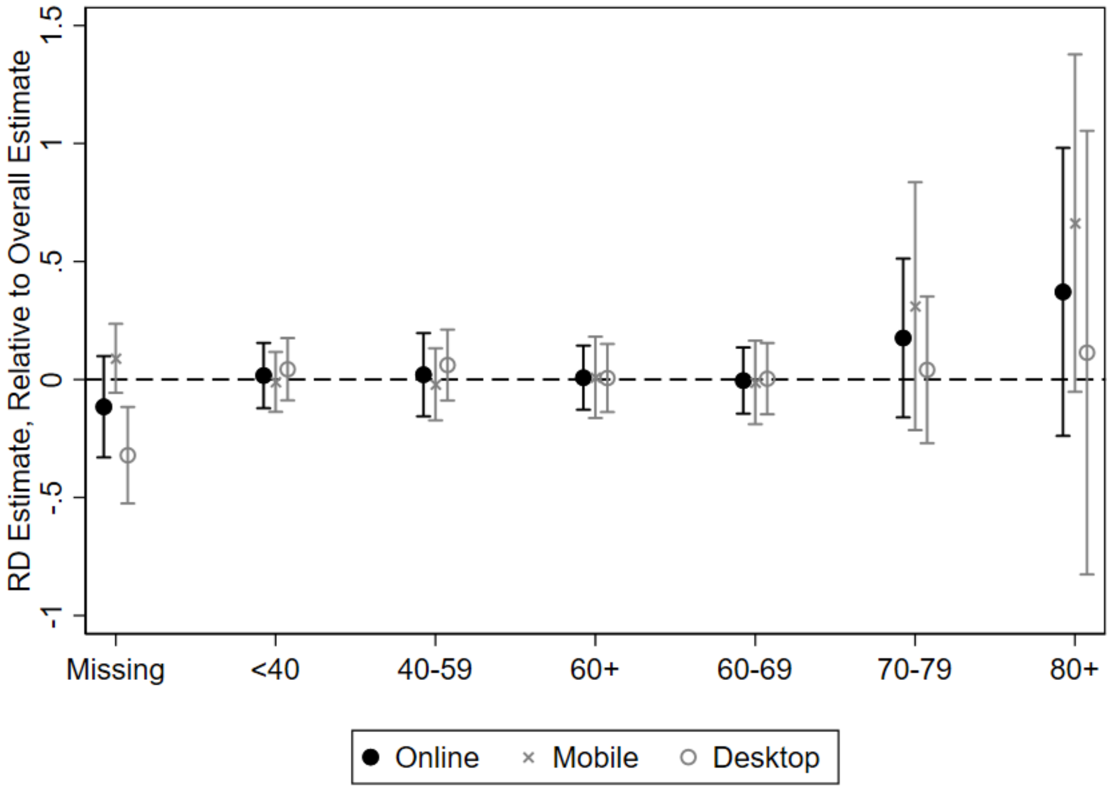
Instead, in Table A15, we take each predicted category (assigned based on maximum probability), and then display the share of complaints whose actual category in Consumer Sentinel is the same as the predicted category, and the actual category with the highest share of complaints. The predicted category has the highest share of complaints from the actual category for 10 of the 13 categories; for Tech Support scams the highest share is Unwanted Telemarketing, and for Prize/Sweepstakes and Diet Plans/Centers the highest share is Unsolicited Text.

B.5 Topic Modeling

In this section, we provide more details on the topic modeling approach pursued in the paper. We estimate the topic model using the *BERTopic* package in Python (Grootendorst, 2022). This approach takes several steps:

1. The first step is to convert the documents into sentence embeddings. Here, we use the *All-MiniLM-L6-v2* model to do so. We also set a maximum length of 512 tokens, as the model cannot handle more than that number of tokens, and longer complaints.
2. The second step is to reduce the dimensionality of the resulting embeddings. Here, we apply the default in *BERTopic* of using the *UMAP* package.
3. The third step is to cluster the documents. Here we use the *HDBScan* package (the default), but a set a minimum cluster size of 120 documents.
4. The fourth step is to turn each cluster into one large document by combining all of the complaints in that cluster, and then developing a "bag of words" representation of each cluster. Here, we vectorize the words by

Figure A4: RD Estimate of Website Redesign on Age Bands Using Vital Statistics



Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the log number of daily complaints by consumers in each age band. The age bands are calculated combining the consumer name, SSA vital statistics on number of births each year with each name, and actuarial tables. The overall effect on total complaints is subtracted from each individual point estimate: 0.395 for online, 0.416 for desktop, and 0.374 for mobile. Consumer can also choose to not report their age. The age 60 and above is the sum of the other older age bands. Robust standard errors clustered at the daily level. Appendix Table A10 shows the estimates that correspond with this figure.

using the SnowBall Stemmer from the *nltk* package, removing stopwords, and including both individual words and bigrams (combinations of two words).

