Amplifying Consumers' Voice: The FTC's Complaint Website Redesign*

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Abstract

We examine a website redesign in which the Federal Trade Commission (FTC) made consumer complaints easier to file. Using a regression discontinuity approach, we find that complaints to the FTC jumped by 28%, driven by increases in complaint completion rates, and that consumers submitted more detailed information. We find relatively small differences in this increase across demographic groups. Complaints after the redesign were shorter and easier to read, which may indicate the redesign induced less sophisticated consumers to complain. Finally, complaints induced by the redesign 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

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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: more than 5 million consumers reported 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.

Most consumers, however, do not exercise their voice. Only 5% of consumers affected by fraud say they complained to a government agency or the Better Business Bureau (Anderson, 2021). Such complaints can be thought of as a public good, as the private benefits to consumers from complaining are often small. They are even smaller 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 consumer finding the costs being less than the benefits from altruism and the low expected private value of recovering one's losses.

In this article, we examine a major undertaking to increase complaint rates.[1] In October 2020, the FTC redesigned its online interface for reporting scams and fraud to make the process substantially easier to complete. By inducing consumers on the margin to complain, the redesign allows us to examine the characteristics of such consumers and the types of problems they report.

The redesign had two major effects on the costs and perceived benefits of complaining. On the cost side, it made it easier for consumers to complain by improving the process for consumers to classify the topic of their complaints, providing an easier to read visual design, and sharply shortening the flow process to complain. On the benefit side, the redesign highlighted the broader societal benefits of complaints – for example, the tagline of the landing page became "Report to help fight fraud!" over a visual of a stylized community. We provide more details on the website

[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.

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 28 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 substantial increases in the share of complaints that voluntarily included consumer geographic information, age, and the name of the company involved.

Increasing the perceived benefits and reducing the costs of complaining can create two countervailing effects. An easier complaining process may mean that consumers with less severe problems begin to complain. On the other hand, it may be difficult for disadvantaged consumers to express their voice when it is difficult to complain, so more such disadvantaged consumers might complain after the redesign.

We assess how the redesign affected the characteristics of complaining consumers, and find some support that vulnerable consumers are more likely to complain after the redesign, in Section 6. After the redesign consumers write complaints that are 36% 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 zipcode level probability that fraud victims complain based on local demographics calculated in Raval (2020*b*), and find that the redesign induced more complaints from communities less likely to complain pre-change.

On the other hand, we do not find substantial differences across demographic groups, defined either by race/ethnicity, age, or sex. For example, the redesign did not close the large disparities in complaining between white and non-white consumers found in Raval (2020*b*); if anything, we find smaller increases for Black and Latino consumers than white and Asian consumers.[2] These

[2]Using data on consumers affected by nine consumer protection law enforcement actions, Raval (2020*b*) found

findings are consistent with Raval (2020*b*)'s argument that racial disparities in complaining are due to feelings of social alienation, rather than difficulties in complaining.

In Section 7, however, we find some evidence that the website redesign induced complaints about less severe problems than before the redesign. The share of consumers reporting a monetary loss did not change. However, consumers were less likely to use words related to an online purchase in their complaint after the redesign, which is 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 expose many consumers 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.

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 redesign 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 redesign 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 42% of complier complaints are about imposter scams, compared to 18% of taker complaints; complier complaints have text that is more than 3 grade levels lower in sophistication.

Consumer reports on fraud have all the hallmarks of an undersupplied public good. Understand-

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.

ing 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). In this paper we study how the characteristics of contributors and contributions to this particular public good changed as a result of this government effort.

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*; Grosz and Raval, 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, 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).

We also contribute to a literature on hassle costs and targeting that has examined how the types of consumers induced into a program varies with the difficulty of signing up for the program (Akerlof, 1978; Nichols and Zeckhauser, 1982). This literature largely focused on disadvantaged groups applying to government programs (Currie, 2006; Diamond and Sheshinski, 1995; Kleven and Kopczuk, 2011).[3] Some of the changes from the redesign can be seen as reducing the hassle costs of complaining. 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).

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",

[3]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).

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.[4]

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

2.1 Website Changes

In response to several issues that users of the previous site had noted in usability studies, the FTC's redesign attempted to increase complaints through two main channels. First, the FTC emphasized

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

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

the public good nature of complaining to increase the self-perceived benefits of filing a complaint. Second, the FTC made the site easier to use in order to reduce the costs of filing a complaint, as users had criticized the complaint categorization, poor visual design, and a lengthy flow. Below, we describe the issues the FTC identified and the resulting changes from the redesign. Appendix C provides more details on the problems the redesign sought to fix, as well as the specific changes made to the site.

In usability testing, consumers noted that they felt disconnected from the FTC and US government. Prior to the redesign, one of the first screens seen when filing a complaint stated that the FTC cannot resolve individual complaints, which made the whole exercise seem a waste of time to many consumers. In addition, users felt that the FTC did not seem like it cared about the consumer, did not provide information to help the user protect themselves from other scams, and did not explain what the next steps were after the complaint was filed.

In response, the new redesign heavily emphasized that consumers were contributing to a public good. The new homepage (seen in Figure 1) has the tagline "Report to help fight fraud!" over a stylized community of houses and walking residents, and an outline of a shield representing how the report can help shield the community from fraud.[6] Below, the website states "Protect your community by reporting fraud, scams, and bad business practices." Scrolling further down, the main landing page provides the main steps after filing a complaint – the FTC would provide consumers next steps to avoid fraud, and the FTC would use the complaint to help stop fraud by sharing the information with law enforcers. A graphic emphasizes how the FTC shares the report with law enforcement agencies across the country. When consumers complete their report, the new website gives them next steps on how to resolve their specific issue.

The remaining issues that users brought up were all different ways in which the FTC's complaint website was difficult for consumers to use. Consumers first assign their complaint to a category of consumer protection issues; Figure 1 provides the old and new category assignment flow. Focus group users complained that it was difficult and stressful to do this, because there were too many categories, that the categories available were unclear, and that often there was no "right" category for their problem. The redesign developed an "accordion" style approach with a few,

[6]The website, including in its name Report Fraud, emphasize "reporting" rather than "complaining"; reporting is more psychologically neutral and may also indicate a broader goal than simply harms to the individual.

sharply distinguished categories to start with, and then a few subcategories that appear after the main categories. The amount of text for each category was sharply reduced for readability, and a "something else" catch-all category provided a category for consumers with unique issues.

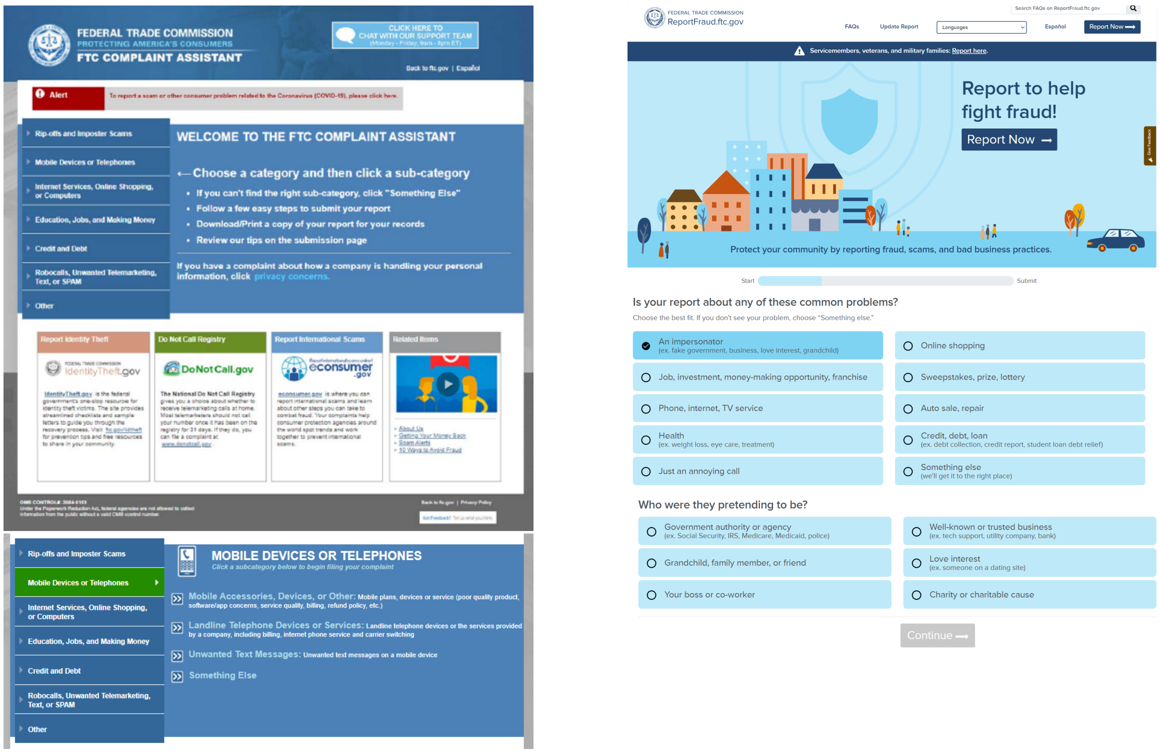
Second, consumers complained about the visual design of the website. The previous website was seen as too cluttered and content heavy, with too small and inconsistent fonts, and so repelled the reader. In response, the FTC reduced the amount of content (i.e. words) on the website as well as unnecessary links to other websites, increased the font size, used fonts that were easier to read, hid content by gating potentially unnecessary questions through Yes/No initial questions, and developed a consistent, clean design overall.

Third, consumers found that the seven step process to file the complaint was too long and daunting, and found it difficult to navigate the website to either file a complaint or go back to the homepage. In the redesign, the seven steps were consolidated into two steps; Figure 2 displays the original and new website flow. The open ended text field where consumers can write the story of what happened to them was moved to the first step, rather than the sixth step; many users wanted to immediately tell their story and were put off by a long wait to do so. A running slider shows consumers how far they have gone in the process, and clear back and forward buttons show the navigation. In addition, the main landing page (seen in Figure 1) had a clear "Report now!" button, as well as several other links for consumers to begin their complaint.

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 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. Five months after the redesign, 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).

