Data Sharing and Website Competition: The Role of "Dark Patterns"

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Regulations like the GDPR require firms to secure consumer consent before using data. In response, some firms employ "dark patterns"—interface designs that encourage data sharing. We study the causal effects of these designs on consumer consent choices and explore how these effects vary across individuals, firms, and the frequency of these choices. We ran a field experiment where participants installed a browser extension that randomized cookie consent interfaces as they browsed the internet. We find that consumers accept all cookies over half of the time absent dark patterns, with substantial preference heterogeneity across users. In addition, users frequently close the window without making an active choice. When the interface hides certain options behind an extra click, users are significantly more likely to select the options that remain visible. Purely visual manipulations have much smaller effects. Larger and better-known firms achieve higher consent rates, giving them a competitive advantage, but dark patterns do not exacerbate this advantage. We use a structural model of consumer choice to show that the consumer surplus maximizing consent banner uses a neutral design and defaults to accepting cookies when users click out of the banner. We also show that giving users a browser level choice improves consumer welfare relative to asking for consent on a site by site basis.

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1. Introduction

Consumer data is widely used as an input into pricing decisions, algorithmic rankings, and targeted advertising. This data collection and use has sparked privacy concerns, leading to pressure from both regulators and society for companies to give consumers more control over their personal information by asking for explicit consent. However, some have raised concerns that the proliferation of data use choices benefits large and prominent firms due to consumers' tendencies to share data with recognizable brands.[1]

Companies seeking consent to use data often design cookie consent interfaces to nudge users toward sharing more data. For example, some companies present users with only two cookie-sharing options—"accept all cookies" and "customize settings", while hiding the option to reject non-essential cookies behind the customize settings button. These choice architectures are often known as *dark patterns* in public discourse,[2] and are prohibited under the EU's Digital Services Act.[3] Strategic choice architecture may exacerbate or moderate any advantages large and prominent companies may have in data collections compared to smaller competitors.

We study how three types of dark patterns affect consumer privacy choices and whether they exacerbate data advantages of large companies. To do so, we conduct a field experiment that randomly varies which consent interface users face as they browse the internet. We find that dark patterns that increase choice friction by hiding options behind a click significantly drive selection of the visible options, whereas designs that merely adjust visual elements have minimal impact. Popular websites generally receive higher consent rates, but the effect of dark patterns does not vary significantly with website popularity or familiarity during organic browsing, suggesting limited effects of dark patterns on competitive advantages for incumbents. Users exogenously assigned to more frequent consent requests do not exhibit systematically different consent patterns.

We use our experimental variation to estimate a structural model of consumers' preferences for data sharing. We find that the cost of clicking 'customize settings' is 50% higher than the utility of choosing a user's preferred option. The design that maximizes consumer surplus in a consent-based regime, which removes deliberate obstruction while defaulting consumers to accept all cookies when they close consent windows, increases welfare by 11% compared to the most common design in the US, which hides the "reject

[1] See, for example, The Digital Markets Act that requires "gatekeeper" platforms to share data with smaller players upon request: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/digital-markets-act-ensuring-fair-and-open-digital-markets_en, and the FTC's report to OECD on how data privacy and competition interacts: https://one.oecd.org/document/DAF/COMP/WD(2024)29/en/pdf

[2] https://www.deceptive.design/

[3] https://ec.europa.eu/commission/presscorner/detail/en/QANDA_20_2348.

all" behind the "cookie settings" option while also adopting a pro-sharing default. It also reduces consent rates by 17%. However, the welfare gain from not having to interact with consent banners at all can be as high as 43% of status quo consumer surplus, outweighing the benefits of having even the best banner design.

Our study is enabled by Cookie Manager, a customized browser extension we developed in order to assign and randomize cookie consent interfaces for users as they browse the internet. Cookie Manager is based on the Webmunk extension framework (Farronato, Fradkin, and Karr 2024), and enforces users' cookie consent choices whenever easily implementable, making user choices incentive compatible. The extension displays one of six different consent interfaces, which vary in their use of three types of dark patterns: deliberate obstruction (i.e., removing options such as 'reject all' from the main banner), reordering options to prioritize those with more data sharing, and highlighting the option to share all data with a different color. We randomize these dark patterns across users and web domains.

The study population consists of US consumers from Prolific who consent to install Cookie Manager. The experiment consists of two phases. In the first phase (*survey browsing*), we prompt participants to visit specific websites. This structured browsing allows us to evaluate their privacy preferences across the same set of websites, regardless of whether they would organically visit them. During their initial visit to each website, a cookie consent banner appears, randomly chosen among the interfaces we designed, against a grayed-out website background. Participants must either make a consent choice or click 'x' to escape the form and continue browsing the website.

In the second phase (*organic browsing*), we observe participants' natural browsing behavior for a week following the survey phase. As before, we randomize the design of the consent pop-ups at the website and participant level. In addition, participants are randomized into two groups: one group experiences consent banners at most every 10 minutes (the "10-minute" frequency treatment), whereas another group experiences consent banners at most every 60 minutes (the "60-minute" treatment). Together, these two phases allow us to identify data sharing preferences and dark pattern effects across websites, and characterize how survey-based results map to field-based choices. Further, randomizing the frequency of pop-ups allows us to explore choice fatigue and test whether user choices change in response to more frequent pop-ups.

In the treatment without dark patterns (*neutral interface*), 66% of participants during the survey phase and 60% during the organic phase choose to "accept all" cookies. With the neutral interface, even though some participants consistently accept or reject cookies, 30% have heterogeneous preferences across sites and are more likely to accept cookies with popular and familiar websites. Across all six interfaces, 91% of consumers change their privacy choices across websites, showing that dark patterns result in additional choice heterogeneity.

We find that deliberate obstruction has the strongest influence on privacy choices, while dark patterns that feature pure visual manipulations have weaker effects. In particular, hiding the "reject all" button from the main user interface reduced the probability of rejecting cookies by 17.1% in survey visits and 9.4% in organic browsing. The sizable effect of deliberate obstruction is consistent with websites' strategic choices. As shown by Utz et al. (2019), deliberate construction is present in 78.5% of cookie banners, making it the most commonly used dark pattern. In comparison, reordering options so that the "accept all" is displayed at the top only increases consent rates by 2-3.5%. Additionally graying out options other than "accept all" increases the acceptance probability by less than 2%.

Perhaps surprisingly, the effects of dark patterns do not vary substantially with website characteristics such as popularity or user familiarity. Absent dark patterns, consumers are more likely to consent to data sharing on popular or familiar websites during the survey phase. Dark patterns do not increase users' propensity to share data with popular or familiar websites during organic browsing, and if anything, they seem to alleviate such a tendency during the survey phase. These findings challenge the hypothesis that dark patterns heighten entry barriers or amplify data-enabled network effects (Hagiu and Wright 2023), which would otherwise reinforce incumbent advantages in the data economy.

We also measure the time participants spent interacting with banners. On average during the organic browsing phase, a participant spent 7.4 seconds interacting with each banner in the neutral condition. Extrapolating this number to scenarios where the banners are present on every domain and assuming a value of time of $69/hour (Greminger, Huang, and Morozov 2023), we estimate the weekly cost of interacting with consent pop-ups to be approximately $7.49 per week per participant as the lower bound.

Lastly, we consider choice fatigue, a growing concern as existing regulations have increased the frequency of consent banners online. Our experiment, which varied the frequency of consent banners, found no significant difference in choice behavior between the groups facing more versus less frequent pop-ups, suggesting that choice fatigue—at least at the frequency levels tested—does not significantly impact user behavior. However, we observed an increased propensity to close the pop-up over time, indicating a potential decline in user engagement independent of banner frequency. The fact that users frequently close banners without making an active choice highlights the importance of websites' tracking defaults.

Our work intersects with the existing literature on the competitive implications of consumers with behavioral biases and high search and switching costs(Huck and Zhou 2011; Spiegler 2014; Ho, Hogan, and Scott Morton 2017; Decarolis, Li, and Paternollo 2023). This literature has examined how factors such as switching costs and obfuscation strategies can limit competition in product markets. Our findings extend this analysis to the realm of data collection strategies, showing that behavioral interventions enable firms to collect more user data. The effectiveness of these interventions appears constant across websites of varying popularity. Thus, policies that target the use of dark patterns may not necessarily have pro-competitive effects. Work by Aridor et al. (2024) on Apple's App Tracking Transparency even suggest that competition may be negatively affected.

We also contribute to the broad literature on dark patterns and choice architecture. Existing empirical work on dark patterns in privacy settings primarily focuses on describing their prevalence (Mathur et al. 2019; Di Geronimo et al. 2020; Warberg et al. 2023). Efforts to measure how dark patterns affect privacy choices have mostly relied on lab or synthetic environments (Acquisti, John, and Loewenstein 2013; Utz et al. 2019; Luguri and Strahilevitz 2021; Habib et al. 2022; Lin and Strulov-Shlain 2023; Bielova et al. 2024; Baviskar et al. 2024), except for D'Assergio et al. (2022); Müller-Tribbensee, Miller, and Skiera (2024), who examines the impact of persuasive language in re-permission emails on encouraging user opt-in. Our study offers greater realism than lab settings, as users make meaningful decisions in the course of their regular internet activity. Moreover, unlike prior studies, our analysis spans a broad array of websites, which is crucial for understanding how dark patterns may influence websites' competitive access to consumer data.

Lastly, our work relates to recent work on the economics of privacy and the measurement of privacy preferences (Lin 2022; Collis et al. 2021; Tomaino, Wertenbroch, and Walters 2023; Tang 2023; Acquisti, John, and Loewenstein 2013) and the impact of different data collection practices on consumers (Miller and Tucker 2018; Tang 2019; Zhao, Yildirim, and Chintagunta 2021; Bian et al. 2023). We note that choices in our setting reflect not only consumers' privacy valuations but also their perceived benefits from cookie tracking. We contribute to existing work by measuring privacy choices in the field and providing an explicit consumer surplus measure for different data collection policies and practices.

The rest of the paper is structured as follows. Section 2 describes dark patterns and their use online. Section 3 presents our experimental design and describes the study participants. We discuss our reduced-form results in Section 4, and our model of user privacy preferences in Section 5. We conclude in Section 7.

2. Institutional Background

The phrase “dark pattern” was coined by a computer scientist, Harry Brignull, to refer to design patterns that “deceive and manipulate users into taking actions they did not intend.”[4] Although the usage of dark patterns is not restricted to data exchange settings, companies routinely use them whenever consent is required for data collection and processing. For example, Utz et al. (2019) crawled major EU websites after the General Data Protection Regulation (GDPR) and found that 57.4% of these websites use dark patterns in their consent banners.[5] Similarly, Nouwens et al. (2020) focused on the top 10,000 UK websites and documented dark pattern deployment in over 80% of them.