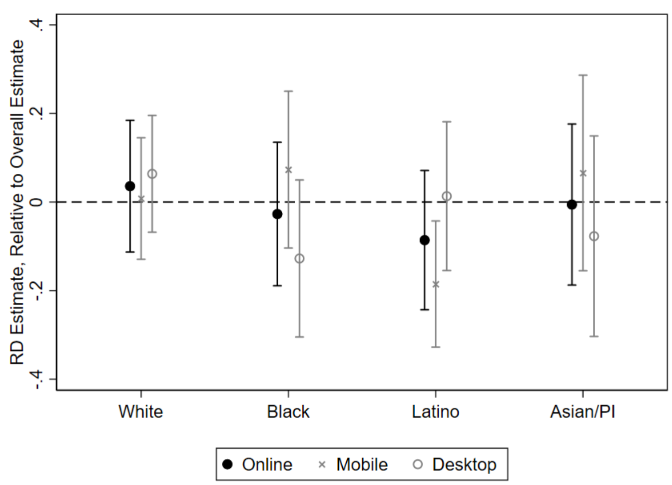
5. The fifth step is to weight these words based on the relative frequency in a given cluster compared to other clusters. Here, we use a "C-TF-IDF" representation, which multiplies the frequency of a term in a cluster by the inverse of its overall frequency across all clusters. We use a class-based BM-25 weighting measure.
6. Finally, in the last step, we fine tune the topic representations using the *KeyBERTInspired* model.

Table A10: RD Estimates, Log Complaints in Each Imputed Age Range, Using Vital Statistics

	(1) <40	(2) 40-59	(3) 60+	(4) 60-69	(5) 70-79	(6) 80+
A. FTC Online						
RD Estimate	0.412***	0.416***	0.403***	0.391***	0.571**	0.766*
	(0.0706)	(0.0899)	(0.0693)	(0.0715)	(0.172)	(0.311)
B. FTC Mobile						
RD Estimate	0.364***	0.354***	0.383***	0.362***	0.685*	1.037**
	(0.0648)	(0.0779)	(0.0879)	(0.0902)	(0.268)	(0.365)
C. FTC Desktop						
RD Estimate	0.460***	0.477***	0.422***	0.420***	0.457**	0.530
	(0.0673)	(0.0766)	(0.0736)	(0.0769)	(0.159)	(0.479)

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of daily complaints by consumers in each age band. The age bands are calculated combining the consumer name, SSA vital statistics on number of births each year with each name, and actuarial tables. The age 60 and above is the sum of the other older age bands. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Figure A5: RD Estimate of Website Redesign on FTC Consumer Imputed Race and Ethnicity, Using Zipcode



Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the log number of daily complaints by consumers in each imputed race or ethnicity category. The overall effect on total complaints is subtracted from each individual point estimate: 0.395 for online, 0.416 for desktop, and 0.374 for mobile. Race and ethnicity are imputed as the highest probability race or ethnicity group using posterior probabilities based on the consumer's first name, last name, and zip code. Robust standard errors clustered at the daily level. Table A11 shows the point estimates and standard errors that correspond to this figure.

Table A11: RD Estimates, Log Complaints in Each Imputed Race, Using Zipcode

	(1) White	(2) Black	(3) Latino	(4) Asian
A. FTC Online				
RD Estimate	0.431***	0.368***	0.309***	0.389***
	(0.0758)	(0.0826)	(0.0802)	(0.0928)
B. FTC Mobile				
RD Estimate	0.382***	0.447***	0.189*	0.440***
	(0.0700)	(0.0903)	(0.0727)	(0.113)
C. FTC Desktop				
RD Estimate	0.480***	0.289**	0.429***	0.339**
	(0.0673)	(0.0904)	(0.0857)	(0.115)

Notes: The table shows of equation (1), where the dependent variable is the fraction of daily complaints by consumers in each imputed race or ethnicity category. Race and ethnicity are imputed as the highest probability race or ethnicity group using posterior probabilities based on the consumer's first name, last name, and zip code. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A12: RD Estimates, Text Analysis Flesch Reading Ease

	(1) Median	(2) 8th gr	(3) college
A. FTC Online			
RD Estimate	2.674**	-0.0636**	-0.0545*
	(0.927)	(0.0222)	(0.0233)
A. FTC Mobile			
RD Estimate	4.312***	-0.112***	-0.107***
	(0.616)	(0.0144)	(0.0154)
B. FTC Desktop			
RD Estimate	1.036	-0.0149	-0.00216
	(0.615)	(0.0159)	(0.0111)