Figure 1: Landing Page and Complaint Categorization

(a) Complaint Assistant (Old Website) (b) ReportFraud (New Website)



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]

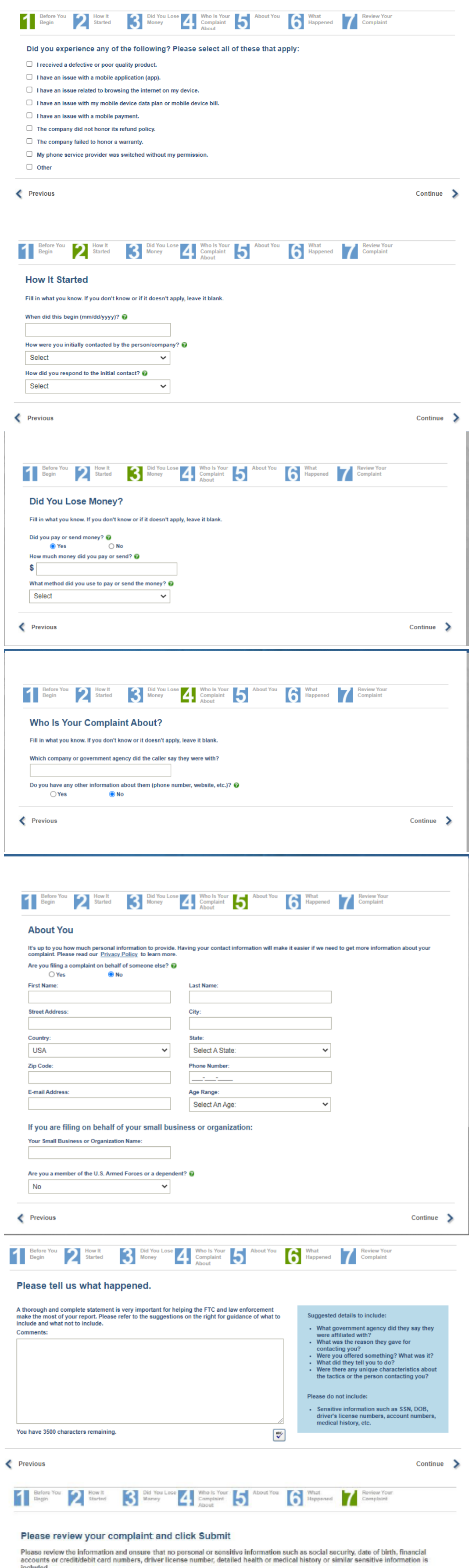
Each complaint in the Consumer Sentinel data includes information about the consumer and the content of the complaint. We observe the consumer's name, zip code, city, state, country, and broad age bands, if the consumer included this information. We also observe the date the complaint was filed, broad categories of complaints, and the open-ended text of the complaint itself. For FTC complaints, we are able to separately identify those 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,

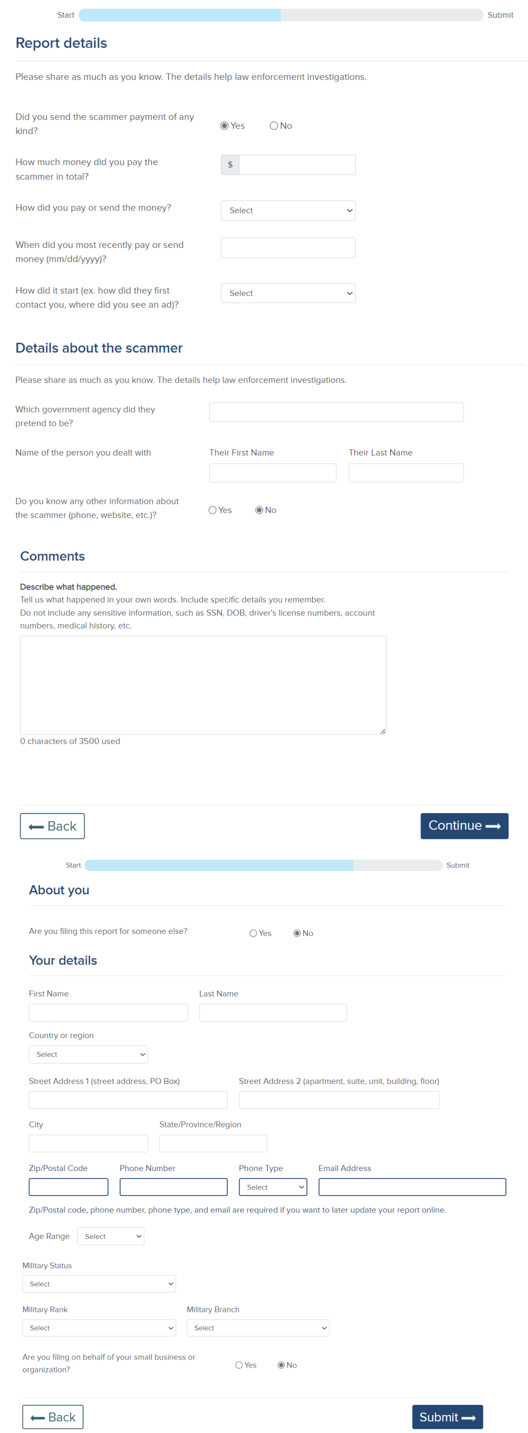
[7]See https://www.ftc.gov/enforcement/consumer-sentinel-network/reports for the Consumer Sentinel Data Book, which contains further detail on the Consumer Sentinel and statistics on the complaints included in it.

Figure 2: Complaint Flow

(a) Complaint Assistant (Old Website)



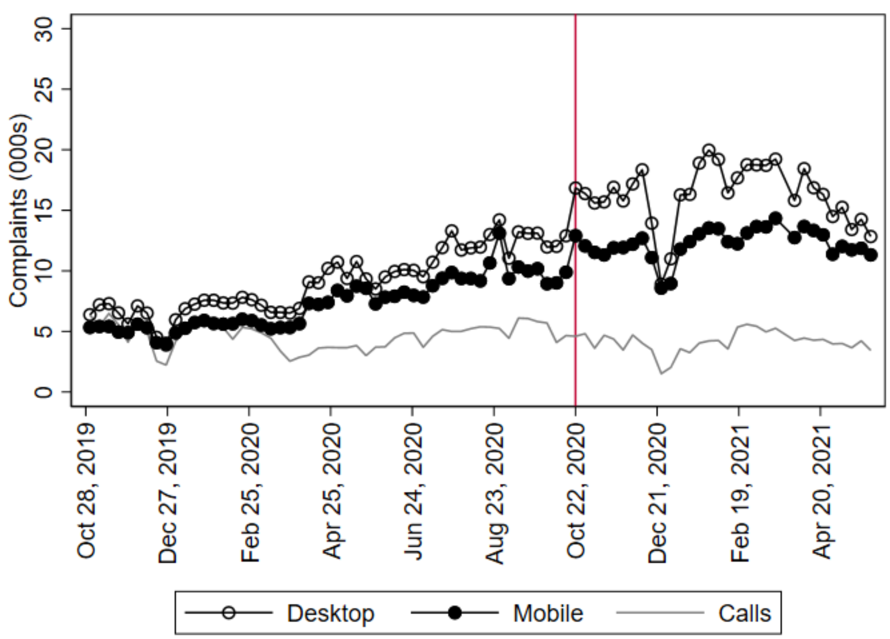
(b) ReportFraud (New Website)



2019 and June 6, 2021. In the first week of data shown in the figure, late October of 2019, 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 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.

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 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.

In a regression discontinuity design, we must choose the order of the local polynomial in the running variable (here, date) that we use to control for trends away from the discontinuity. Pei et al. (2022) show that increasing the order of the local polynomial results in a bias-variance tradeoff: higher order polynomials reduce the bias but increase the variance. We follow Pei et al. (2022) to determine the optimal polynomial order p by estimating the asymptotic mean squared error (AMSE) under different polynomial orders. Table A2 shows the AMSE for the different sources of complaints for polynomials of orders 1 through 4. Based on these results we use the local linear ($p = 1$) for our main specifications. In Table A3, we show that our main estimates of the regression discontinuity effect are not sensitive to the choice of p.

We estimate the following empirical specification:

$$y_t = \beta Post_t + \gamma_1(t - C, t \geq C) + \gamma_2(t - C, t < C) + g(DOW_t) + \epsilon_t, \tag{1}$$

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 coefficients γ_1 and γ_2 control for the days since the date of the redesign C on either side of the cutoff through a polynomial of order 1. To account for differences in complaint rates over the course of a week, we also control for day-of-the-week effects through $g(DOW_t)$.

The coefficient β captures the change in complaints on the date of the redesign. Because the redesign was not announced prior to the date, we do not believe that consumers changed their complaint behavior—to the FTC or to other sources—in anticipation of the change. However, the FTC did begin a publicity campaign, including a press release, on the day of the redesign. Thus, by capturing the change in complaints at the time threshold, β combines the effect of the website's improved design as well as the immediate effects of the short-term publicity campaign itself. Our approach does not measure, however, any changes in trends in complaint behavior over time due to the FTC's continued publicity campaign and outreach efforts.

Any changes due to the redesign could be because existing consumers are more likely to complete complaints, or because of changes in the number of users visiting the website. We examine these channels in detail in Section 5.3.

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.

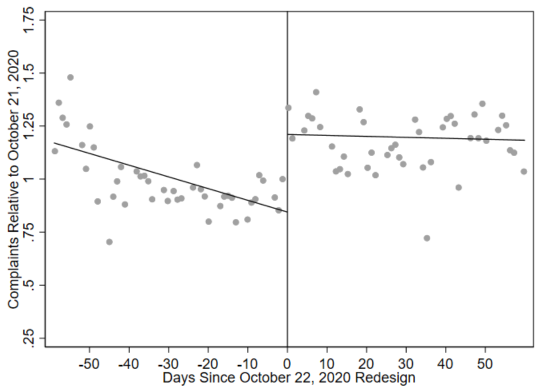
5.1 Quantity of Complaints

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.

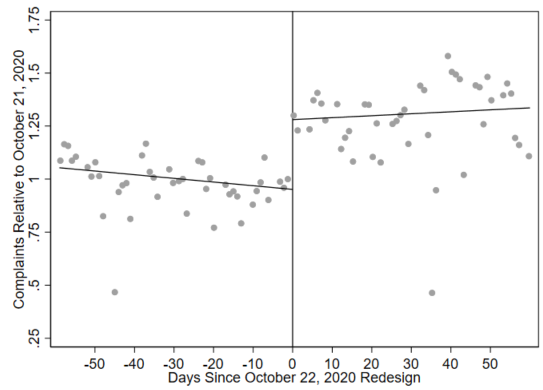
The FTC phone complaints provide a comparison for consumers with complaints that would be appropriate to file with the FTC. The complaints filed with the BBB are broadly similar to the FTC in terms of the types of industries and scams (Raval, 2020*a*), although the BBB is not a government agency. The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

Figure 4 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 first 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.

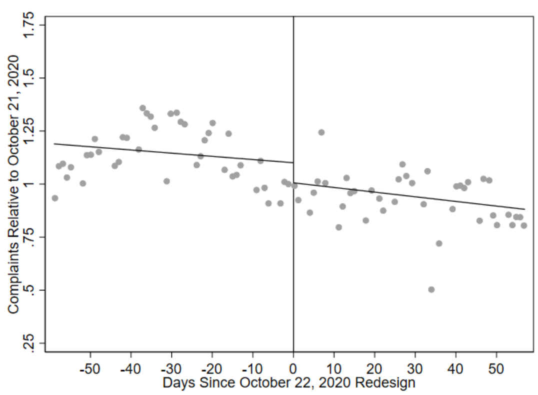
Figure 4: RD Estimate of Website Redesign on Number of Complaints



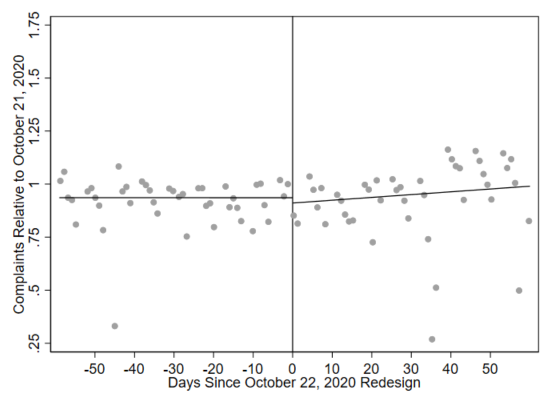
a) FTC Mobile



b) FTC Desktop



c) FTC Calls



d) BBB & CFPB

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 first-degree polynomial and controls for the day of the week.

The number of FTC mobile and desktop complaints clearly jump at the date of the website redesign. In contrast, the FTC's phone complaints have a smaller and not statistically significant decline, while the BBB and CFPB complaints are flat.[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 28% due to the change in the user interface, with a slightly higher jump for desktop

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

(31%) than mobile (26%) complaints. The effect on FTC calls is negative, but not statistically significant, at 9%. Similarly, the coefficients are smaller and not statistically significant for the BBB and CFPB. Table A3 shows similar results using polynomials of different orders.