Since these manipulative patterns could lead consumers to make choices that they would not otherwise select, policymakers worry that the widespread deployment of dark patterns can cause consumer harm. Regulatory and legal intervention soon followed. For example, the Federal Trade Commission has fined large companies such as Epic Games and Amazon for user interface designs that induce accidental purchases and obstruct cancellation of subscriptions.[6] US States such as California, Colorado, and Connecticut have enacted privacy regulations that explicitly ban companies from using dark patterns to increase data collection.[7] In the European Union, the General Data Protection Regulation requires consent for data collection to be “freely given, specific, informed and unambiguous;” Recital 32 specifically requires that consent should be granular to the purposes of data processing, and that default settings and inactions do not constitute consent.[8] However, Bielova, Santos, and Gray (2024) argue that GDPR still leaves ample ambiguity on whether other dark patterns are allowed for encouraging consent. In 2023, regulators also tried to prohibit the usage of dark patterns beyond the privacy realm in the bipartisan bill—Deceptive Experiences To Online Users Reduction (DETOUR) Act.[9]

Prior research has documented a variety of dark patterns that companies deploy to advance data collection (Habib et al. 2022; Bielova, Santos, and Gray 2024). These different practices can be categorized into three main groups. The first group includes information

[4] https://hallofshame.design/about/

[5] GDPR is a European Union regulation passed in 2018 that requires consumer explicit consent as one of the major legal basis for data collection.

[6] See, for example, the Federal Trade Commission’s actions: https://www.ftc.gov/news-events/news/press-releases/2023/03/ftc-finalizes-order-requiring-fortnite-maker-epic-games-pay-245-million-tricking-users-making and https://www.ftc.gov/news-events/news/press-releases/2023/06/ftc-takes-action-against-amazon-enrolling-consumers-amazon-prime-without-consent-sabotaging-their.

[7] https://insightplus.bakermckenzie.com/bm/technology-media-telecommunications_1/united-states-consumer-protection-regulators-set-sights-on-dark-patterns.

[8] https://gdpr-info.eu/issues/consent/; https://gdpr-info.eu/recitals/no-32/.

[9] https://www.warner.senate.gov/public/index.cfm/2023/7/warner-fischer-lead-bipartisan-reintroduction-of-legislation-to-ban-manipulative-dark-patterns

or persuasion-based tactics. These strategies involve describing data sharing as more appealing than it may otherwise appear. Examples of this design include pre-prompts that apps can show users before Apple's app tracking transparency (ATT) prompt,[10] and wording that associates the non-sharing option with negative emotions, commonly known as the "confirm shaming" technique.[11] Recent work has failed to find evidence of the efficacy of these techniques. For example, Bielova, Santos, and Gray (2024) show that changes in consent banner texts do not significantly change privacy choices, presumably because consumers do not pay attention to these texts when interacting with the banners. Similarly, D'Assergio et al. (2022) show that adding persuasive language (other than giving incentives) in emails that request data collection opt-in does not improve the consent rates.

The second type of pattern consists of obstruction tactics, or designs that increase frictions associated with consumer choices undesirable to the firm. The two most prominent examples involve setting defaults to "share all," and designing what are known as "unequal paths." The latter strategy refers to designs that include "share all" on a main screen while the "reject all" option is hidden behind additional clicks (for example, under "settings"). These designs are the most popular dark patterns on websites. Indeed, Habib et al. (2022) show that unequal paths and defaults are present in 78.5% and 26% of consent banners, respectively.

The third and final type of pattern consists of designs that influence choices by changing the visual display of different options. One example of a visual manipulation is differential salience, in which designs gray out undesirable options or make the fonts smaller and harder to see. Another example is the reordering of the options to have the company's preferred option on top. For instance, Apple's ATT banner is accused by advertisers of nudging consumers away from sharing by ranking the "ask app not to track" on top and for using the phrase "tracking," which has a negative connotation. Although there is research comparing how Apple's ATT prompt and its native app prompt affect sharing rates differently (Baviskar et al. 2024), no one has measured whether reordering options alone meaningfully influences data-sharing choices.

We evaluate common dark patterns across many websites, making our results broadly applicable. In particular, we evaluate the effect of three different designs: deliberate obstruction (via hiding different options from the main screen), reordering options, and differential salience.[12] By combining browsing to websites of our choice and browsing

[10] https://www.appsflyer.com/blog/tips-strategy/apps-boost-att-opt-in/

[11] https://www.deceptive.design/types/confirmshaming

[12] It is impossible to include all possible design patterns in a single study, as companies can always uncover new dark patterns via frequent testing and optimization.

that consumers organically engage in, we can validate the consistency of synthetic choices with real-world behavior.

3. The Experiment

3.1. Experimental Design

The goal of our experiment is to identify how people make privacy choices across many websites and choice architectures. To do this, we use Cookie Manager, a browser extension based on the Webmunk framework for browsing-based experiments (Farronato, Fradkin, and Karr 2024). Study participants install the extension on their Chrome browser. The extension manipulates the browsing experience by displaying pop-ups that prompt users to make consequential cookie tracking choices.

Figure 1 displays all the six interfaces we designed. Design C ("Set-Acc-Rej") is what we consider a neutral setting, where we remove all the dark patterns we set out to test. The other interfaces are manifestations of three types of dark patterns. For example, Design A ("Acc-Set") *hides* the reject option (*deliberate obstruction*); Design D ("Acc-Rej-Set") prioritizes accepting cookies by listing it as *the first option* (*reordering options*); and Design F ("Acc-GreyRej-GreySet") emphasizes the accept button with a *brighter color* than the other options (*differential salience*). Participants can click on any of the options displayed, or avoid making an explicit choice by clicking the *X* in the top right corner. If they click on cookie settings, they are presented with six different types of cookies to choose from, such as "information storage and access," "performance and analytics," and "ad selection, delivery, and reporting" (see Appendix Table A1). Selecting all options is equivalent to accepting all cookies; selecting none of the options is equivalent to rejecting all cookies. To minimize choice friction in the "cookie setting" page, we allow consumers to either accept all cookies in one click, or reject all cookies with ease (as the default on this page is selecting none of the category-specific cookies). If they click "X", the website will implement its default data-sharing setting, which is normally "accept all" for US websites.

In total, we have six different banner variations. In addition to the neutral interface, we have two designs with deliberate obstruction (one removes "Reject all cookies," the other removes "Accept all cookies"), two reordered interfaces (one with "Accept all cookies" on top, the other with "Reject all cookies" on top), and one interface with differential salience (where "Accept all cookies" is at the top in blue, whereas the other options are below in gray).

Our banner can appear on any website. It replaces the organic cookie choice interface when one is present, and provides a consent interface when one is absent.[13] To ensure participants' data-sharing choices are incentive-compatible, we enforce their decision to the greatest extent possible by integrating our extension with a script that detects elements of a webpage related to cookie consent through a set of rules, some of which were taken from other open-source packages (e.g., DuckDuckGo's AutoConsent) and others custom-made by Audacious software. Cookie Manager attempts to enforce the decision made through our own banner by selecting the appropriate option in the cookie consent form natively displayed on the website. When users hit 'x' on our banner, Cookie Manager does not attempt to change any settings on the website. We communicate the cookie choice enforcement to our participants.

The randomization of banners is at the *user-by-domain* level: the browser extension randomly selects a cookie interface to show to the participant when they first visit a domain since enrollment in the study, and tracks the corresponding user selection.[14] We chose this randomization strategy to increase statistical power. Note that after a user has made a choice, a pop-up will not show up again on that domain.

After eligibility screening and instructing participants to install the browser extension, the study proceeds in two phases. The first phase is survey-based. Here, we ask participants to visit 20 pre-selected websites.[15] Websites are randomly ordered when we ask participants to visit them. As they visit each of the websites, they make cookie-sharing choices as a function of the assigned pop-up. We choose websites to cover a wide range of categories (social media, e-commerce, news/information, and functionality) and popularity levels.

The survey phase is useful for two reasons. First, it ensures that we have choices across many individuals for each website. This design allows us to have a fixed-effect specification to characterize dark pattern effects across websites and characterize potential unobserved heterogeneity. Second, it allows us to more precisely measure a participant's familiarity with each website by directly asking about their familiarity and visit frequency

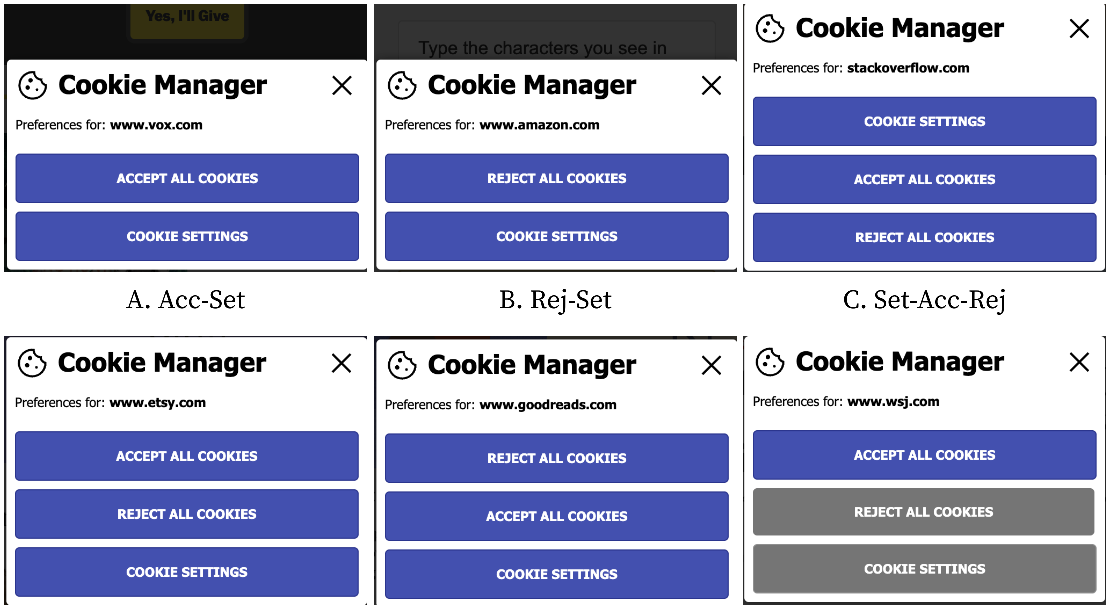
[13] Note that we experiment on US residents, so most of them rarely see such banners, given the lack of federal legislation on the topic.