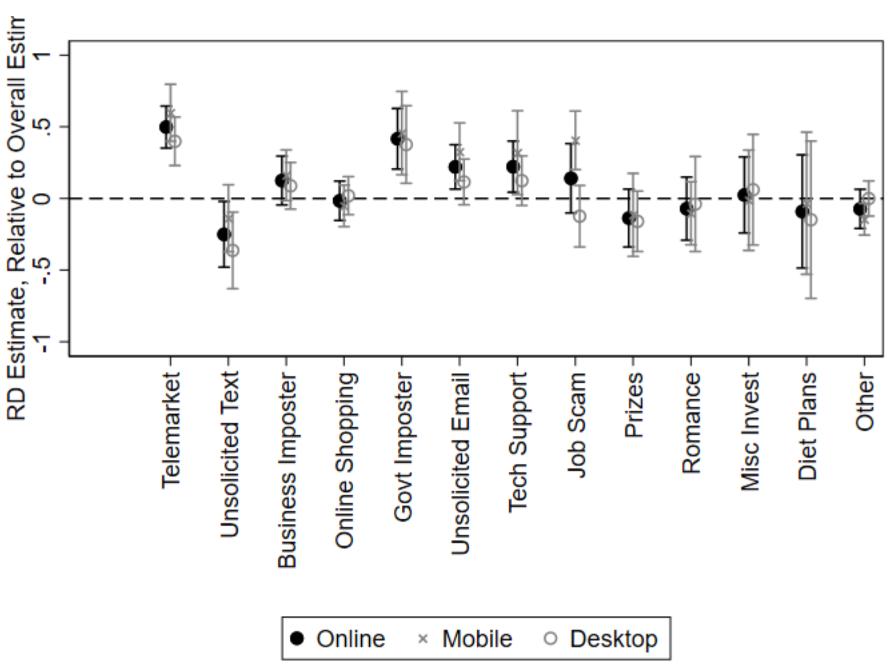
Notes: In the first column the dependent variable is the median Flesch-Kincaid Reading Ease Score, and the final two columns are the fraction of complaints above 8th grade or college according to the Flesch Reading Ease score. The specification includes a third degree polynomial and controls for day of the week. Data includes complaints at the daily level across FTC desktop and mobile platforms. The data include complaints from 60 days before and after the FTC's website redesign on October 22, 2020. Robust standard errors clustered at the daily level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A13: Confusion Matrix for Baseline Categorization

Predicted Category	Actual Category				
	Other	Telemarketing	Unsolicited Text/Email	Imposter Scams	Online Shopping
Other	57%	6%	26%	8%	2%
Telemarketing	8%	36%	0%	55%	1%
Unsolicited Text/Email	11%	0%	79%	8%	1%
Imposter Scams	6%	12%	15%	65%	2%
Online Shopping	7%	13%	6%	9%	66%

Notes: We use data from the 10% test set and predict categories based on the category with the maximum probability for each complaint. Each cell is the share of complaints assigned to a predicted category (the row) whose actual category in Consumer Sentinel is the given column.

Figure A6: RD Estimate of Website Redesign on Imputed Product Category, More Detailed Categorization



Notes: The figure shows point estimates and 95% confidence intervals for estimates of equation (1), where the dependent variable is the log sum of the predicted probability of each category using the text of consumer complaints. The overall effect on total complaints is subtracted from each individual point estimate: 0.395 for online, 0.416 for desktop, and 0.374 for mobile. Robust standard errors clustered at the daily level. Table A14 shows the point estimates and standard errors that correspond with this figure.

Table A14: RD Estimates, Imputed Categories, More Detailed Categorization

	(1) Online	(2) Mobile	(3) Desktop
All Other	0.322***	0.229***	0.416***
	(0.0695)	(0.0562)	(0.0626)
Unwanted Telemarketing	0.893***	0.972***	0.815***
	(0.0747)	(0.102)	(0.0863)
Unsolicited Text	0.145	0.236	0.0534
	(0.117)	(0.119)	(0.136)
Business Imposter	0.520***	0.536***	0.504***
	(0.0869)	(0.0903)	(0.0833)
Online Shopping	0.379***	0.322***	0.435***
	(0.0699)	(0.0741)	(0.0677)
Govt. Imposter	0.811***	0.830***	0.792***
	(0.108)	(0.148)	(0.138)
Unsolicited Email	0.615***	0.699***	0.531***
	(0.0790)	(0.103)	(0.0815)
Tech Support	0.617***	0.693***	0.540***
	(0.0909)	(0.149)	(0.0880)
Job Scams	0.536***	0.779***	0.292**
	(0.124)	(0.104)	(0.110)
Prizes Sweepstakes	0.258*	0.259	0.257*
	(0.103)	(0.148)	(0.107)
Romance	0.324**	0.270*	0.377*
	(0.112)	(0.112)	(0.169)
Misc. Investments	0.419**	0.361*	0.477*
	(0.136)	(0.179)	(0.197)
Diet Plans/Centers	0.304	0.341	0.268
	(0.202)	(0.253)	(0.280)