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	0.282***	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.
$*p < 0.05, **p < 0.01, ***p < 0.001$

5.2 Quality of Complaints

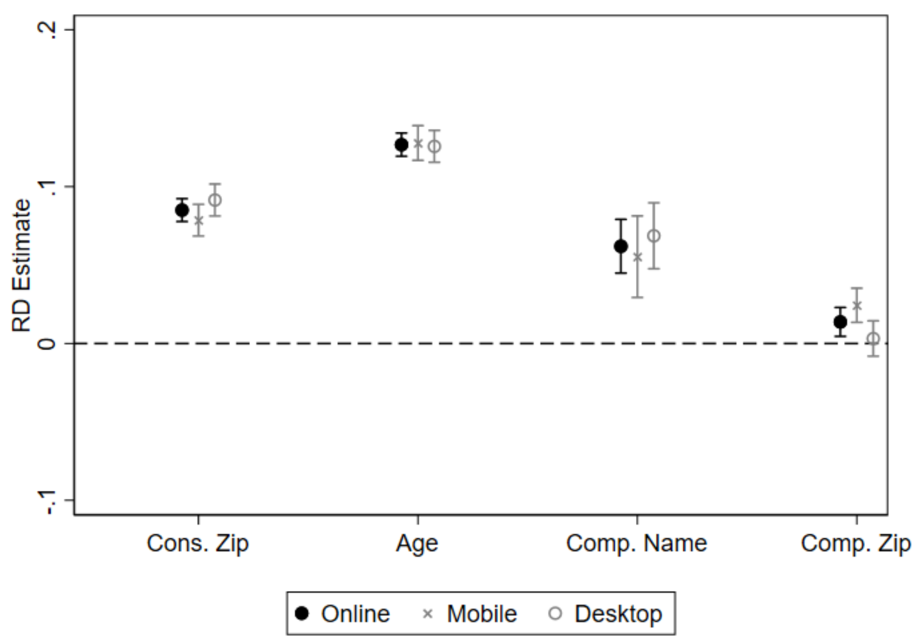
We then investigate how the quality of complaints changed as a result of the website redesign, as a key goal of the redesign was to make it easier for consumers to provide information in complaints. Our proxy for complaint quality is whether consumers input optional personal information in complaints, 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 5 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 13 percentage points. Consumers were also almost 6 percentage points more likely to report the name of the company or individual who had defrauded them. The redesign had a statistically significant but small effect (1.6 pp) on the share of consumers who provided information on the location of the offending company or individual.

These increases in quality likely reflect the change in flow with the redesign. On the old website, consumers provided information on the company that defrauded them at Step 4 and about themselves (including age and demographics) at Step 5, and could only provide a narrative of their issue afterwards on Step 6 (see Figure 2). With the new website, consumers provided information about the scammer at Step 1, with the self-narrative directly underneath, and about themselves at Step 2. We suspect that many consumers wanted to tell their story first and so skipped through some of the requested information in the intervening steps. We likely find smaller effects for the company variables than personal variables because not all consumers will know the address or name of the scammer that defrauded them.

Figure 5: 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 A5.

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. These results support 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 in a statistically significant way. Figure A4 shows the graphical evidence for these two estimates. However, the completion rate rose by 7 percentage points.

We have limited information on user behavior before and after the redesign. Table A1 shows average session time and time on page for the pre- and post-redesign periods. The session duration is almost the same, while the average time on the page is actually longer after the redesign. Google Analytics calculates time on page as zero if a user closes the window before moving on to another page, which accounts for the differences between the session duration and time on page metrics. All told, these limited metrics support the idea that users actually spent longer on the website after the redesign, presumably making it farther along the process to filing a complaint.

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	-0.0628	-0.0602	0.0689***
	(0.0442)	(0.0511)	(0.00988)

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 A4 shows that, overall, there was not a statistically significant increase in FTC online complaints overall, at 4%, although the effect was statistically significant for mobile complaints at 7%. 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.

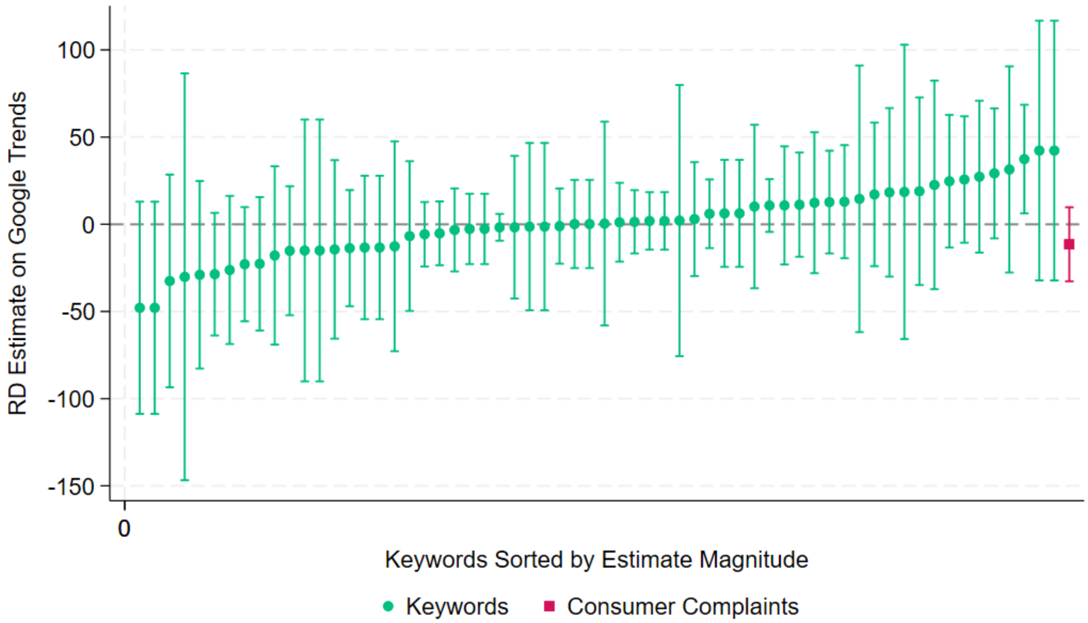
Third, we examine Google Analytics data on web searches that lead consumers to the FTC's complaint website. We have data on the keywords on Google that consumer use to reach the FTC's website as of November 2023. We can match these keywords to weekly data on Google trends, and so examine how "demand" 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 6 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 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.

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

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

Figure 6: 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 first 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 Characteristics of Complaining Consumers Change with the Redesign?

A major goal of the website redesign was to improve complaint rates among groups that are less likely to complain. In this section, we examine complaint rates by demographic groups. We largely find small and insignificant differences across demographic groups, although we see a decline in the sophistication of the writing style of complainants and increases from zip codes less likely to complain before the redesign.

6.1 Demographics

We summarize our findings on differences in the regression discontinuity effect by demographic groups; Appendix D provides more details on our estimates.

We find fairly similar increases in complaints across age groups, with a 40% increase for consumers aged both under 40 and 60+. These effects are larger than the overall increase of 28% because more consumers report their age after the redesign. While the increase in complaints at the regression discontinuity is similar across age groups, complaints for older adults, but not younger adults, trend upwards after the redesign. Because the reporting of age increases with the redesign, we also infer age using the age distribution of first names from vital statistics data and obtain similar estimates of age effects as in our main estimates.

We examine race and ethnicity by estimating race probabilities based on consumers' first and last names, which almost all consumers provide. We find similar increases post-redesign across race/ethnicity groups, with a 31% increase from white consumers, compared to a 27% increase for Black consumers, 24% for Latino consumers, and 34% for Asian consumers. If we also use consumers' location (zipcode) to estimate race probabilities through the BIFSG algorithm (Voicu, 2018), we find slightly smaller increases for Black (20%) and Hispanic (22%) consumers, compared to white (32%) and Asian (33%) consumers.

Finally, we examine whether increases in complaints vary by sex using consumers' first names and counts of sex by first name from the SSA. We find slightly higher increases in complaints from women (32%) compared to men (28%), but we cannot reject the hypothesis that these effects are the same.

6.2 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 in the pre-redesign period. These demographics included median income, the share of consumers with a college education, median household size, and the share of consumers in different race/ethnicity groups. Using these estimates, Raval (2020*b*) developed a set of weights designed to be the inverse of the propensity to complain (i.e, 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.

In Table 3, we examine how these weights change with the redesign. The average weight increases by about 11% after the redesign, which means that the average likelihood of complaining for victims, estimated based upon demographics in the pre-redesign period, fell post-redesign. We interpet this finding as increased complaints from communities, defined by zip code demographics, that are less likely to complain after fraud victimization.

Table 3: RD Estimates (Percentage Change), Victim Complaint Weights

	(1) Online	(2) Mobile	(3) Desktop
RD Estimate	0.0882***	0.0792***	0.0971***
	(0.00711)	(0.0112)	(0.00831)

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. $*p < 0.05, **p < 0.01, ***p < 0.001$

6.3 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.[11] In Table 4, 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.

We only find significant interaction effects for desktop complaints. The effect of the redesign increases by 0.83 percentage points for a 10 percentage point increase in broadband access, and by 1.1 percentage points for every 10 percentage point increase in computer access. However, since mobile complaints increase more in areas with worse internet access, we find smaller and insignificant increases for all online complaints with greater broadband or computer access. These reduced effects may reflect substitution between the mobile and desktop channel based on the degree of Internet access.

[11] In the median zipcode, 77% of consumers had access to broadband 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.

Table 4: RD Estimate of Website Redesign, by Zipcode 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 zipcode level. In the first row the dependent variable interacts the post-change dummy with a zipcode'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.
$*p < 0.05, **p < 0.01, ***p < 0.001$

6.4 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 36% after the redesign, with a 21% fall in the length of mobile complaints and a 51% 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.[12] We find substantial declines in the 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

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

$$0.39\left(\frac{words}{sentences}\right) + 11.8\left(\frac{syllables}{words}\right) - 15.59. \tag{2}$$

Section B.1 shows analogous results using the Flesch Reading Ease score.

the website redesign, the share of complaints with text with at least an 8th grade level falls by 9 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 1.6 grade levels and desktop complaints fell by 0.2 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	-36.09***	-0.905***	-0.0909***	-0.0800***
	(3.356)	(0.113)	(0.00856)	(0.0127)
B. FTC Mobile				
RD Estimate	-21.42***	-1.622***	-0.142***	-0.157***
	(2.547)	(0.130)	(0.00940)	(0.00987)
C. FTC Desktop				
RD Estimate	-50.76***	-0.188*	-0.0393***	-0.00276
	(4.167)	(0.0727)	(0.00753)	(0.00820)

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 on 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 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.

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.

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 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).[13] 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.2 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 out test dataset.[14]

We then estimate the RD using data on the sum of predicted probabilities of each category by day; Figure 7 depicts the RD results for the imputed categories. 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

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

[14] We provide a "confusion matrix" comparing predicted to actual categories in Appendix B.2. In some cases, a complaint is assigned to multiple category codes. In these cases, we include the same complaint text for each category.

by 66% and 53%, respectively. Complaints about spam text and email see the smallest increase, at an insignificant 7%.

For both telemarketing and imposter scams, many consumers are exposed to the scam but only a minority lose money. For example, in the case of telemarketing, consumers often report 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 A5 in Appendix B.2.[15] We find fairly consistent results to our main approach. We find increases for all categories except Unsolicited Text and Diet Plans / Centers (the latter of which we predict poorly). The more detailed categories show that the disproportionate increase in imposter scams is driven by an increase in complaints for both government imposters (58% increase) and business imposters (46%). Telemarketing again sees a large increase post-redesign, although we also find larger increases than the overall effect for Tech Support, Unsolicited Email, Job, and Investment scams.