[13] We tell users "Whenever you visit a website for the first time. If you make a choice, the extension will try to pass on your choices to the website. In most cases, if the website has already been collecting consent from users, it will recognize your choice and decide whether to continue tracking you based on your choice."

[14] In pilot studies, we tested for carryover effects of exposure to the initial choice architecture on all subsequent cookie choices, and found null effects.

[15] The websites are the following: youtube.com, nytimes.com, appleinsider.com, yahoo.com, amazon.com, ebay.com, target.com, etsy.com, turo.com, stockx.com, espn.com, facebook.com, funnyordie.com, weather.com, duckduckgo.com, truewerk.com, thomannmusic.com, merrysky.com, seattletimes.com, semafor.com.

FIGURE 1. Consent Interface Design across Treatment Groups



A. Acc-Set B. Rej-Set C. Set-Acc-Rej

D. Acc-Rej-Set E. Rej-Acc-Set F. Acc-GreyRej-GreySet

Notes: The figure provides screenshots of the six cookie preference interfaces. Captions correspond to the labels used throughout the paper to refer to the treatment conditions. "Acc-Set": accept-settings; "Rej-Set": reject-settings; "Set-Acc-Rej": settings-accept-reject; "Acc-Rej-Set": accept-reject-settings; "Rej-Acc-Set": reject-accept-settings; "Acc-GreyRej-GreySet": accept-grey reject-grey-settings.

with each of the 20 sites, whereas such a measure would be impossible to obtain for sites that participants visit organically.

The second phase relies on participants' organic browsing behavior. We ask participants to keep the extension installed for a week, during which we track their browsing behavior. Instead of showing banners for every new web domain visited, we randomize *users* into one of two treatment conditions: in the *frequent pop-ups* condition, a pop-up appears every 10 minutes a user spends browsing the internet; in the *infrequent pop-ups* condition, a pop-up appears every 60 minutes.[16] At the end of the week, we ask participants to fill out a short outtake survey and uninstall the extension. We pay each participant $7.50 upon study completion. The full set of survey questions is available in Appendix B.

[16]As stated earlier, a participant only sees the banner from one domain once. Thus in our implementation, a countdown starts as soon as the last time the participant sees and interacts with the banner, and the next banner shows up when the 10-minute/60-minute countdown has passed and the participant interacts with a new domain, whichever one is longer.

3.2. Sample Description

We recruited participants on Prolific, and restricted our participants to adults residing in the US who primarily speak English and use Chrome as their main browser.[17] We pre-registered recruiting 800 participants and expected 640 of them to complete the study.[18] Our actual participants are close to the pre-registered numbers (see Appendix Table A1 for the conversion funnel). A total of 1,227 Prolific users started the study; 75% of respondents were eligible. Among these, 877 consented to the study, and 613 participants fully completed the study. Our final sample included everyone who completed the baseline survey and generated valid data points during the organic browsing phase, regardless of whether they proceeded to the outtake survey stage. For our main analysis, we further excluded participants who were not randomized into either the 10-minute or 60-minute treatment during the organic browsing phase.[19] These restrictions allow us to maintain a consistent sample for the analysis of both organic and survey responses. As a result of these selection criteria, we have a total of 656 participants in our main analysis sample.

Table 1 presents descriptive statistics for the main sample. We have a balanced sample between men (54%) and women (46%), and the average age is 38 years old. The median household income in our sample was $50,000-$74,999, with substantial variation, including 12% of households with an income of over $150,000. For the week preceding enrollment in the study, users visit an average of 51 unique domains. During the week of the study after the survey, participants visited 53 unique domains on average, suggesting that most users do not avoid using the browser on which they are tracked.

During the organic phase, our pop-up banners show up in 41 percent of the visited domains. This average masks heterogeneity induced by our experiment. Participants in the 10-minute frequency treatment are exposed to the pop-up for 53% of the domains visited. In comparison, participants in the 60-minute frequency treatment see the pop-up in 30% of the domains visited (see Appendix Table A2).

We verify pop-up design randomization in two ways. First, we run a proportion test on pop-up distribution per website. The proportion test for the distribution of pop-ups across the survey websites has a p-value of 0.99, which fails to reject the null of balanced proportions across the 6 pop-up designs. Second, we perform covariate balance tests by regressing user- and domain-level covariates on treatment conditions (Appendix Table A3). We find no statistically significant differences across pop-up designs.

[17] https://www.prolific.com/.

[18] https://www.socialscienceregistry.org/trials/12862.

[19] Due to an implementation challenge, 3% of the users were not randomized into either the 10- or 60-minute treatment after they completed the survey.

TABLE 1. Summary Statistics

		Mean	Median	Std. Dev.
During Survey	Unique Domains in Prior Week	51.43	47.00	39.11
	Domains w. Banner	18.59	20.00	3.96
Post-Survey	Domains w. Banner	21.69	15.00	21.80
	Unique Domains Visited	52.58	36.00	50.32
	Unique URLs	640.02	370.00	786.98
	End Survey Completed	0.85	1.00	0.35
Demographics	Age	38.16	36.00	13.04
	Female	0.46	0.00	0.50
	Bachelor's or Above	0.18	0.00	0.39
Cookie Behavior	Accept-All Rate	0.53	0.62	0.37
	Close-Window Rate	0.28	0.15	0.33
	Reject-All Rate	0.15	0.00	0.28
Experimental Group	10-Minute Group	0.47	0.00	0.50
	60-Minute Group	0.53	1.00	0.50

Notes: The table shows descriptive statistics for the final study sample. Number of observations: 656.

In the organic browsing phase, in addition to randomizing the pop-up design at the user-domain level, we also randomize the frequency of pop-up appearance at the user level. Appendix Table A2 provides descriptive statistics broken down by the two treatment groups. The two groups are balanced across all user characteristics. None of the differences are statistically significant, except for the number of banners shown in the two groups, which is induced by the experimental randomization. The proportion test for the distribution of pop-ups across the organic visits has a p-value of 0.00093, rejecting the null. Although significantly different, the proportions range from 0.158 to 0.175, which are close to the intended proportions (0.166).

4. Reduced-Form Results

In this section, we describe the causal effects of dark patterns, additional determinants of consent decisions, heterogeneity across users and domains, and results on choice fatigue. We present most results separately for survey and organic phases, since users may behave differently during these two stages. We find that the majority of users accept all cookies in the neutral condition, and dark patterns that increase choice friction substantially affect consent decisions. There is little heterogeneity in choices across domain popularity but substantial heterogeneity across users. Lastly, we find limited evidence of choice fatigue.

4.1. The Effect of Dark Patterns on Data Sharing Choices

Figure 2 presents the choice distribution across treatment conditions, separately for the survey (top panel) and organic phases (bottom panel). There are three main findings. First, participants share their data with the websites more than 50% of the time, even when the design is neutral. In the conditions for which the "Accept Cookies" option is immediately displayed, the accept rate is between 62 and 70 percent in the survey and 55 to 60 percent in organic browsing.[20] The exception to this is for the interface where "Accept Cookies" is excluded from the main screen. In this condition, 21 percent in the survey and 17 percent in organic browsing choose to accept all cookies by going to the "cookie settings" page.

Second, granular choices are infrequent. Across all treatment conditions, participants make selective cookie choices only occasionally, ranging from 3% in the neutral condition to 6-9% in conditions that deliberately hide either the "accept" or the "reject" option.

Third, participants react similarly to dark patterns when engaging in the survey and when browsing organically. This finding gives us confidence that choices during the survey, which may be considered more artificial, nonetheless represent dark pattern effects. The most notable difference between survey and organic behavior is that participants are more likely to close the window in lieu of making active cookie choices during the organic browsing phase.

Next, we quantify the causal effects of dark patterns on consumer choices using the following regression:

$$y_{ij} = \beta_{acc-set} + \beta_{acc-greyrej-greyset} + \beta_{acc-rej-set} + \beta_{rej-acc-set} + \beta_{rej-set} + \mu_i + \nu_{c(j)} + \epsilon_{ij}. \quad (1)$$

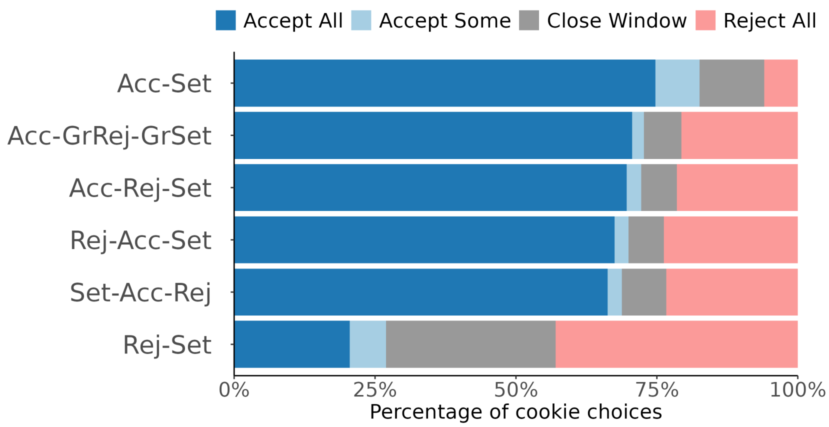
Here, i denotes the participant, and j denotes the website. We include participant fixed effects μ_i and website category fixed effects $\nu_{c(j)}$.[21] Each of the β coefficients measures the effect of a specific treatment condition relative to the neutral setting (Condition C in Figure 1).[22] We focus on three outcomes: accepting all cookies, rejecting all cookies, and

[20] Our acceptance rates are high but if lower than prior evidence. For example, Bielova et al. (2024) show that 83% of participants in their artefactual study accept cookie tracking when the choice is offered with a "neutral" design.

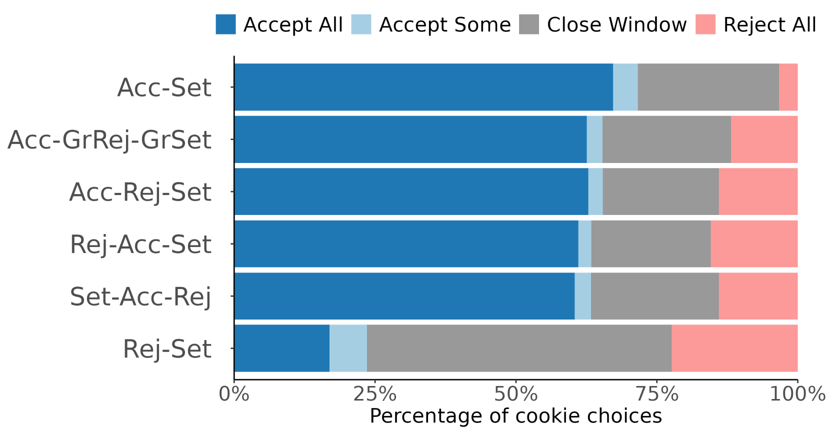
[21] We obtain website category information using WebShrinker (https://webshrinker.com/), a popular web categorization API that categorizes websites using labels from the Interactive Advertising Bureau (https://www.iab.com/).