Notes: The outcomes are the log sum of predicted probabilities for each imputed category based on the text of complaints. The specification includes a third degree polynomial and controls for day of the week. Data includes complaints at the daily level across FTC desktop and mobile platforms. The data include complaints from 60 days before and after the FTC's website redesign on October 22, 2020. Robust standard errors clustered at the daily level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A15: Predictive Accuracy, More Detailed Categorization

Predicted Category	Share Correct	Highest Share Category
All Other	56%	All Other
Unwanted Telemarketing	46%	Unwanted Telemarketing
Unsolicited Text	89%	Unsolicited Text
Business Imposter	34%	Business Imposter
Online Shopping	66%	Online Shopping
Govt. Imposter	73%	Govt. Imposter
Unsolicited Email	69%	Unsolicited Email
Tech Support	19%	Unwanted Telemarketing (32%)
Job Scams	52%	Job Scams
Prizes Sweepstakes	39%	Unsolicited Text (41%)
Romance	68%	Romance
Misc. Investments	66%	Misc. Investments
Diet Plans/Centers	2%	Unsolicited Text (93%)

Notes: We use data from the 10% test set and predict categories based on the category with the maximum probability for each complaint. Each row is a predicted category; the two columns are the share of complaints whose actual category in Consumer Sentinel is the same as the predicted category, and the actual category with the highest share of complaints (with that share in parentheses if it is different from the predicted category).

C Derivation of Complier Mean

Let Y be the variable of interest, $E(Y_{post})$ be the mean for Y after the redesign, and $E(Y_{pre})$ be the mean for Y before the redesign. N_{pre} and N_{post} are the number of complaints before and after the redesign.

Our object of interest is $E(Y_{complier})$, which is the mean of Y for compliers, consumers who are induced to complain because of the redesign. We assume that there are no defiers, so before the redesign all consumers are always takers and after the redesign consumers are either takers or compliers:

$$\begin{aligned} N_{post} &= N_{complier} + N_{taker} \\ N_{pre} &= N_{taker}. \end{aligned}$$

Our RD estimate (in percentages) γ for the total number of complaints identifies the percentage change in complaints:

$$1 + \gamma = \frac{N_{post}}{N_{pre}} = \frac{N_{complier} + N_{taker}}{N_{taker}}.$$

Our RD estimate (in levels) Δ for the change in the mean of Y identifies the mean change in Y from the redesign:

$$\Delta = E(Y_{post}) - E(Y_{pre})$$

Finally, we can identify the mean for takers from the period before the redesign: $E(Y_{taker}) = E(Y_{pre})$.
We can then identify $E(Y_{complier})$ by rearranging the expression for $E(Y_{post})$ in terms of γ, Δ, and $E(Y_{complier})$.
By definition,

$$E(Y_{post}) = \frac{E(Y_{complier})N_{complier} + E(Y_{taker})N_{taker}}{N_{complier} + N_{taker}}.$$

Using the definition of γ:

$$E(Y_{post}) = \frac{\gamma}{1+\gamma}E(Y_{complier}) + \frac{1}{1+\gamma}E(Y_{taker}).$$

Subtracting $E(Y_{taker})$ from both sides:

$$\begin{aligned} E(Y_{post}) - E(Y_{pre}) &= \frac{\gamma}{1+\gamma}E(Y_{complier}) - \frac{\gamma}{1+\gamma}E(Y_{taker}) \\ E(Y_{post}) - E(Y_{pre}) + \frac{\gamma}{1+\gamma}E(Y_{taker}) &= \frac{\gamma}{1+\gamma}E(Y_{complier}) \\ (E(Y_{post}) - E(Y_{pre}))\frac{1+\gamma}{\gamma} + E(Y_{taker}) &= E(Y_{complier}). \end{aligned}$$

The last expression is just:

$$E(Y_{complier}) = \Delta\frac{1+\gamma}{\gamma} + E(Y_{taker}).$$

In some cases, we estimate the RD effect in percentage terms rather than in level terms. That is, we estimate RD effect $1+\delta$, where:

$$1 + \delta = \frac{E(Y_{post}) - E(Y_{pre})}{E(Y_{pre})}.$$

In that case, the expression for the complier mean is:

$$E(Y_{complier}) = (1+\delta)E(Y_{taker})\frac{1+\gamma}{\gamma} + E(Y_{taker}).$$