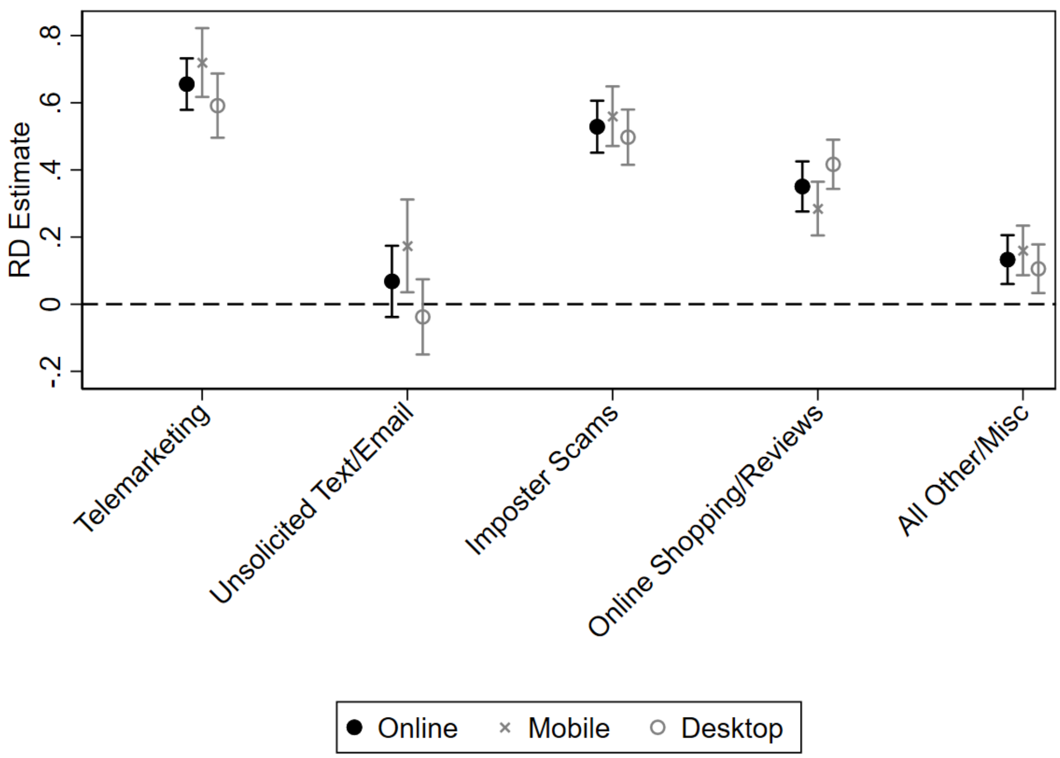
7.2 Topic Modeling

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 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

[15] 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 7: 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. Robust standard errors clustered at the daily level. Table A6 is the corresponding table.

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.3.

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 8, 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 44 topics and significant decreases for 13 topics. The topic modeling approach provides a representation for each topic based on a set of representative words and documents. Table 6 contains a list of the topics with statistically significant changes and, for simplicity, over 2,000 complaints. The table includes 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. Table A8 through Table A10 show the full list of topics for those with statistically significant negative and positive estimates.

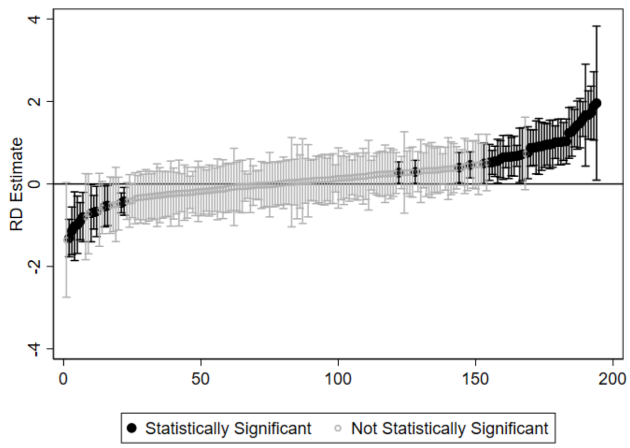
Perhaps the most surprising finding is that five of the topics with a significant increase (and two with over 2,000 complaints) are about different identity theft scams, where scammers file for government loans or unemployment benefits in someone else's name. The FTC operates a separate website specifically 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. By making it easier for identity theft victims to file complaints at the fraud website, many may have filed fraud complaints as opposed to filing identity theft complaints at *identitytheft.gov*.

The remaining significant topics that we classify parallel our earlier category analysis. The most common category, at 16 of 44 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. The remaining topics are scattered across several issues, with three topics about job scams (including paid surveys or "mystery shoppers") and three topics involving claims of a hack of the consumer's computer.[16] Of the 13 topics with a significant decline, seven of the thirteen involve spam texts

[16] Interestingly, a few topics are not about a specific type of scam. One topic clusters together complaints describing a money transfer, while another groups complaints with the word "Update", a third groups complaints in Spanish rather than English, and a fourth is consumers complaining that it is difficult to copy paste information into the complaint.

while only two are related to imposters. These differences match the smaller increase in spam texts in the category analysis.

Figure 8: 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. However, as Table 7 shows, consumers are not less likely to report losing money after the redesign.

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. In addition, if the redesign increased consumers' willigness to report how much money they lost (similar to increases in quality in other fields documented in Section 5.2), we could see increases in reports of losses.

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.[17] Using equation (1), we estimate which of these words saw a statistically

[17]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

Table 6: RD Estimate of Website Redesign on Selected Topics

Representation	Est.	(S.E.)	Total Complaints	Assigned Category
Positive and Significant				
9_ifidonotreceivethebitcoin idefinitelywillsendoutyourvideorecordingto	1.96	(0.13)	3373	Hack Claim
21_unemployment claim_illinois dept_filed claim_unemployment benefit	1.73	(0.24)	2624	Identity Theft
23_unemployment fraud_unemployment claim_filed claim_fraudulent claim	1.67	(0.20)	2552	Identity Theft
181_update help_update just_update ne_update problem	1.03	(0.10)	2730	"Update" Word
1_icloud breach_saying icloud_icloud account_apple icloud	1.01	(0.11)	9218	Imposter
28_contacted ebay_fake ebay_ebay contact_ebay email	0.87	(0.08)	2366	Online Shopping
3_calls com_calls differ_caller_caller id	0.68	(0.07)	6612	Unwanted Calls
17_federal bureau_payment_transfer_bureau investig	0.66	(0.18)	2826	Money Transfer
0_ss number_number suspend_ssa_ssn suspend	0.65	(0.13)	28618	Imposter
27_iphone amazon_calling amazon_amazon fraud_contacted amazon	0.55	(0.20)	2402	Imposter
30_withdraw profit_withdraw money_withdraw fund_tried withdraw	0.55	(0.17)	2094	Investment
6_won million_scammer_prize money_told won	0.52	(0.15)	4068	Lottery/Prize
19_charged amazon_charge amazon_amazon account_calling amazon	0.50	(0.17)	2771	Imposter
13_landlord_craigslist ad_tenant_craigslist org	0.46	(0.16)	3086	Rental
26_medicare inform_medicare report_medicare told_calling medicar	0.39	(0.11)	2422	Imposter
8_grant program_grant money_000 grant_free grant	0.29	(0.16)	3926	Imposter/Grant
10_scammer_asked money_send money_asking money	0.27	(0.16)	3374	Romance
Negative and Significant				
20_received check_applied job_offered job_send check	-0.42	(0.13)	2747	Job
2_spam text_unwanted text_received text_receiving text	-0.46	(0.16)	9213	Spam Text
24_unsubscribed email_unsubscribe email_emails unsubscrib_email unsubs	-0.69	(0.17)	2520	Spam Email
16_political text_text polit_political spam_messages polit	-1.14	(0.24)	2983	Spam Text
15_scam email_spam email_email threaten_hacked account	-1.31	(0.54)	2850	Hack Claim

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. We only include topics with at least 2,000 complaints over the period.

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	-0.00745	0.0732
	(0.00621)	(0.0857)
B. FTC Mobile		
RD Estimate	-0.0156	0.0132
	(0.00889)	(0.134)
C. FTC Desktop		
RD Estimate	0.000693	0.133
	(0.00734)	(0.109)

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. $*p < 0.05, **p < 0.01, ***p < 0.001$

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.[18] Although 18% of words increased in relevance for desktop and 28% increased for mobile, relatively few had a statistically significant increase or decrease.

Among words that saw statistically significant increases, the main theme that emerges is words related to automotive issues, such as "vehicle," "license,", "repair", and "drive." One explanation for this increase may be the change in how complaints were initially categorized. On the old website, auto-related issues were not a major category, and so consumers had to click on "Other" and then "Automobile" for auto-related issues. On the new website, "Auto sales, repair" was a major category. Thus, the redesign may have made consumers realize that the FTC's complaint website was the right place to complain about auto related issues.

Many more words had statistically significant decreases. One clear theme that emerges is that consumers were less likely to report situations that may have led to monetary losses. Terms related to payments and purchases, such as "deposit," "money," "offer," "order," "refund," "return,"

months following the redesign are October 22 through December 21, 2020.

[18] Table A7 shows the words that had statistically significant increases and decreases for just mobile or desktop interfaces.

"dollar," "bought," and "purchase" all saw declines in both interfaces, as did methods of payment such as "credit," "debit," "check," and "paypal" and Internet related words such as "websit," "onlin," and "facebook". Some of the terms also point to a theme of a decrease in scams related to impersonations, one type of imposter scam, with terms such as "accent," "famili," "friend," convers," and "pretend."

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, impersonation, and computer related issues.

Table 8: Terms with Statistically Significant Changes

Increases	
	vehicl, licens, repair, known, worth, drive, wouldnt, seller, union, replac, failur, breach, consid, robocal, schedul, hello, press, novemb, pleas, thank
Declines	
	email, contact, money, person, compani, inform, updat, check, never, state, provid, order, offer, websit, credit, someon, respond, servic, purchas, answer, didnt, still, request, return, refund, direct, septemb, peopl, actual, think, without, complaint, payment, start, password, place, onlin, repres, deposit, offic, later, point, proof, happen, believ, decemb, accent, suppos, spoke, thought, month, refer, anyth, refus, taken, dollar, famili, certain, polic, notic, given, wasnt, pictur, probabl, realiz, obtain, complet, final, individu, delay, friend, howev, consum, initi, facebook, situat, solut, contract, paypal, sound, simpli, wrong, promis, demand, heard, store, threaten, bought, experi, though, instead, correct, convers, chase, debit, almost, couldnt, releas, medic, agenc, advertis, pretend, mother

Notes: The table shows the terms that saw a statistically significant increase or 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. The statistically significant terms are listed in decreasing order of coefficient estimate magnitude.

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:

$$E(Y_{complier}) = \Delta\frac{1+\gamma}{\gamma} + E(Y_{taker}), \tag{3}$$

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 (3) in Appendix E.[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. Since we do not find many differences in the effect size across age groups, we also do not find that compliers and takers are substantially different in their

[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 (3) with $(\delta + 1)E(Y_{taker})$, where $\delta + 1$ is the RD estimate in percentage terms. See Appendix E for more details.

age composition. We also 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.

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 1.34 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 less sophisticated text than takers. The fraction with language above an 8th grade level declined precipitously. In addition, compliers are slightly less likely to report a loss; on average, 23% of taker complainants report a loss, compared to 20% 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 slightly more likely to report issues with online shopping, and much less likely to report text and email problems. Table A11 splits out this compliers analysis by the mobile and desktop complaints, with similar implications.