[22] Relative to the pre-registered specification, we have changed the baseline design to a neutral design to be consistent with the existing literature in computer science (see Bielova et al. (2024) for example).

FIGURE 2. Cookie Choices by Experimental Condition



A. Survey Choices



B. Organic Choices

Notes: This figure displays the proportions of cookie choices across banner design treatments. The possible choices are: Reject all cookies, Close window (i.e., the user clicks on the *X* of the pop-up window to close it), Accept some cookies (i.e., a user clicks on settings and select a subset of cookie types), and Accept all cookies. All choices indicate the final choice, e.g., "Accept All" includes instances where a participant clicks into the "settings" page and manually selects all cookies. Each row corresponds to a treatment condition. The mapping of the labels to each interface is presented in Figure 1.

closing the window without making an active choice. Given its small share, the analysis of the decision to select specific types of cookies is left to Appendix A5.

Table 2 displays our main results, with standard errors clustered at the participant level. Columns 1 through 3 focus on survey choices, whereas columns 4 through 6 focus on organic choices. Under the neutral design baseline, 66% of participants accept all cookie tracking, 23% reject all tracking, 8% close the window, and the rest select to accept a subset of the cookies. Removing the reject button increases tracking the most, by 7.9 percentage points (or a 12% increase). Next, the design with “accept all” at the top and the other options grayed out leads to a 3.6 percentage point increase (5%) in the share of participants choosing tracking. Putting the accept option at the top without differential salience moderately increases acceptance rates by 2 percentage points. Having the reject option at the top is statistically equal to the neutral setting with small point estimates. Finally, removing the accept button has a large negative effect on the tracking share, which decreases by 46 percentage points (a 70% reduction).

Moving to the effect on rejection rates in column 2, even the most privacy-preserving design (i.e., removing the accept all option) fails to move the reject rate above 50%. Specifically, this design increases the share of users who reject cookies from 23% to 43%. In contrast, hiding the reject button reduces the proportion of rejecting by 17 percentage points (a 74% decline). Other conditions have smaller effects.

Lastly, we consider rates of closing the pop-up window (Column 3). When the accept button is hidden, the proportion of participants closing the pop-up increases by over 200%. This suggests that a large share of users prefer to accept cookies when that option is easily available, but avoid explicitly rejecting cookies even when that is possible with the click of a button. The other conditions have smaller effects.

Similar to the survey choices, dark patterns have important effects on organic websites as well (Columns 4 to 6). One main difference between the survey and organic choice patterns is that participants close windows much more frequently in the organic than in the survey phase (23% in organic vs. 8% in survey). This pattern may reflect the fact that consumers allocate less attention to cookie choices when browsing the internet organically, as they would be primarily focused on other tasks such as browsing the internet or completing a shopping activity. As we show below, users’ beliefs about the implications of closing the window translate to similar proportions of users who accept and reject cookies across survey and organic choices.

We then quantify the effect of the three dark patterns rather than the effect of each treatment condition. This means estimating the following regression:

TABLE 2. Cookie Choices by Experimental Condition

	Survey			Organic		
	Accept All (1)	Reject All (2)	Close Window (3)	Accept All (4)	Reject All (5)	Close Window (6)
Acc-Set	0.079***	-0.172***	0.039***	0.055***	-0.094***	0.016
	(0.012)	(0.014)	(0.009)	(0.011)	(0.012)	(0.012)
Rej-Set	-0.464***	0.199***	0.228***	-0.429***	0.094***	0.299***
	(0.019)	(0.016)	(0.017)	(0.022)	(0.012)	(0.022)
Acc-Rej-Set	0.020*	-0.007	-0.010	0.035**	0.002	-0.041***
	(0.010)	(0.008)	(0.006)	(0.011)	(0.007)	(0.009)
Rej-Acc-Set	0.005	0.012	-0.013*	0.006	0.022**	-0.026**
	(0.009)	(0.009)	(0.006)	(0.010)	(0.008)	(0.009)
Acc-GrRej-GrSet	0.037***	-0.019*	-0.012*	0.033**	-0.017*	-0.019*
	(0.009)	(0.009)	(0.006)	(0.010)	(0.008)	(0.009)
Benchmark group mean	0.66	0.23	0.08	0.60	0.14	0.23
R^2	0.653	0.582	0.573	0.580	0.522	0.510
Observations	12,142	12,142	12,142	14,163	14,163	14,163
Participant fixed effects	✓	✓	✓	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓	✓	✓	✓

Notes: Regression results of Equation 1 for three outcomes: accept all cookies, reject all cookies, and close the window without making a choice. The results are presented separately for two different sets of choices: survey choices (columns 1 through 3) and organic choices (columns 4 through 6). *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

$$y_{ij} = \gamma_{reject\ hidden} + \gamma_{accept\ hidden} + \gamma_{accept\ on\ top} + \gamma_{reject\ on\ top} + \gamma_{highlight\ accept} + \mu_i + \nu_{c(j)} + \epsilon_{ij}. \tag{2}$$

Compared to Equation 2, the dummies for treatment conditions are replaced with dummies describing which choice option is on top (accept or reject), which option is hidden (accept or reject), and which option is highlighted (accept).

Table 3 displays the results. Deliberate obstruction is the most effective pattern. Hiding the "reject" button from the main screen increases the probability of accepting all cookies by 7.9 percentage points during the survey phase and 5.3 percentage points during the organic browsing phase. This disadvantages privacy-conscious users, who would choose to reject cookies in a neutral interface but fail to do so instead.

The effect of hiding the "accept" button is even more drastic, decreasing the probability of accepting cookies by 47 percentage points during survey phase and 43.4 percentage points during organic browsing. Another impact of deliberate obstruction is increasing disengagement. In particular, hiding the "accept" button increases the probability of closing the pop-up window by 24.2 percentage points (during the survey) to 32.6 percentage points (during organic browsing). The fact that hiding the "accept" button has a higher impact on cookie-sharing choices than hiding the "reject" button reflects the fact that the baseline sharing probability is high, and thus hiding this option affects choices more.

In comparison, designs that rely on changing the visual presentation alone, mainly reordering and differential salience, are less effective in changing choices, reflected by both the small coefficients associated with them and the statistical insignificance of most estimates. Their effects increase during the organic phase, but still with small magnitudes.

TABLE 3. Cookie Choices by Dark Pattern

	Survey			Organic		
	Accept All (1)	Reject All (2)	Close Window (3)	Accept All (4)	Reject All (5)	Close Window (6)
Reject Hidden	0.079^{***}	-0.172^{***}	0.039^{***}	0.055^{***}	-0.094^{***}	0.016
	(0.012)	(0.014)	(0.009)	(0.011)	(0.012)	(0.012)
Accept Hidden	-0.469^{***}	0.187^{***}	0.240^{***}	-0.435^{***}	0.071^{***}	0.325^{***}
	(0.019)	(0.016)	(0.017)	(0.022)	(0.011)	(0.022)
Accept Top	0.020^{*}	-0.007	-0.010	0.035^{**}	0.002	-0.041^{***}
	(0.010)	(0.008)	(0.006)	(0.011)	(0.007)	(0.009)
Reject Top	0.005	0.012	-0.013^{*}	0.006	0.022^{**}	-0.026^{**}
	(0.009)	(0.009)	(0.006)	(0.010)	(0.008)	(0.009)
Highlight Accept	0.017	-0.012	-0.002	-0.002	-0.019^{**}	0.022^{*}
	(0.010)	(0.009)	(0.006)	(0.010)	(0.007)	(0.009)
Benchmark group mean	0.66	0.23	0.08	0.60	0.14	0.23
R^2	0.653	0.582	0.573	0.580	0.522	0.510
Observations	12,142	12,142	12,142	14,163	14,163	14,163
Participant fixed effects	✓	✓	✓	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓	✓	✓	✓

Notes: Regression results of Equation 2 for three outcomes: accept all cookies, reject all cookies, and close window without making a choice. The results are presented separately for two different sets of choices: survey choices (columns 1 through 3) and organic choices (columns 4 through 6). Appendix Table A6 presents similar results for the decision to accept a subset of cookie types. $^{*}p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

These results point to three main conclusions: Users often accept cookie tracking absent dark patterns while browsing the web; dark patterns that increase choice frictions are effective in changing people's choices;[23] closing the window without making an active choice is a frequent selection, even more true in the wild than in a synthetic survey-based

[23]These causal effects are broadly in line with existing findings in artefactual or survey experiments. For instance, Habib et al. (2022) compare a design where the reject option is hidden with a design where rejecting is the default, and found a sizable difference in choices among the two groups. Both Utz et al. (2019) and Vásquez Duque (2024) examined the effect of differential salience designs and found small to no effect on choices.

setting, signifying the importance of website default tracking options in the absence of a choice.

Our results show that closing the window without making an active choice is a frequently chosen option. It is thus critical to identify users' beliefs when they make this choice, which we measure in the outtake survey. Among our participants, 60% believe that closing the window is identical to rejecting cookies; another 26.2% believe the opposite. The rest of the participants believe neither is true, and instead conjecture that the website will fall back to its default settings, ask for consent during the next visit, or simply express uncertainty about what the website will do. Users who believe that closing the window is akin to rejecting cookies close the window at the same rate as those who think closing the window implicitly accepts cookies. However, both groups are 50% more likely to close the window than participants with ambivalent beliefs.

Incorporating user beliefs when closing the window into our results confirms that the implied choices between the two phases are much more similar than they may appear at first. Indeed, imputing inactive choices using user beliefs implies that 68 percent ($0.66 + 0.262 * 0.078$) of users in the survey and 66 percent ($0.6 + 0.262 * 0.23$) in organic browsing mean to accept cookies. Similarly, 28 percent (0.232+0.6*0.78 in the survey and 0.139+0.6*0.23 in organic browsing) of users mean to reject cookies in either phase.

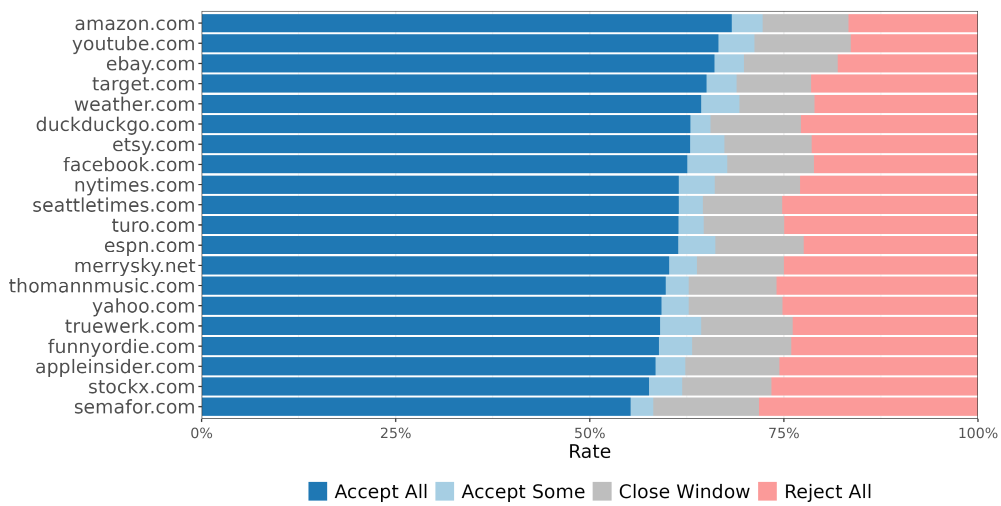
Table A6 indicates that consumers tend not to make granular cookie choices, and would rather opt out of making choices altogether by closing the consent window. In the neutral design group, only 3% of participants accept a subset of cookie types; deliberately hiding either "accept all" or "reject all" options from the main screen encourages participants to check out the settings menu, but only increases the probability of granular choices by 2-5 percentage points. Among those who make granular selections, 83% choose to accept cookies for *preferences and functionality*, while only 7% accept cookies for *ad selection, delivery, and reporting* (see Appendix Table A7). This result suggests that targeted advertising is the least preferred use of consumer data, at least among the few users who make selective choices.

4.2. Heterogeneity of Cookie Choices by Domain Characteristics and User Familiarity

A key question of our paper is how cookie consent forms and dark patterns affect competition. To investigate competitive effects, we consider the heterogeneity of consent rates across domains and website categories. We find that users are more likely to consent to tracking from more familiar websites, but familiar and popular websites do not enjoy a differential advantage of using dark patterns.

We begin by looking at survey phase choices, for which we have a balanced panel of user-by-domain interactions. The most known domains in our survey have the highest accept rates. Figure 3 displays cookie choices across individuals and treatments for each website separately, ranked by the probability that participants choose to accept all of their cookies. The websites at the top, such as amazon.com, youtube.com, and ebay.com, are well-known and frequently used. At the other extreme are lesser-known websites such as truewerk.com, merrysky.net, semafor.com, which only 2-3% of participants indicate they normally visit.

FIGURE 3. Cookie Choices by Survey Website



Notes: The figure shows the breakdown of user choices across the 20 websites in the survey.

To understand how cookie-sharing choices vary across websites and user experience, we construct measures of user familiarity with the website and popularity. The first two measures come from our survey phase, where for each website, we ask consumers whether they have *heard of* it and whether they *normally visit* it. These variables are available for the 20 websites featured in the survey phase.We then construct two other metrics that are available for both survey and organic websites. To measure site familiarity, we compare each site visited during our study with the participant's browsing history in the previous two weeks, and flag *pre-exp visit* as one when the website is listed in their browsing history. We also use log *domain rank* as a proxy for website popularity. The domain rank data comes from Tranco, which provides a stable ranking of websites based on an aggregation of several ranking approaches.[24]

Table 4 shows how participants' sharing decisions vary with these variables. Each of the three panels represents a set of regressions of Equation 1, to which we add additional

[24] https://tranco-list.eu/methodology

controls: *normally visit* and *heard of* in Panel *a*, *pre-exp visit* in Panel *b*, and *domain rank (log 10)* in Panel *c*.

TABLE 4. Heterogeneity in Cookie Choices across Websites

	Survey			Organic		
	Accept All	Reject All	Close Window	Accept All	Reject All	Close Window
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Panel a: Familiarity based on survey answers						
Normally Visit	0.062***	-0.065***	-0.013*			
	(0.009)	(0.010)	(0.006)			
Heard Of	0.012	-0.024*	0.004			
	(0.010)	(0.010)	(0.008)			
Panel b: Familiarity based on browsing history						
Pre-Exp Visit	0.024*	-0.027*	-0.002	0.039***	0.003	-0.043***
	(0.011)	(0.010)	(0.007)	(0.008)	(0.005)	(0.007)
Panel c: Website popularity						
Domain Rank (Log 10)	-0.017***	0.014***	0.002	0.001	-0.002	0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: Regression results of Equation 1, in which we add explanatory variables to explore heterogeneity in cookie tracking choices. In Panel *a*, we add two dummies to indicate whether the study participant has heard of the website and whether they study participant normally visits the website. In Panel *b*, we add a dummy to indicate whether the study participant visited the website in the two weeks preceding the study (we obtain this information by collecting their Chrome browsing history). In Panel *c*, we add the website popularity rank (in logs). *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

In the survey websites, all measures of familiarity and popularity are positively correlated with cookie acceptance decisions. If a user normally visits a website, has visited the website in the preceding two weeks, or if the website is more popular (i.e., lower rank), the user is more likely to accept cookies (columns 1 and 2). In particular, having a user interacting with a site that they normally visit is associated with a 6 percentage point increase in the acceptance rate (panel a). On the other hand, having visited a website in the prior two weeks (panel *b*), and increasing site popularity 10-fold (panel *c*) are both associated with a 2 percentage point increase in the acceptance rate. Despite the positive correlation, these effects are relatively small compared to the baseline acceptance rate.

During the organic phase, a user is 3.9 percentage points more likely to accept cookies in lieu of closing windows on websites they have visited in the previous two weeks (column 4). On the other hand, the correlation between domain rank and acceptance decision is absent. This presumably happens because participants are browsing their site of choice, thus a site being popular has less additional effect in changing their cookie tracking decision. In comparison, surveyed sites are pre-specified, in which case the ranking and credibility of a site could matter more. This is consistent with participants' stated reasons for sharing data: in our endline survey where we ask open-ended questions on why they may choose to accept/reject cookies, trust and familiarity with a website are the most commonly cited reasons.

Next, we examine heterogeneity in treatment effects across websites. Figures A2 and A3 show that there is some heterogeneity in dark pattern effects across surveyed site domains. Interestingly, whenever dark patterns have different effects across sites, they seem to alleviate participants' inclination to share data with popular and familiar sites (see Appendix Tables A8, A9, and A10).

On the other hand, we do not find evidence of substantial treatment effect heterogeneity during organic visits for domain ranking (A11). Neither do we find any evidence of treatment effect heterogeneity in terms of whether we observe a user having visited the website before (A12). Taken together, the ability to use dark patterns does not differently help popular and incumbent websites over others, at least in terms of the types of data collected.

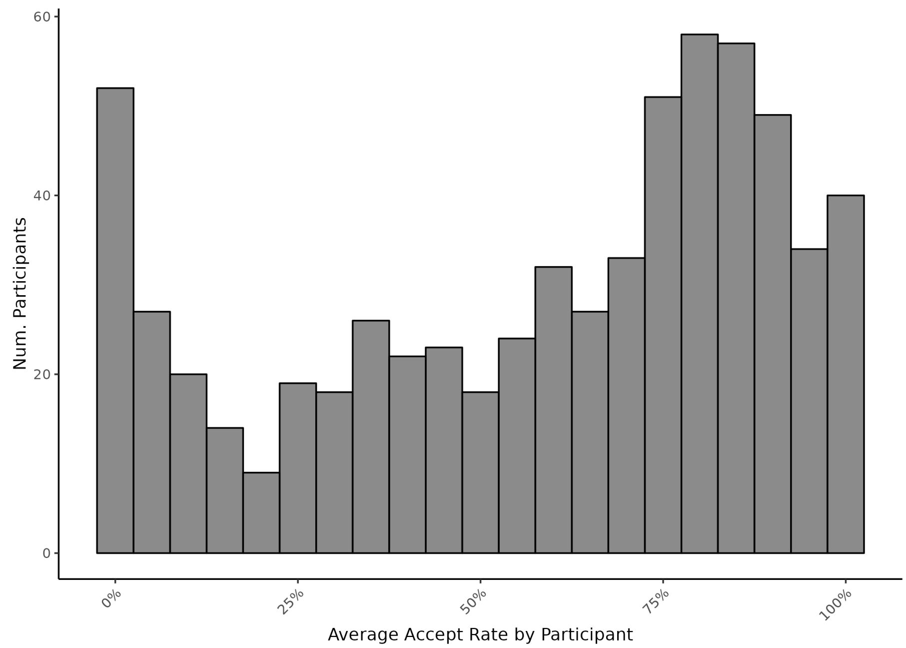
4.3. Heterogeneity across Individuals

Next, we consider individual choice patterns and how these choices vary across websites within individuals. We observe some heterogeneity in cookie choices across websites, consistent with the previous literature that privacy choices vary heavily with the economic context (Nissenbaum 2004; Lin 2022). That said, we find that individual heterogeneity in decisions to accept cookies is much bigger than domain-level heterogeneity.

Figure 4 displays the distribution of accept rates across individuals, combining data from both survey and organic data. We see a bimodal distribution, with some users never accepting and other users accepting most of the time. An overwhelming majority have at least some variation in choices—91.8% of participants change their cookie-sharing decisions across sites at least once. These variations, however, can reflect either systematic variation across websites and variation in the underlying benefit-cost trade-offs, or choice mistakes, e.g., one induced by varying choice architecture.

To isolate the choice variation induced by dark patterns from the variation explained by website differences, we examine the extent to which each user makes different cookie choices across websites when faced with the neutral design (*settings-accept-reject*). To allow for variation, we exclude participants who get exposed to the neutral design only

FIGURE 4. Distribution of Accept-All Rates by Participant (All Sites)



Notes: The figure shows the distribution of accept-all rates across users across all sites in both samples.

once during organic browsing.[25] Holding the neutral design fixed and excluding "closing window" choices, 30% of participants change their data sharing decisions across sites; 55% choose to always accept cookies, and another 9% choose to always reject cookie tracking.[26] We conclude that while a substantial share of users discern across websites when making data-sharing decisions, the majority of users in our sample prefer sharing data to all websites.