9 Discussion and Conclusion

In this article, we have studied the effect of a major website redesign to the FTC's consumer complaint website, using regression discontinuity techniques to evaluate the effect of the change. Online complaints to the FTC rose 28% overnight due to the change; we found no significant increase in complaints to other sources such as calls to the FTC or complaints to the BBB or CFPB.

We found evidence for countervailing effects of the redesign on complaining. On the one hand, the redesign led to reductions in the length and grade level of the text of the complaint as well as more complaints from communities previously less likely to complain. Thus, the redesign may have led less sophisticated or more vulnerable users to complain. On the other hand, the complaint text was less likely to relate to purchases and payments, and complaints were more likely to concern

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

	(1) Takers	(2) Compliers
Demographic Characteristics		
Age under 40	0.363	0.340
Age 40-59	0.345	0.386
Age Over 60	0.292	0.274
Age 60-69	0.179	0.157
Age 70-79	0.090	0.092
Age Over 80	0.023	0.025
White	0.726	0.757
Black	0.104	0.092
Latino	0.100	0.070
Asian/PI	0.048	0.057
Female	0.501	0.576
Demographic Weight	0.945	1.341
Text and Losses		
Reported Loss	0.230	0.196
Grade Level	9.161	5.044
Grade Level >8th	0.599	0.185
Imputed Product Category		
Telemarketing	0.071	0.222
Unsolicited Text or Email	0.250	0.069
Imposter Scams	0.183	0.424
Online Shopping and Reviews	0.099	0.126
All Other and Misc.	0.397	0.159

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 (3).

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 redesign were 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 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.

A natural question is whether the effects found in this article can be generalized to other settings. Answering this question is difficult as the main "treatment" affected both the perceived benefits and costs of complaining. On the cost side, the improvements in visual design and reduction in the flow process to complain are qualitatively similar to efforts to make other websites easier to use. To give a recent example, the FTC recently alleged that Amazon deliberately complicated the cancellation flow for Prime subscribers in order to reduce cancellations, which was internally named the "Iliad Flow" due to its length. Amazon internally evaluated potential user design changes that would have simplified the flow to cancel but increased cancellations.[20]

On the other hand, the redesign also affected the potential benefits to complaining by emphasizing how complaints help stop fraud and protect communities. This type of "pro-social" messaging would not make sense on most websites; for example, there are no clear public good benefits from a user joining or cancelling Prime. Complaints to other consumer protection organizations, such as the CFPB and BBB, also have similar pro-social benefits. However, unlike the FTC, these organizations forward complaints on to firms for resolution, which may increase the likelihood of restitution and so provide a stronger private benefit to complaints. If stronger pro-social messaging means less emphasis on the private benefits of recovery, it is unclear whether the net effect of the change in messaging would increase or decrease complaints.

In addition, many websites host online reviews, such as Yelp, TripAdvisor, Google, and AirBnB, which may also provide pro-social benefits. For example, reviews on AirBnB may steer consumers towards better hosts and away from worse hosts, and may help hosts correct deficiencies that they were unaware of. Raval (2024) indeed finds lower average reviews for business with likely consumer protection problems, although the magnitude of this effect varies considerably across review platforms. Thus, pro-social messaging has the potential to increase online reviews in certain circumstances as well.

However, pro-social messaging could also affect the mix and content of reviews; for example, if consumers are more likely to post negative reviews to protect other consumers, messaging about "protecting the community" could lower average ratings by disproportionately increasing negative

[20]See `https://www.ftc.gov/legal-library/browse/cases-proceedings/2123050-amazoncom-inc-rosca-ftc-v`.

reviews. Similarly, pro-social messaging could mean more discussion and content on consumer protection issues as opposed to other attributes of the product or business such as prices or customer service.

10 Funding and Competing Interests

We have no competing interests.

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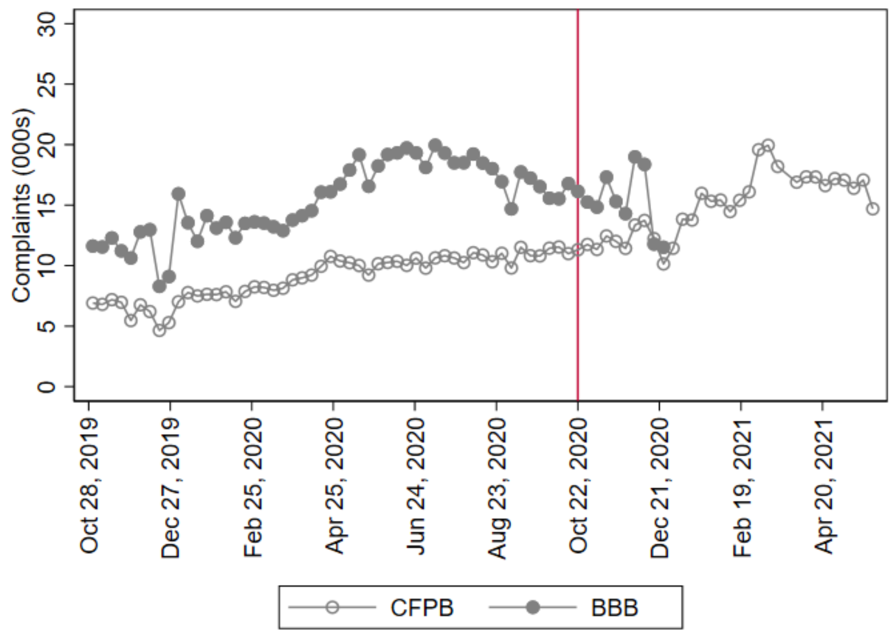
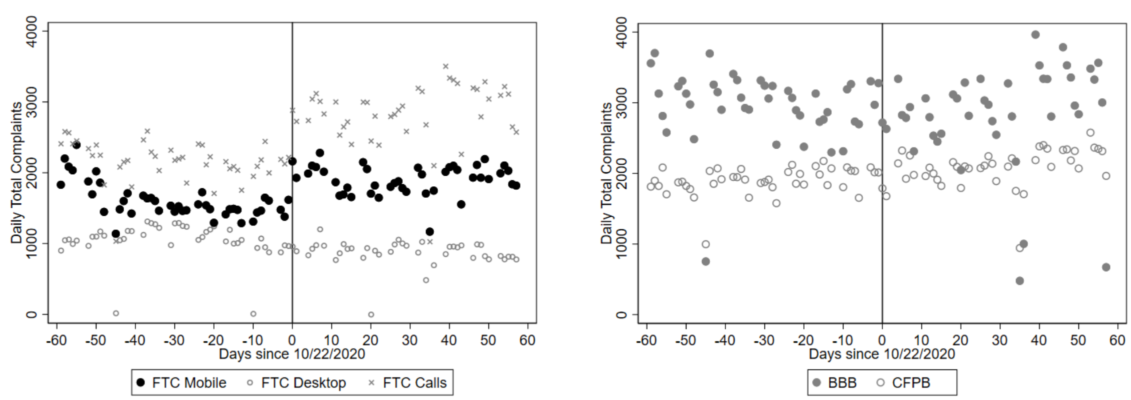
A Appendix Tables and Figures (For Online Publication)

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

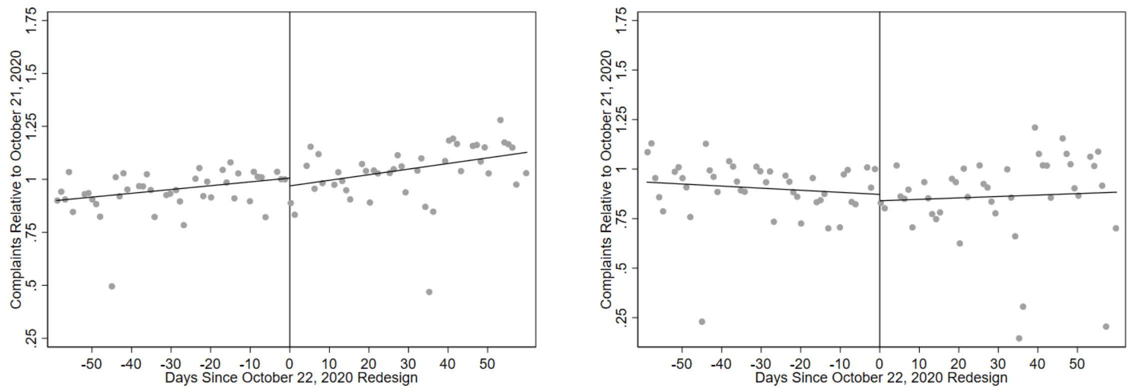


a) FTC

b) BBB/CFPB

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

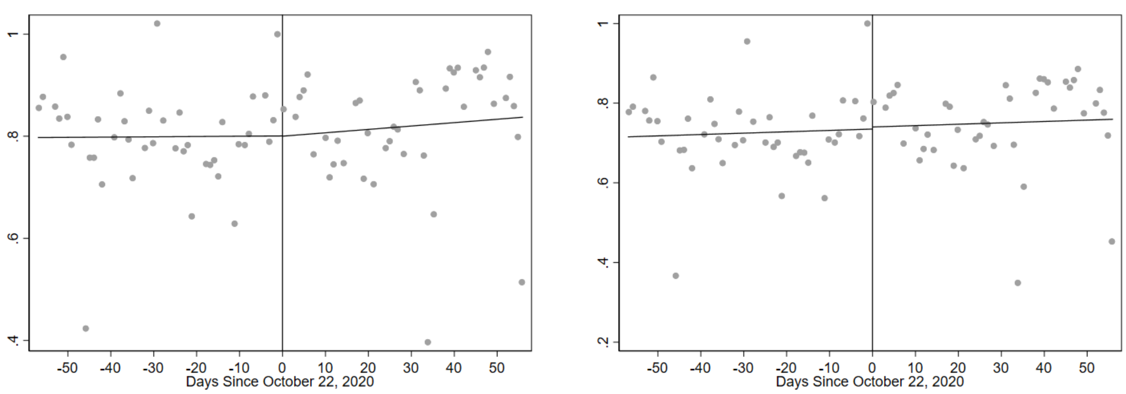
Figure A3: RD Estimate of Website Redesign on Number of Complaints, BBB and CFPB



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 first-degree polynomial and controls for the day of the week.

Figure A4: Total and New Users to FTC Complaints Website



a) Total Users b) New Users

Notes: The figure shows the daily number of total users and new users to the FTC's complaint website, from 60 days before and after the FTC's website redesign on October 22, 2020. For each panel, the number of users are expressed relative to the number of users 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 first-degree polynomial and controls for the day of the week.

Table A1: Website metrics before and after redesign

	(1) October 2019 - October 20, 2020	(2) October 22, 2020 - July 31, 2021
Average session duration	00:05:33	00:05:30
Average time on page	00:01:10	00:02:28
Average page load time (sec)	1.72	3:29

Notes: The table shows Google Analytics metrics of the FTC website before and after the redesign.

Table A2: Estimates of AMSE with Varying Polynomial Degree

Order	(1) FTC Online	(2) FTC Mobile	(3) FTC Desktop	(4) FTC Calls	(5) BBB/CFPB
1	0.017	0.001	0.005	0.004	0.030
2	0.030	0.006	0.009	0.006	0.054
3	0.057	0.011	0.017	0.011	0.136
4	0.118	0.031	0.032	0.021	0.289

Notes: The table shows the resulting estimates of the asymptotic mean squared error (AMSE) from estimates of equation (1), where the dependent variable is the log number of daily complaints. The specification includes polynomials up to the specified order 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. AMSE is calculated as in Pei et al. (2022).