To quantify and compare the magnitudes of different sources of choice heterogeneity, we estimate a random effects model where the accept-all outcome is a function of treatments, participant random effects, and domain random effects. Table **??** displays the results of this model across both survey and organic domains. The standard deviation of the participant random effect is more than 5 times higher than the standard deviation of the domain random effect. This finding demonstrates that user heterogeneity plays a significant role in determining data-sharing choices compared to domain-specific differences, such as domain popularity and website category. Note that consumer familiarity and trust towards a website is user-domain specific, and choice variation induced by familiarity and trust is captured by the residual term rather than domain random effect.

[25] 5% of study participants see the neutral design only once during the organic phase of the study.
[26] The remaining 6% of participants always close consent window while in the neutral design condition.

We also explore the differences between consumers who always make the same choice and those who make discerning choices in Table A13. Generally speaking, better-educated participants and women are more likely to always reject all cookies, and less digitally active participants are more likely to share all cookies.

4.4. Choice Fatigue

Next, we examine whether the attention users pay to choices changes as they receive more pop-ups. We compare the differences in choices between our 10-minute and 60-minute treatments to show that there isn't choice fatigue when we increase the frequency of pop-ups.

The 10-minute treatment see our banners in 53% of the domains they visited, while the 60-minute treatment see these banners in 30% of the domains. Given this difference, we can see whether the frequency of choice types varies between these two conditions. We estimate the effects of this treatment in the following regression specification.

$$y_{ij} = \beta_{10\ minutes} + \gamma * time\ in\ study_{ij} + \nu_{c(j)} + \epsilon_{ij}. \tag{3}$$

The baseline is the condition where a user sees the pop-up every 60 minutes, while the alternative condition displays a pop-up every 10 minutes. We also control for the time a user has been in the study (post-survey), since this may be correlated with their overall engagement with the study.[27]

Table 5 displays the results. We highlight two findings. First, we do not find a differential impact of pop-up frequency on data-sharing choices, whether it is the acceptance rate or the inclination to close banners. Users make similar choices, whether they see a pop-up every 10 or 60 minutes. These null effects are precisely estimated, as the 95% confidence interval excludes effects greater than 7%.

Second, time spent in the study has an effect on choice. Each additional day in the study increases the share of people closing the pop-up by two percentage points. Since study participants remain in the study for 7 days, this implies that they are 14 percentage points more likely to close the window at the end of the study compared to the first day.

It is tempting to directly interpret the time in the study as another measure of choice fatigue, but it is not randomly allocated and could be correlated with underlying consumer characteristics and privacy preferences. To address this concern, in Appendix Table A14 we add individual and hour-of-the-day fixed effects, as well as control for the order of the

[27] Adding this covariate does not affect whether we detect any treatment effects.

TABLE 5. Fatigue in Cookie Choices During Organic Browsing

	Accept All (1)	Reject All (2)	Close Window (3)
10 Min Pop-up	0.003	0.008	-0.007
	(0.035)	(0.023)	(0.030)
Time in Study (Days)	-0.009*	-0.005*	0.016***
	(0.004)	(0.002)	(0.004)
R^2	0.008	0.004	0.011
Observations	14,163	14,163	14,163
Domain Cat. fixed effects	✓	✓	✓

Notes: This table shows estimates of Equation 3, where '10 Min Pop-up' is an indicator for whether the user was in the treatment where pop-ups occurred at a frequency of once every 10 minutes. *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

domain visit. Even with these covariates, we see that time in the study reduces acceptance and increases close-out. The most likely explanation for this effect is that participants reduce their engagement with the study over time.

5. A Model of Privacy Choices and Dark Pattern Effects

In this section, we introduce a model of consumer decision to share data. Consumers have preferences over data-sharing options and dark patterns influence data-sharing choices by altering the frictions and salience of different options. The model allows us to quantify consumer preferences for data-sharing options and the costs of the frictions induced by dark patterns.

Our model works as follows. (For ease of comparison, Section 5 summarizes the utilities for all options in the model and how they vary across conditions.) When faced with a consent pop-up, a consumer can choose among four different actions: {accept all, reject all, customize settings, close window}. Let θ_{kj} represent the utility of data-sharing option k for site j. In particular, $k = 1$ refers to accepting all cookies; $k = 2$ refers to rejecting all cookies, whose utility is normalized to zero; and $k = 3$ refers to the customized settings.[28] The utility of closing the consent banner depends on user beliefs about the website's data collection default and the cost of clicking to close the pop-up, κ_t. The cost

[28]Our design does not allow us to separately identify the benefit of making granular cookie choices and the cost of making them. Therefore, it is possible that a consumer has a high utility from only sharing selected cookies, but does so rarely in practice because the cost of making them is too high.

term κ_t, which we allow to change over time t, captures many reasons why closing the pop-up is differentially attractive than making an explicit choice.[29] We solicit user beliefs on the website default directly in the endline survey, and use b_i to represent their subjective probability that closing window leads to sharing all cookies, which takes different values: $\{0(\text{reject}), 1(\text{accept}), 0.5(\text{unsure})\}$. We let those who are uncertain about the effect of closing a window ($b_i = 0.5$) have a weight discount on their belief, denoted as ρ.[30] Lastly, some consumers (10%) did not disclose their belief in our survey question. Instead of imputing their beliefs, we simply assign them a different utility shifter κ_2 for closing windows.

Dark patterns steer these choices either by increasing choice frictions or changing the salience of different options. Consumers face a cost, C_1, of clicking on the settings button to access more options, and an additional cost C_2 of clicking on 'accept all' conditional on being already on the "settings" page (recall that they need to make an extra click to accept all cookies compared to rejecting all on this page). Lastly, ranking an option on top and graying out an option can change their salience. We model these salience effects as factors multiplying the utility of the options where these visual elements apply. For example, ranking the "select all" option on top would change its utility from θ_1 to $(1+\delta_1)\theta_1$. Similarly, the utility of a grayed-out option is multiplied by $(1+\delta_2)$.

TABLE 6. Utilities Across Interface Conditions

Treatment	**Accept All**	**Reject All**	**Customize Settings**	**Close Window**
Acc-Set	$(1+\delta_1)\theta_1$	$-C_1$	$\theta_3 - C_1$	$\theta_1(b + \rho(b = .5)) + \kappa_t$
Rej-Set	$\theta_1 - C_1 - C_2$	0	$\theta_3 - C_1$	$\theta_1(b + \rho(b = .5)) + \kappa_t$
Set-Acc-Rej	θ_1	0	$\theta_3 - (1-\delta_1)C_1$	$\theta_1(b + \rho(b = .5)) + \kappa_t$
Acc-Rej-Set	$(1+\delta_1)\theta_1$	0	$\theta_3 - C_1$	$\theta_1(b + \rho(b = .5)) + \kappa_t$
Rej-Acc-Set	θ_1	0	$\theta_3 - C_1$	$\theta_1(b + \rho(b = .5)) + \kappa_t$
Acc-GrRej-GrSet	$(1+\delta_1)\theta_1$	0	$\theta_3 - (1-\delta_2)C_1$	$\theta_1(b + \rho(b = .5))$

A consumer i picks the option k that maximizes their utility given the treatment (we remove the dependence on site j for simplicity):

$$\max_{k \in \{acc, rej, cust, close\}} U_{ik|treatment} + \epsilon_{ik}.$$

[29] For instance, a consumer may dislike closing the pop-up because it is less front and center compared to other options, or that the exact consequences of closing windows is ambiguous.

[30] We do not impose a weight discount on explicitly expressed beliefs (i.e., when participants state that closing window equals accepting all cookies or rejecting all cookies), as the data shows that people who hold these beliefs substitute close-window and the (subjectively) implied action in a 1-1 ratio.

Assuming that the errors are iid distributed according to a Type-1 extreme value distribution, we have the following choice probabilities:

$$Pr(\text{choose option j}|treatment) = \frac{exp(U_{ij|treatment})}{\sum_{j\in\{acc,rej,cust,close\}} exp(U_{ij|treatment})}.$$

We estimate the model using maximum likelihood based on data from both the survey and organic phases. To allow for preference heterogeneity, we also estimate the model on three different subsets: those who always accepted in the neutral condition (acceptors), those who always rejected in the neutral condition (rejectors), and those who varied the choices in the neutral condition (discerners).

Table 7 displays our estimates. The utility of accepting all cookies is high for acceptors, an equally large negative for rejectors, and modrate for discerners. The utility of making a granular choice is negative for both acceptors and rejectors, and moderately positive for discerners. Meanwhile, the cost parameters indicate substantial frictions caused by the dark patterns. The cost of clicking on the settings button ranges from 1.49 to 2.22 across three subsets, and is similar in magnitude to the utility (or disutility) of accepting all cookies for acceptors and rejectors. The cost of clicking "accept all" after entering the settings menu is smaller but still significant, suggesting that even minor additional steps deter users. The salience effects matter to a lesser degree compared to choice frictions. Lastly, the utility of closing the window is much lower among discerners than the other subgroups. Still, the magnitude of κ_t is smaller than C_1, suggests that closing the window is much less costly than going to the "settings" menu.

5.1. Consumer Surplus under Counterfactual Policies

The structural estimates allow us to consider the welfare effects of different dark patterns and data collection policies. We find that the utility-maximizing interface is the neutral design "Set-Acc-Rej", combined with a site default that collects all cookies when consumers close the consent window. Together, this design increases consumer surplus by 11% compared to the most common dark pattern in the US, an "Acc-Set" interface with an accept-all site default. On the other hand, our calculation reveals that even the optimal consent interface still delivers suboptimal surplus compared to a policy that removes the need of interacting with banners by site, which can increase the surplus by up to 43%.