Table A3: RD Estimate of Website Redesign on Number of Complaints, Varying Polynomial Order

	(1) FTC Online	(2) FTC Mobile	(3) FTC Desktop	(4) FTC Calls	(5) BBB/CFPB
B. P=1					
Post	0.282***	0.256***	0.307***	-0.0856	0.0255
	(0.0379)	(0.0357)	(0.0395)	(0.0456)	(0.0677)
C. P=2					
Post	0.264***	0.266***	0.262***	0.0699	-0.0691
	(0.0577)	(0.0613)	(0.0518)	(0.0520)	(0.109)
D. P=3					
Post	0.395***	0.416***	0.374***	0.0808	0.185
	(0.0721)	(0.0657)	(0.0634)	(0.0531)	(0.104)
E. P=4					
Post	0.279**	0.239**	0.320***	-0.0388	-0.217*
	(0.0846)	(0.0707)	(0.0745)	(0.0567)	(0.109)

Notes: The table shows estimates of equation (1), where the dependent variable is the log number of daily complaints. The specification includes polynomials up to the specified order 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.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A4: RD Estimate of March 3 2021 Press Release on Number of Complaints

	(1) FTC Online	(2) FTC Mobile	(3) FTC Desktop
Post	0.0420	0.0707*	0.0133
	(0.0386)	(0.0297)	(0.0353)

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 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 A5: RD Estimates, Quality of Data

	(1) Has Zip	(2) Has Age	(3) Company Name	(4) Company Zip
A. FTC Online				
RD Estimate	0.0850***	0.127***	0.0620***	0.0137**
	(0.00372)	(0.00377)	(0.00872)	(0.00468)
B. FTC Mobile				
RD Estimate	0.0786***	0.128***	0.0553***	0.0243***
	(0.00516)	(0.00565)	(0.0133)	(0.00556)
C. FTC Desktop				
RD Estimate	0.0914***	0.126***	0.0687***	0.00315
	(0.00519)	(0.00518)	(0.0107)	(0.00574)

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. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A6: RD Estimates, Imputed Categories

	(1) Telemarket	(2) Text/Email	(3) Imposter	(4) Online Shopping	(5) Other/Misc
A. FTC Online					
RD Estimate	0.656***	0.0680	0.529***	0.351***	0.133***
	(0.0391)	(0.0541)	(0.0395)	(0.0381)	(0.0371)
A. FTC Mobile					
RD Estimate	0.720***	0.174*	0.560***	0.285***	0.160***
	(0.0523)	(0.0705)	(0.0453)	(0.0408)	(0.0377)
B. FTC Desktop					
RD Estimate	0.591***	-0.0377	0.497***	0.417***	0.106**
	(0.0488)	(0.0571)	(0.0420)	(0.0374)	(0.0369)

Notes: The outcomes are the log sum of predicted probabilities for each imputed category based on the text of complaints. The specification includes a first 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 A7: Terms with Statistically Significant Changes

	(1) Positive	(2) Negative
FTC Mobile Only	requir, america, possibl, support	phone, address, messag, right, insur, numer
FTC Desktop Only	unemploy, subject	phone, address, account, receiv, number, anoth, charg, includ, report, amount, cancel, transfer, chang, follow, first, remov, found, clear, immedi, comput, verifi, appear, attempt, question, instruct, problem, addit, action, block, sever, associ, investig, bitcoin, anyon, search, longer, attorney, covid, submit, might, resolv, receipt involv practic unabl posit enter, approv, theft

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 first 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.

Table A8: RD Estimate of Website Redesign on Selected Topics, Positive and Significant

Representation	Est.	(S.E.)	Total Complaints	Assigned Category
9_ifidonotreceivethebitcoin idefinitelywillsendoutyourvideorecordingto	1.96	(0.13)	3373	Hack Claim
49_unemployment claim_kansas dept_ks dept_unemployment benefit	1.89	(0.17)	1446	Identity Theft
21_unemployment claim_illinois dept_filed claim_unemployment benefit	1.73	(0.24)	2624	Identity Theft
23_unemployment fraud_unemployment claim_filed claim_fraudulent claim	1.67	(0.20)	2552	Identity Theft
187_data video_monitoring internet_uploaded trojan_letter video	1.67	(0.13)	485	Hack Claim
57_gift card_itunes gift_ebay gift_play gift	1.57	(0.17)	1308	Imposter
47_esto_cuando_que el_como	1.47	(0.20)	1508	Spanish Language Cluster
80_calls marriott_called marriott_marriott hotel_vacation marriott	1.43	(0.12)	840	Prize/Imposter
39_online interview_hiring manag_google hangout_interview	1.35	(0.18)	1729	Job
48_unemployment claim_filed claim_fraudulent claim_filed fraudul	1.27	(0.14)	1451	Identity Theft
91_number fraudul_ss number_robocall claim_scam robocal	1.24	(0.14)	766	Imposter
60_phone robo_number robo_robo claim_robo tel	1.03	(0.07)	1189	Imposter
181_update help_update just_update ne_update problem	1.03	(0.10)	2730	“Update” Word
112_regards outlook_outlook io_urgent task_email soon	1.02	(0.08)	600	Imposter
188_transaction ebay_deal ebay_buyer contact_ebay select	1.02	(0.08)	322	Online Shopping
1_icloud breach_saying icloud_icloud account_apple icloud	1.01	(0.11)	9218	Imposter

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 first 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.

Table A9: RD Estimate of Website Redesign on Selected Topics, Positive and Significant (Continued)

Representation	Est.	(S.E.)	Total Complaints	Assigned Category
118_cashier check_receive check_payment_payment address	0.97	(0.09)	550	Advance Fee
95_sba fraud_sba loan_loan sba_contacted sba	0.96	(0.14)	713	Identity Theft
121_stop robo_number robo_robo_calls robocal	0.96	(0.13)	547	Unwanted Calls
144_paste text_unable copypast_copy text_paste don	0.94	(0.08)	448	Want to Copy Paste
152_foods market_food market_quality survey_survey	0.91	(0.11)	422	Job
170_robocall amazon_amazon robocal_scam robocal_robocall claim	0.91	(0.15)	371	Imposter
173_amazon sign_amazon password_respond amazon_https amazon	0.89	(0.13)	363	Imposter
37_order confirm_shipment_order ship_shipping spe	0.88	(0.15)	1780	Imposter
28_contacted ebay_fake ebay_ebay contact_ebay email	0.87	(0.08)	2366	Online Shopping
68_amazon fraud_fraud amazon_amazon fraudul_amazon account	0.76	(0.15)	1010	Imposter
125_foods market_shoppers work_shopper_store evalu	0.72	(0.13)	638	Job
92_amazon fraud_amazon robo_amazon account_robo amazon	0.69	(0.14)	725	Imposter
3_calls com_calls differ_caller_caller id	0.68	(0.07)	6612	Unwanted Calls
123_hacked taken_send video_video btc_traced hack	0.67	(0.19)	526	Hack Claim
17_federal bureau_payment_transfer_bureau investig	0.66	(0.18)	2826	Money Transfer
133_refund_fraud_asked pay_told pay	0.66	(0.18)	499	Job
0_ss number_number suspend_ssa_ssn suspend	0.65	(0.13)	28618	Imposter
62_windows defend_defender protect_protection plan_threat protect	0.64	(0.12)	1117	Tech Support
36_received voicemail_issue arrest_warrant arrest_left voicemail	0.60	(0.19)	1843	Imposter
27_iphone amazon_calling amazon_amazon fraud_contacted amazon	0.55	(0.20)	2402	Imposter
30_withdraw profit_withdraw money_withdraw fund_tried withdraw	0.55	(0.17)	2094	Investments
6_won million_scammer_prize money_told won	0.52	(0.15)	4068	Lottery/Prize
45_theft_attorney_court_fraud	0.52	(0.14)	1519	Unrelated Misc
19_charged amazon_charge amazon_amazon account_calling amazon	0.50	(0.17)	2771	Imposter
13_landlord_craigslist ad_tenant_craigslist org	0.46	(0.16)	3086	Rental
26_medicare inform_medicare report_medicare told_calling medicar	0.39	(0.11)	2422	Imposter
8_grant program_grant money_000 grant_free grant	0.29	(0.16)	3926	Imposter/Govt Grant
10_scammer_asked money_send money_asking money	0.27	(0.16)	3374	Imposter/Romance

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 first 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.

Table A10: RD Estimate of Website Redesign on Selected Topics, Negative and Significant

Representation	Est.	(S.E.)	Total Complaints	Assigned Category
20_received check_applied job_offered job_send check	-0.42	(0.13)	2747	Job
2_spam text_unwanted text_received text_receiving text	-0.46	(0.16)	9213	Spam Text
59_order norton_contacted norton_subscription norton_norton antivirus	-0.52	(0.18)	1227	Imposter/Tech Support
114_survey mcguireresearch_selected survey_surveys random_survey text	-0.54	(0.17)	589	Spam Text
106_weight loss_losing weight_weightloss_loose weight	-0.67	(0.13)	635	Spam Text
24_unsubscribed email_unsubscribe email_emails unsubscrib_email unsubs	-0.69	(0.17)	2520	Spam Email
159_skin cream_skin product_skin trial_remove skin	-0.71	(0.17)	397	Spam Text
140_tumors ovarian_cancer femal_cancer_tumor	-0.80	(0.12)	486	Spam Text
46_giftcard_cards email_scammer_gift card	-0.90	(0.36)	1493	Imposter
119_money 3500_money 4000_money 1500_money 4500	-0.99	(0.17)	560	Spam Text
115_covid 19_topic covid_ss number_fraud	-1.03	(0.18)	573	Imposter
16_political text_text polit_political spam_messages polit	-1.14	(0.24)	2983	Spam Text
15_scam email_spam email_email threaten_hacked account	-1.31	(0.54)	2850	Hack Claim

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 first 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.

Table A11: Differences between Takers and Compliers, FTC Mobile and Desktop Complaints

	(1)	(2)	(3)	(4)
	Mobile		Desktop	
	Takers	Compliers	Takers	Compliers
Demographic Characteristics				
Age under 40	0.447	0.509	0.279	0.157
Age 40-59	0.358	0.374	0.332	0.403
Age Over 60	0.195	0.118	0.389	0.439
Age 60-69	0.135	0.082	0.223	0.237
Age 70-79	0.051	0.026	0.129	0.162
Age Over 80	0.010	0.009	0.037	0.040
White	0.704	0.735	0.749	0.778
Black	0.107	0.102	0.1000	0.0811
Latino	0.121	0.0739	0.0792	0.0685
Asian/PI	0.0451	0.0621	0.0512	0.0503
Female	0.533	0.526	0.469	0.638
Demographic Weight	0.952	1.285	0.937	1.408
Text				
Reported Loss	0.251	0.185	0.208	0.212
Grade Level	9.644	2.745	8.678	7.758
Grade Level $<$ 8th	0.623	0.0173	0.575	0.382
Imputed Product Category				
Telemarketing	0.0616	0.198	0.0805	0.249
Unsolicited Text or Email	0.248	0.150	0.252	-0.0249
Imposter Scams	0.180	0.399	0.186	0.453
Online Shopping and Reviews	0.108	0.0848	0.0902	0.175
All Other and Misc.	0.402	0.169	0.391	0.149

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.

B Additional Details on Empirical Approaches

B.1 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

$$206.835 - 1.015(\frac{words}{sentences}) - 84.6(\frac{syllables}{words}). \tag{4}$$

The scores can also be grouped into grade level difficulty, with lower than 70 being apt for 8th grade and above, 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 5 points, and the share of texts with at least an 8th grade or college reading ease declined by approximately 11 percentage points. We find small changes for the desktop site.

Table A12: RD Estimates, Text Analysis Flesch Reading Ease

	(1) Median	(2) 8th gr	(3) college
A. FTC Online			
RD Estimate	2.401***	-0.0574***	-0.0488***
	(0.502)	(0.0111)	(0.0116)
A. FTC Mobile			
RD Estimate	4.969***	-0.117***	-0.113***
	(0.437)	(0.00871)	(0.00927)
B. FTC Desktop			
RD Estimate	-0.168	0.00185	0.0158*
	(0.373)	(0.00870)	(0.00752)

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 first 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.
$*p < 0.05, **p < 0.01, ***p < 0.001$

B.2 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.

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.

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.

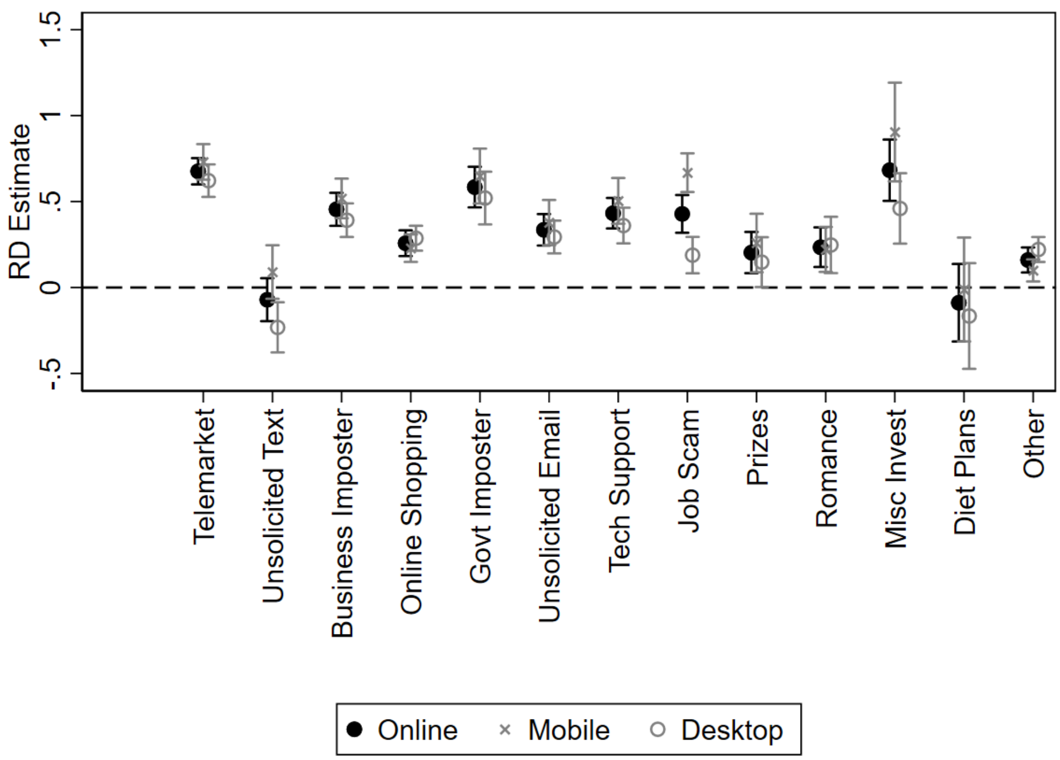
Figure A5 and Table A14 display the RD estimates from this broader categorization. The predictive model has a predictive accuracy of 58% on the test set. Given the number of categories, we do not display the full confusion matrix. Instead, in Table A15, we take each predicted category (assigned based 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.3 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 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.

Figure A5: 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. 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	0.160***	0.0993**	0.221***
	(0.0371)	(0.0327)	(0.0370)
Unwanted Telemarketing	0.676***	0.731***	0.622***
	(0.0390)	(0.0528)	(0.0483)
Unsolicited Text	-0.0707	0.0903	-0.232**
	(0.0638)	(0.0794)	(0.0744)
Business Imposter	0.455***	0.518***	0.392***
	(0.0490)	(0.0588)	(0.0499)
Online Shopping	0.258***	0.229***	0.287***
	(0.0381)	(0.0407)	(0.0370)
Govt. Imposter	0.584***	0.648***	0.520***
	(0.0603)	(0.0814)	(0.0782)
Unsolicited Email	0.336***	0.378***	0.294***
	(0.0468)	(0.0671)	(0.0487)
Tech Support	0.432***	0.504***	0.360***
	(0.0452)	(0.0679)	(0.0529)
Job Scams	0.428***	0.668***	0.188***
	(0.0560)	(0.0575)	(0.0540)
Prizes Sweepstakes	0.203**	0.259**	0.148*
	(0.0612)	(0.0868)	(0.0740)
Romance	0.235***	0.221**	0.248**
	(0.0588)	(0.0667)	(0.0836)
Misc. Investments	0.682***	0.905***	0.460***
	(0.0909)	(0.146)	(0.105)
Diet Plans/Centers	-0.0885	-0.0114	-0.166
	(0.115)	(0.154)	(0.157)

Notes: The outcomes are the log sum of predicted probabilities for each imputed category based on the text of complaints. The specification includes a first 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 Website Changes

We first describe deficiencies in the original FTC Complaint Assistant Website uncovered by usability testing, and then go over the changes made in the new Report Fraud website that addressed these concerns.

Broadly speaking, we can divide the issues that users had with the previous website into two categories. First, many users felt disconnected from the FTC and the government and that complaining seemed to be a waste of time. The new website responded to these critiques by highlighting the public good benefits of complaints. Second, users found the complaint categorization difficult to use, the process of complaining too long, and the visual design difficult to parse; all of these are forms of “hassle costs” that made the website difficult to use. The FTC responded by improving the visual design and complaint categorization and simplifying the complaint process. We provide more details below.

C.1 Alienation from FTC / Government

A major issue that users flagged is that users felt alienated and disconnected from the FTC and from government. First, users felt that the FTC immediately stated that they cannot resolve individual complaints, which turned off consumers who found the whole exercise of filing a complaint a waste of time. In addition, the FTC did not provide any information about what would happen to the complaint after it was filed, provide empathy to consumers for helping them in filing the complaint, or provide information about steps to protect themselves from scams in future. Users also felt that the FTC also did not explain why they asked for personal information like the age and military status of consumers.

These issues extended to the visual design of the website, the issue of the next subsection. Users complained that the design did not communicate that this was an official FTC government website or that the FTC cared about the consumer’s complaint and wanted to help the user.

The new website addressed these concerns by highlighting the public good nature of reporting: that consumers’ reports were used to help the community by fighting fraud. First, the name of the website itself was changed to “reportfraud.gov”, and the immediate tagline when visiting the website is “Report to help fight fraud!”. The main graphic on the homepage has a bunch of houses with people walking by, which was meant to emphasize the community aspect of reporting. An outline of a shield emphasized how the report would help shield the community. Below, the website states “Protect your community by reporting fraud, scams, and bad business practices.”

In addition, the FTC made clear what happened to the complaint after filing. Below the main screen, the FTC provided a three step guide to the complaint process, which emphasized that after the consumer filed a complaint (step 1), the FTC would provide next steps on how consumers could protect themselves (step 2), and that the reports would be used to help stop fraud (step 3). Building on step 3, consumers scrolling further down learn that reports are shared with more than 2,800 law enforcers, and that while “We can’t resolve your individual report, but we use reports to investigate and bring cases against fraud, scams, and bad business practices.”. A graphic below visually displays how a consumers’ report is shared with law enforcers across the country.

Consumers had also complained that the FTC did not provide steps to take to protect themselves from scams in future. As explained above in “step 2”, the FTC now provides several tips for users to reduce their risk of falling victim to scams, together with links to other FTC resources. These steps are also somewhat customized to the consumers’ issue.

In order to make clear that the website was a government website, the top left includes the FTC logo as well as “Federal Trade Commission”, and the official name for the website includes both ”ftc” and ”gov” (ReportFraud.ftc.gov).

C.2 Complaint Categorization

For both the FTC Complaint Assistant and Report Fraud websites, the first thing the user has to do is classify their complaint into one of several categories. One major concern of participants in the usability testing focus group was that it was difficult to classify their complaint.

Focus group users complained that there were too many categories on the homepage and so the site immediately put over users as not easy to navigate. In particular, there were too many sub-categories to choose from (after an initial broad category), the categories were stressful and users didn’t know how to report, the categories were repetitive and not clear, the categories were too general and so it wasn’t clear if the FTC could address their complaint, and users couldn’t find a category that fit their problem and didn’t want to choose a “wrong” category.

In response, the FTC considered multiple ways for users to choose their complaint category, including a menu including all categories, and ultimately chose an “accordion” style approach in which a user first picks among a broad set of categories and then sees a narrow set of options within the broad category. In focus groups, users preferred the accordion style approach to seeing all of the options at once, but were more likely to pick the most accurate category for their complaint seeing all of the options. These findings prompted a broader and more differentiated initial set of categories.

In the final accordion style menu, users first have to choose amongst one of ten possible broad categories, such as "impersonator", "online shopping", or "health". Given their choice, there are a few additional options. For example, users choosing "health" could narrow the product to "weight loss product", "eye care", "someone pretending to be a government agency", "fake or misleading treatment or cure", or "any other problem".

Importantly, the initial menu included "something else", so consumers who did not feel like the other options fit had somewhere to click. The previous website did not have this option.

C.3 Visual Design

Users also found the FTC's website difficult to process visually for several reasons. The website's homepage appeared cluttered and content heavy, creating the impression that navigation might be challenging. The layout was overwhelming with an overabundance of text was spread across the site, leading users to overlook crucial instructions. Unfortunately, the content suffered from repetitiveness and lack of clarity. Users tended to gravitate toward the bottom of the homepage, likely because it was easier to read. Internal pages suffered from excessive white space and gray areas on either side. Font inconsistencies—ranging from being too small to overly bold—made readability difficult.

The new website saw a full scale redesign of the visual design. In general, the main principles were to reduce the amount of content, increase the font size and improve font consistency and readability, and have a common visual design throughout the website. This started with the homepage – there is much less text and the text that remained was in much larger font. Fonts were easier to read throughout the website, with dark blue indicating section headings, and a dark blue box indicating that consumers could proceed to the next section. Yes/No questions also gated the information that consumers were asked, in order to reduce the amount of content that consumers saw unless that content made sense given the consumers' choice (for example, detailed information about a company's address / phone / email are only inputted if the consumer says they know more about the company). The landing page also removed prominent links to other FTC websites (such as identitytheft.gov, DoNotCall.gov, etc.) below the main screen and replaced them with an explanation of the various steps involved in the complaint.

C.4 Flow

Users' main complaint with the process of filing a complaint was that it took too long – users felt overwhelmed when faced with a 7-step process, and so were hesitant to proceed. Rather than engaging thoughtfully, they tended to fill out the form mechanically. In addition, users wanted more intuitive guidance on where to click to initiate a complaint, clear demarcations of different sections on the review page, and clear links to return consumers to the homepage if needed.

The new website responded to these issues by sharply reducing the length of the process required to file a report. After deciding on a category (described above), there are now only two steps. In the first step, the consumer provides details about what happened (such as the amount of money lost and how the consumer was contacted) and about the scammer. In addition, an open ended text box allows consumers to write their full story of what happened. In the second step, the consumer can provide details about themselves, such as their name and address, and then submit the complaint.