To convert the utility and choice friction estimates into policy relevant numbers, we calculate the consumer surplus under different counterfactual privacy policy regimes. We consider the following proposals:

TABLE 7. Parameter Estimates Across Consumer Subsets

Parameter	Explanation	Pooled Estimate	Accepters	Rejectors	Discerners
θ_1	Utility of accepting all	0.999***	2.106***	-2.129***	0.490***
		(0.018)	(0.005)	(0.060)	(0.014)
θ_3	Utility of granular choice	-0.425***	-1.324***	-0.975***	0.452***
		(0.008)	(0.007)	(0.008)	(0.009)
C_1	Cost of clicking settings	1.445***	1.493***	2.221***	1.779***
		(0.006)	(0.006)	(0.003)	(0.005)
C_2	Cost of clicking accept after settings	0.337***	0.599***	0.630***	0.161***
		(0.013)	(0.021)	(0.039)	(0.018)
δ_1	Effect of ranking on top	0.249***	0.370***	-0.117**	0.068***
		(0.011)	(0.006)	(0.054)	(0.012)
δ_2	Effect of being grayed out	-0.087***	-0.059***	-0.307***	-0.095***
		(0.022)	(0.010)	(0.014)	(0.014)
κ_t	Utility shifter of closing window	-0.456***	-0.078***	-0.814***	-1.013***
		(0.003)	(0.008)	(0.004)	(0.010)
ρ	Risk aversion upon uncertain belief	-0.536***	-0.186**	0.026	-0.900***
		(0.036)	(0.082)	(0.026)	(0.017)

Notes: Acceptors (55%), rejectors (9%), and discerners (30%) are defined using choices in the neutral design condition; these three groups consist of 94% of the sample, while the rest are participants who alwasy close window in the neutral condition. Standard errors are clustered at the participant level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

1. US status quo: An "accept-settings" design, with websites defaulting to collect all cookies upon inaction (closing the window);
2. Consumer welfare maximizing banner: a neutral design, with websites defaulting to collect all cookies upon inaction (closing the window);
3. EU norm: a neutral design, with websites defaulting to collecting no cookies upon inaction (closing the window);
4. Pro sharing: forcing everyone to accept (the world before GDPR);
5. Pro privacy: forcing everyone to reject (common implementations of COPPA and children's privacy laws in general, see Johnson et al. (2024)).

Of the above, policies 1, 3, 4, 5 already exist in the current policy landscape. We also include policy 2, which allows us to decompose the comparison between the US and EU norm into a dark pattern effect and a website default effect. Policy 2 is also the one that maximizes average consumer welfare across all the banner design and website default combinations we have tested.

The correct welfare calculation needs to account for how consumers' incorrect beliefs about what happens when they close the consent window. To this end, we allow choice probabilities to be guided by consumer beliefs, while computing the actual utility using websites' default action upon consumer inaction. Based on Train (2015), consumer surplus under potentially mistaken belief can be expressed as the following:

$$CS = log\left(\sum_{k=1}^{4} e^{u_k}\right) + \sum_{k=1}^{K} Pr_k \cdot d_k,$$

where u_k is the perceived utility associated with different options, Pr_k is the probability of consumers choosing option k, and d_k is the difference between actual and the perceived utility.[31]

We then calculate the surplus for each of the policies above. For choices under the US status quo, we incorporate choice frictions and associated utilities under Treatment 1, and let $\sum_{k=1}^{K} Pr_k \cdot d_k$ be $Pr_4 \cdot (u_1 - (b_i \cdot u_1 + (1 - b_i) \cdot u_2)) = Pr_4 \cdot (1 - b_i)(u_1 - u_2)$. For consumer surplus under the post-GRPR norm, we incorporate frictions under Treatment 3 when calculating the utilities, while expressing $\sum_{k=1}^{K} Pr_k \cdot d_k$ as $Pr_4 \cdot b_i(u_2 - u_1)$. The surplus under forced choices including the utility loss from not being able to customize the choice and the gain from time savings. To reflect both of these components, we replace $log\left(\sum_{k=1}^{4} e^{u_k}\right)$ with u_k, where $k \in 1, 2$ represents the forced option. We then add in the time savings from not having to interact with banners: Treating C_1 as reflecting the time cost alone, we obtain this time saving utility as $C_1 \times$ (time spent per banner / time to click "settings").[32]

Lastly, we want to scale the welfare numbers into dollar values. Before describing our approach, we note the challenges associated with this calculation. Our data does not include consumers' dollar valuation of their cookies, nor their valuation for reducing one additional click to the settings. Instead, we need to resort to other papers that provide dollar-value estimates on either of the two. We then use this number to scale the welfare numbers, leveraging the fact that the relative scale of consumer surplus to friction parameters are known.

To achieve this goal, we perform a back-of-the-envelope calculation using the time spent data we have and time value estimates from existing work (Greminger, Huang, and Morozov 2023). Our lower bound for the cost of clicking settings is the opportunity cost of time. Column 4 of Table A15 shows that users who have to click "settings" as a result of the deliberate obstruction design spend 6.73s longer on the choice during the organic period. With a time cost of $69/hour (Greminger, Huang, and Morozov 2023), this extra time translates to a value of 12.9¢ per choice. In our sample, users visit an average of 52.6 domains per week, thus the dollar value of *time cost* C_1 is $6.79 per week. However, this lower bound is quite conservative in that it does not include the "hassle cost" of clicking

[31] It is important to note that we consider the error term associated with hitting 'x' as a separate i.i.d. draw, even though the choice is perceived as resulting in the same outcome as one of the other choices.

[32] For time spent per banner, we take the average time a consumer interacts with the banner in the organic phase during the neutral design treatment, which captures the cost of making the choice when no deliberate obstruction added.

settings. Our upper bound for the hassle cost comes from the search cost per link also from Greminger, Huang, and Morozov (2023). They estimated the search cost per product link to be \$0.67 to \$8.19 across product categories. Using the lowest search cost to approximate the cost of clicking on settings gives us a friction cost estimate of \$35.24 per week.

Table 9 displays our consumer surplus estimates across consumer subsets using the dollar value estimates from above; for the ease of comparing the welfare values with utility from each choice, we also provide the welfare numbers in their original utility scale in Table 8. Our back-of-the-envelope calculation suggests that while each choice has small consequences, the aggregate impacts of better interfaces are sizable.

TABLE 8. Consumer Surplus Under Counterfactual Policies (Utility Scale Results)

Counterfactual Policy	Pooled Estimate	Accepters	Rejectors	Discerners
US Status Quo	2.006	2.909	-0.596	1.524
CS Maximizing Banner	2.232	3.137	0.719	1.813
EU Norm	2.051	2.747	1.051	1.755
Force Accept All	2.883	3.837	0.053	4.515
Force Reject All	1.927	1.809	2.279	4.044

Notes: The values represent unscaled consumer surplus *per choice* under various counterfactual policies in the original scale. "Pooled estimate" refers to the estimate across all subjects, and the other columns correspond to subset-specific estimates. "US status quo" refers to an accept-settings interface, combined with an accept-all default when consumers close window; "CS maximizing" refers to a neutral interface with an accept-all default when consumers close window; "EU norm" refers to a neutral interface with a reject-all default when consumers close window.

TABLE 9. Consumer Surplus Under Counterfactual Policies (Dollar-Value Weekly)

Counterfactual	Lower Bound				Upper Bound			
	Pooled Estimate	Accepters	Rejectors	Discerners	All Subjects	Accepters	Rejectors	Discerners
US Status Quo	9.422	13.418	-2.375	3.672	48.931	68.643	-9.458	30.193
CS Maximizing Banner	10.483	14.470	2.865	4.369	54.448	74.046	11.407	35.913
EU Norm	9.633	12.671	4.188	4.229	50.037	64.837	16.680	34.778
Force Accept All	13.541	17.699	0.211	10.879	70.313	90.572	0.841	89.442
Force Reject All	9.050	8.344	9.081	9.745	46.997	42.701	36.162	80.112

Notes: The table reports scaled consumer surplus dollar-value estimates under various counterfactual policies. Lower bounds are constructed using the opportunity cost of time, and upper bounds are estimated using the unit cost of clicking on a search link in Greminger, Huang, and Morozov (2023)."US status quo" refers to an accept-settings interface, combined with an accept-all default when consumers close window; "CS maximizing" refers to a neutral interface with an accept-all default when consumers close window; "EU norm" refers to a neutral interface with a reject-all default when consumers close window. "Pooled estimate" refers to the estimate across all subjects, and the other columns correspond to subset-specific estimates.

Our welfare estimates show that compared to the US status quo, the consumer-surplus maximizing policy, which adopts a neutral interface while defaulting consumers to accepting cookies upon inaction, increases consumer surplus by 11% (\$1.16-\$5.52 per week).

This welfare gain comes from minimizing choice frictions while defaulting users to the option that an average consumer prefers.

Defaulting users to rejecting cookies upon inaction has two opposing effects on consumer welfare: They could increase welfare by using a default that is consistent with the majority belief, but can also decrease welfare by defaulting consumers to an undesirable option. Our countefactual results show that the net effect of the two is negative: Holding the design fixed, the EU Norm policy decrease welfare by 9% ($0.85-$4.41) compared to the CS-maximizing policy. Still, the EU Norm outperforms the US status quo and increases consumer surplus by 2%, due to the fact that it uses a neutral design that miminizes choice friction.

On the other hand, the Forced Accept All policy increases surplus by 43.7% ($4.12-$21.38) when compared to the status quo, and by 32.7% when compared to the CS-maximizing banner design. Given that most consumers in our sample prefer sharing their data to all websites absent dark patterns, a design that enables site-specific choices does not increase welfare sufficiently to justify the cost of interacting with banners for each websites. The Forced Reject All policy decreases surplus by 4% ($0.08 -$1.93), due to the fact that it forces consumers to the option that they prefer less on average. Yet this average number masks substantial heterogeneity: For instance, the always rejectors increase their surplus by $11.46-$45.62 under the forced reject policy. These results suggest further welfare gain from a global privacy design that allows each consumers to specify the global option of their own choosing.

6. The Time Cost of Consent

One criticism of existing regulations that mandate consent is that consent pop-ups degrade user experiences and waste their time. In this section, we consider the costs of asking users for consent.

We begin by calculating how much time people spend interacting with our consent banners and how it varies by banner type. To measure time spent on the pop-up, we calculate the time elapsed between the cookie pop-up and the recorded *final* action. This time spent measure includes the time spent on intermediate clicks and when someone goes back and forth before closing the banner. We censor the time spent at 60 seconds, which is well above the 99th percentile of time spent on the banner (13 seconds during organic browsing) and likely reflects task switching rather than genuine time spent.

In the neutral design condition, consumers on average spent 5.42 seconds/banner in the survey phase and 7.43 seconds/banner in the organic phase. Table 10 displays the results of regressions of time spent on the treatment conditions in columns (1) and (3). The only design that significantly affects time spent is the Reject-Settings design, which hides the most commonly chosen option–accept all–under the neutral condition. In Columns (2) and (4) we measure which of the four actions takes the most time, conditional on user, domain, and treatment condition. Unsurprisingly, "Accept Selected" takes the most time, since it requires users to click the settings button and make additional sub-selections.