The "flow" to complain is also much more straightforward. On the homepage, there is a large "Report now" button, as well as multiple other links at the top right and farther down the screen for consumers to click to start their report. Once they start the report, a slider shows consumers that they are already halfway done at the first step and 2/3rds done at the second step. Clear Back and Forward links allow consumers to move forward or backward through this process.

Users in the usability tests found the new website easy to use, and were happy with how short and simple the form was. In addition, they liked having the open ended text box on the first page to be able to tell their story in their own words. The previous website had included the open ended text box on the sixth step, frustrating users who wanted to explain what happened to them.

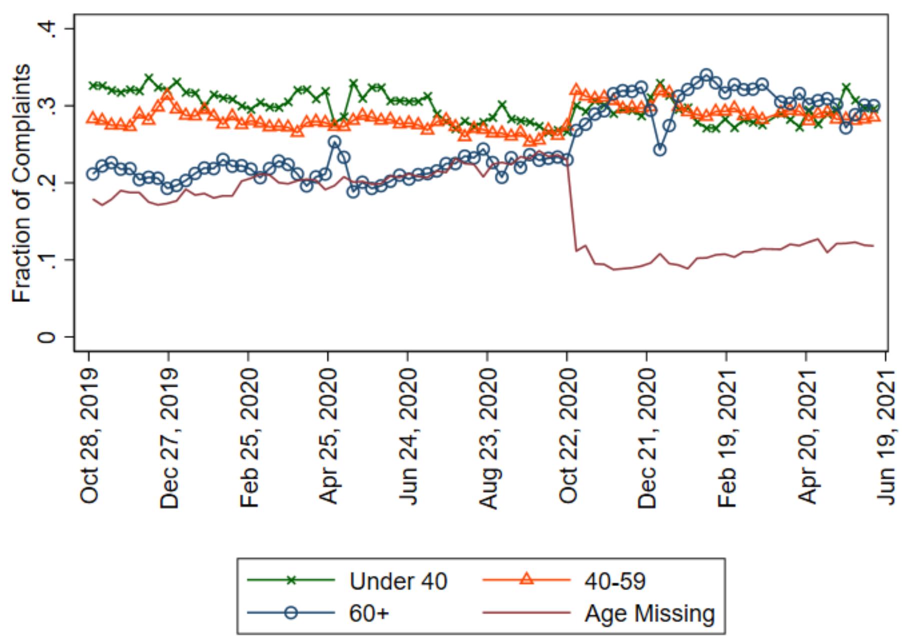
D Demographics of Complaining Consumers

D.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).

The complaint data also include self-reported information about consumers' age. Figure A6 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.

Figure A6: 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 FTC online sources and age bands. The weeks are defined as starting on Thursdays, since the website redesign was a Thursday.

Table A16 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 headline number because the share of consumers not reporting their age fell. For example, the under 40 band grew at 40%, which is only slightly higher, and not statistically significantly different from, the overall increase in complaints. We find similar increases in complaints across age bands; complaints from consumers below 40 increased by 40%, as did consumers 60+, compared to 46% for consumers aged 40-59.

These results may seem surprising given that we found a large increase in the share of complaints from consumers 60+ in the time series plot reported in Figure A6. We thus plot the RD graphs by age group in Figure A7; the jump at the discontinuity appears to be quite similar across all age groups. However, consumers that are 60+ or 70+ have a pronounced upward trend in complaints after the website redesign. While this increase might reflect longer run effects of the redesign, it could also be due to other factors affecting complaint rates such as changes in fraud victimization over time.

Table A16: 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	0.404***	0.464***	0.404***	0.397***	0.416***	0.470***
	(0.0424)	(0.0496)	(0.0318)	(0.0353)	(0.0419)	(0.0736)
B. FTC Mobile						
RD Estimate	0.494***	0.474***	0.372***	0.370***	0.371***	0.490***
	(0.0431)	(0.0442)	(0.0437)	(0.0488)	(0.0664)	(0.134)
C. FTC Desktop						
RD Estimate	0.315***	0.455***	0.437***	0.424***	0.462***	0.450***
	(0.0453)	(0.0397)	(0.0380)	(0.0407)	(0.0481)	(0.0653)

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.
$*p < 0.05, **p < 0.01, ***p < 0.001$

As shown previously, though, the redesign of the FTC's interface increased the proportion of consumers who recorded their age. 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 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.

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 table 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 immigration.

These estimates, shown in Table A17, are similar to our main results that use the actual age bands from the FTC website. The main difference is we find a much larger, albeit noisy, differences for older adults, with smaller increases for the 60-69 age band and large, albeit noisy, increases for the 80+ band. Thus, estimates using the median age of their name are broadly consistent with our findings from Table A16.

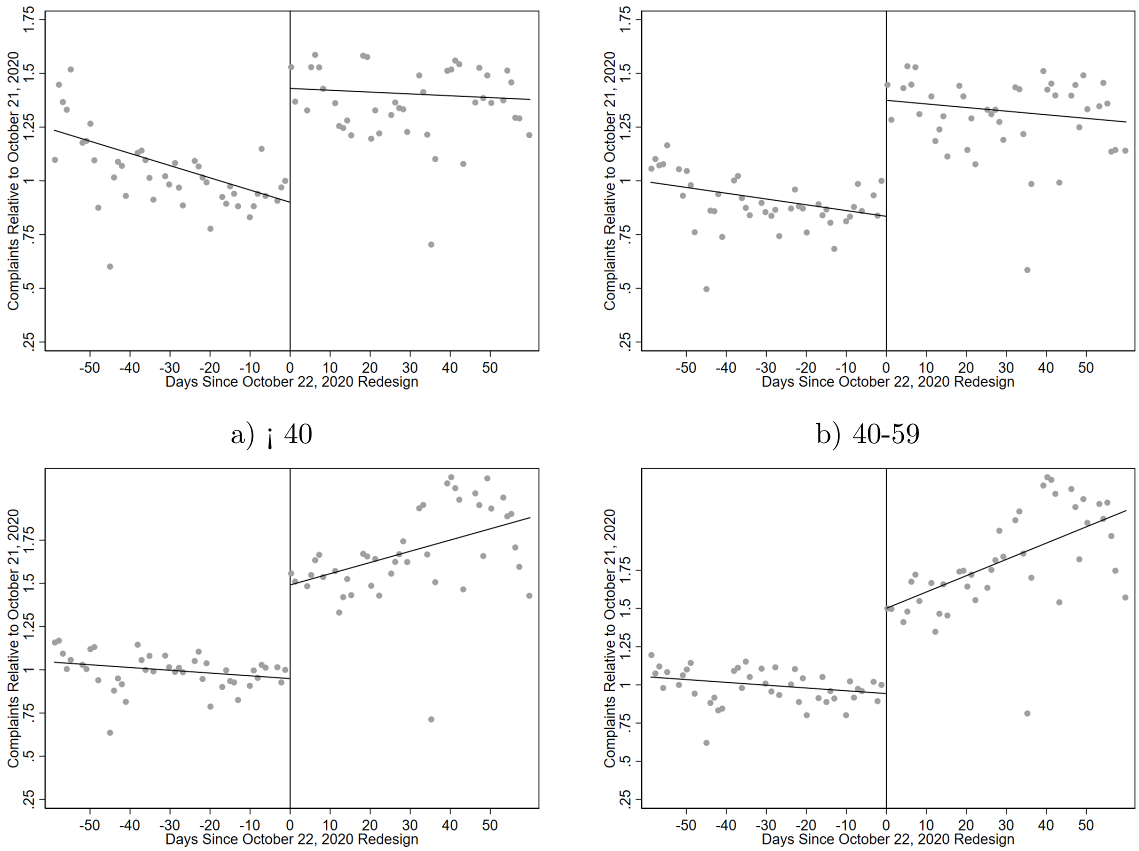
D.2 Race/Ethnicity

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.[21]

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

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

Figure A7: RD Estimate of Website Redesign on Number of Complaints by Age Group



a) ¡ 40

b) 40-59

c) 60+

d) 70+

Notes: The figure shows the daily number of complaints report to the FTC by age group, 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 first-degree polynomial and controls for the day of the week.

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:

$$Pr(r|f,s) = \frac{p(r|f) * q(s|r)}{\sum_{r \in R}(p * q)}, \tag{5}$$

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.[22] We convert the resulting probabilities to proxy race and ethnicity by assigning the consumer a race according to their highest probability (Zhang, 2018).

Table A18 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 31% increase from

[22]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.

Table A17: 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***	0.298***	0.356***	0.728***
	(0.0706)	(0.0899)	(0.0693)	(0.0379)	(0.0713)	(0.149)
B. FTC Mobile						
RD Estimate	0.364***	0.354***	0.383***	0.296***	0.277*	0.707***
	(0.0648)	(0.0779)	(0.0879)	(0.0472)	(0.112)	(0.179)
C. FTC Desktop						
RD Estimate	0.460***	0.477***	0.422***	0.300***	0.435***	0.749**
	(0.0673)	(0.0766)	(0.0736)	(0.0460)	(0.0797)	(0.231)

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. $*p < 0.05, **p < 0.01, ***p < 0.001$

white consumers, compared to a 27% increase for Black consumers, 24% for Latino consumers, and 34% 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 21% after the redesign, compared to 31% for white consumers, 29% for Black consumers, and 39% for Asian consumers.

Table A18: RD Estimates, Log Complaints in Each Imputed Race

	(1) White	(2) Black	(3) Latino	(4) Asian
A. FTC Online				
RD Estimate	0.311***	0.274***	0.241***	0.342***
	(0.0413)	(0.0360)	(0.0416)	(0.0404)
B. FTC Mobile				
RD Estimate	0.312***	0.290***	0.205***	0.390***
	(0.0439)	(0.0376)	(0.0469)	(0.0500)
C. FTC Desktop				
RD Estimate	0.309***	0.259***	0.278***	0.295***
	(0.0387)	(0.0402)	(0.0416)	(0.0517)

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. $*p < 0.05, **p < 0.01, ***p < 0.001$

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

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

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.

In Table A19, 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 32%, Black consumers by 20%, Latino consumers by 22%, and Asian consumers by 33%. These estimates are broadly similar to those in Table A18, although we find larger gaps in the effect of the redesign between Black and Latino consumers compared to white and Asian consumers after using zip code for race imputation.

Table A19: RD Estimates, Log Complaints in Each Imputed Race, Using Zipcode

	(1) White	(2) Black	(3) Latino	(4) Asian
A. FTC Online				
RD Estimate	0.317***	0.200***	0.216***	0.331***
	(0.0403)	(0.0432)	(0.0432)	(0.0426)
B. FTC Mobile				
RD Estimate	0.315***	0.279***	0.191***	0.381***
	(0.0425)	(0.0465)	(0.0478)	(0.0551)
C. FTC Desktop				
RD Estimate	0.319***	0.122*	0.242***	0.280***
	(0.0379)	(0.0559)	(0.0432)	(0.0519)

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. $*p < 0.05, **p < 0.01, ***p < 0.001$

D.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.

Table A20 shows estimates of the effect of the website redesign on the complaints from consumers who were imputed to be male and female.[23] Complaints increase more after the redesign for female consumers (32%) than male consumers (28%). However, we cannot reject that the increase for both female and male consumers is the same as the overall effect across all consumers.

[23]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.

Table A20: RD Estimates, Log Complaints in Each Imputed Sex

	(1) Female	(2) Male
A. FTC Online		
RD Estimate	0.316***	0.277***
	(0.0409)	(0.0387)
B. FTC Mobile		
RD Estimate	0.305***	0.271***
	(0.0433)	(0.0421)
C. FTC Desktop		
RD Estimate	0.328***	0.284***
	(0.0395)	(0.0362)

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. $*p < 0.05, **p < 0.01, ***p < 0.001$

E 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:

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