TABLE 10. Effects of Dark Patterns on Time Spent

	Survey		Organic	
	Time Spent (Seconds)			
	(1)	(2)	(3)	(4)
Acc-Set	0.506		-0.484	
	(0.288)		(0.382)	
Rej-Set	2.172***		0.996*	
	(0.276)		(0.402)	
Acc-Rej-Set	-0.364		0.045	
	(0.236)		(0.410)	
Rej-Acc-Set	-0.206		-0.435	
	(0.245)		(0.377)	
Acc-GrRej-GrSet	-0.061		-0.250	
	(0.252)		(0.378)	
Accept Selected		7.892***		5.731***
		(0.643)		(0.860)
Close Window		-0.158		0.967*
		(0.456)		(0.484)
Reject All		-0.657*		0.534
		(0.301)		(0.599)
Omitted Category Mean	5.42	5.3	7.43	6.66
R^2	0.210	0.231	0.126	0.129
Observations	12,247	12,247	14,116	14,116
Participant fixed effects	✓	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓	✓
Condition fixed effects		✓		✓

Notes: Regression of the time spent between a cookie pop-up and final action, where each observation is a user by domain. Columns (1) and (3) contain controls for the treatment arms, with the neutral design treatment as the omitted category; columns (2) and (4) control for the final action chosen, with "accept all" as the control group. *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

We can estimate the time costs of interacting with the consent banners. During the organic phase, a participant spent on average 7.43 seconds per domain to interact with the consent banner absent dark patterns. If the banner is shown on every unique domain they visit throughout the week (52.6/week in our study), their time spent on consent would be 6.5 minutes/week. To perform a back-of-the-envelope calculation on the dollar value of time spent, we use the time costs of browsing online from Greminger, Huang, and Morozov (2023), at $69/hour.[33] Our back-of-envelope calculation indicates the cost of interacting with consent banners amounts to $7.49/week per consumer. Hiding the "accept" button increases the time costs to $8.49/week. If consumers were to make selective cookie choices for each banner, the cost of time would go up to 12.4 seconds/domain, which amounts to a time cost of $12.50/week. In this sense, deliberate obstruction decreases consumer welfare not only because it distorts choices, but also because it increases the time cost of consent decisions.

Consider an alternative design in privacy policy discussions, which allows users to configure cookie choices at the browser level (aka. global privacy choice). Our calculation suggests that site-specific choices would benefit consumers *if* the value they get from site-level customization is greater or equal to $7.49/week.

7. Conclusions

We examine the impact of dark patterns on consumer privacy choices through a field experiment that randomizes cookie consent interface designs during their organic browsing. We find that the most potent dark pattern involves concealing consent options behind an additional click, which substantially increases consent rates. In contrast, less intrusive manipulations such as reordering or visually highlighting options exert smaller impacts.

While larger and better-known firms enjoy modestly higher consent rates, dark patterns do not disproportionately benefit popular or familiar websites. If anything, such patterns seem to alleviate consumers' inclination to share more data with these sites. As a result, dark patterns are unlikely to hinder the competitive standing of smaller firms. In fact, if smaller firms benefit more from the same amount of data, dark patterns could potentially intensify competition.

[33] In Greminger, Huang, and Morozov (2023), the time costs can come from both the opportunity costs of not working, often reflected by the hourly wages, and the disutility from shopping and searching for products online. To the extent that interacting with banners is less pleasurable than online shopping and searching, we believe that the actual cost of interacting with consent banners per second is either equal to or higher than the cost of online shopping. The US hourly wage, at $35.07 (see https://www.bls.gov/news.release/empsit.t19.htm), would provide a conservative lower bound to our time cost estimate.

Any benefit of displaying frequent consent requests needs to be balanced against the time cost they induce. We show that the average time cost of interacting with consent banners under site-specific consent mandates amounts to $7.49 per week, and dark patterns that hide certain options increase the time cost by 12%. Therefore, deliberate obstruction decreases consumer welfare by not only distorting their choices but also imposing additional time costs.

We estimate a model of privacy choices to measure welfare and consider counterfactual policies. Our model estimates showed that an interface displaying all three options upfront increases consumer surplus by 11%, compared to the common design in which 'Reject All' is hidden behind the "Settings" menu. This finding is critical for privacy regulations, suggesting the effectiveness of consent mandates could be substantially influenced by the design of the interface.

We do not find evidence that more frequent pop-ups affect the quality of privacy decisions. However, consumers increase the frequency of directly closing windows over time, which could indicate a decline in engagement or rising fatigue, albeit not directly related to the frequency of interactions. It is important to note that the frequency of consent windows in our experimental interventions is lower than those in actual consent-based privacy regimes and, as such, may not fully capture potential fatigue effects at higher frequency margins.

We observe high consent rates even absent dark patterns. This fact raises the question of why consumers are willing to share their data in the first place. Possible explanations include an appreciation for personalized services and targeted advertising, or concerns about diminished user experience upon rejecting cookies. This is a fruitful area for future research.

Our study has several limitations. First, the use of a browser extension with standardized consent banners across websites may not perfectly mimic real-world browsing environments, as participants knew they were being observed. Second, we focused on the short-term effects of dark patterns, leaving the long-term effects and changes in consumer behavior as avenues for future research. Finally, our findings are primarily relevant to the context of cookie consent and may not immediately generalize to other privacy decisions or dark patterns in other contexts.

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Appendix A. Additional Tables and Figures

FIGURE A1. Cookie Manager's User Interface

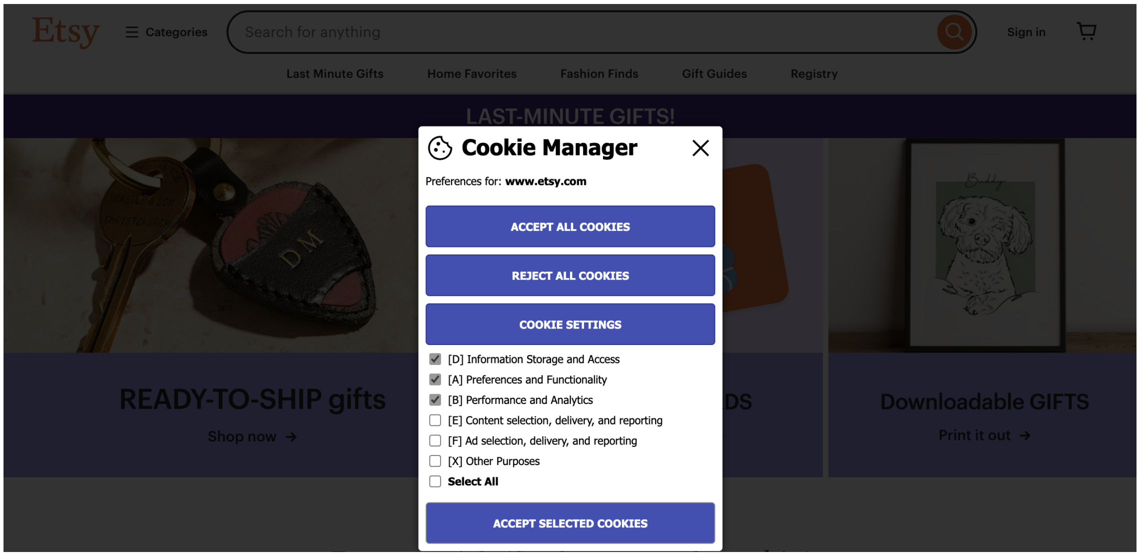


TABLE A1. Number of Participants across the Experimental Funnel

Stage	N	Percent	10 min	Percentage	60 min	Percentage
1) Start Survey	1,227	100.00				
2) Eligible for Study	917	74.74				
3) Study Consent	877	71.48				
4) Finished Survey	807	65.77				
5) Clicked All Links	804	65.53	359	100.00	418	100.00
6) Have Browser Cookie Data	789	64.30	357	99.44	415	99.28
7) Have Cookie Choice Data	787	64.14	356	99.16	414	99.04
8) Main Analysis Sample*	656	53.46	306	85.24	350	83.73
9) Finished Endline Survey	613	49.96	273	76.04	325	77.75

Notes: This table presents the number of study participants at every step of the study. After completing the initial survey, participants are randomly allocated to two treatment conditions: 10 minutes (where cookie pop-ups appear every 10 minutes of browsing), and 60 minutes (where cookie pop-ups appear every 60 minutes. Due to an implementation glitch, not all users are randomized into either the 10- or 60- minute treatment; 3% of participants kept seeing a banner for every new domain visited.
$*$: The main analysis sample in the second-to-last line restricts attention to users who have treatment assignment to either the 10-Minute or 60-Minute group, and for whom we observe at least one cookie selection both during and after the survey.

Appendix B. Survey Questions

This appendix presents the Qualtrics surveys used in the study:

- Intake.
- Outtake.

Device Transfer

The rest of the survey needs to be done on a Chrome browser. Please copy the link of the survey and reopen it in a Chrome browser to continue.

First Page

Would you like to help us understand online behavior and privacy choices? We are a team of Harvard and Boston University researchers who study the internet and how it affects society.

The study will take 30 minutes of your time over the course of the next day. We will ask you to fill out two surveys, clear the cookie data stored in your browser, install a browser extension vetted by Harvard and Boston University and keep it installed for seven days, and share information about your online behavior. Click below if you want to know more and discover if you qualify!

Eligibility Questions

Do you live in the United States?

No
Yes

Are you over 18 years old?

Yes
No

What is 12 minus 4? Regardless of the correct answer, you should always select the option with the value "seven". This is an attention check question.

6

8

7

5

What is the language you primarily speak?

Spanish

English

Other (please specify)

Which browser do you primarily use?

Others

Internet Explorer

Chrome

Microsoft Edge

Safari

Firefox

What was your total household income before taxes during the past 12 months?

Less than $25,000

$25,000-$49,999

$50,000-$74,999

$75,000-$99,999

$100,000-$149,999

$150,000 or more

Prefer not to say

What is the highest level of education you have completed?

Some high school or less

High school diploma or GED

Some college, but no degree

Associates or technical degree

Bachelor’s degree

Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.)

Prefer not to say

Not Eligible

Thank you for your answers! Unfortunately, you do not qualify to participate in our study. **Can you please return your submission on Prolific?**

Consent

Congratulations! You are qualified to participate in our study.

Study Overview

The following is a summary with key information to help you decide whether you want to participate.

Why am I being invited to take part in a research study?
We invite you to take part in this research study because you are an English-speaking resident of the United States who uses Chrome to browse the web.

What should I know about a research study?
Research studies are conducted to better understand the choices we make. Whether or not you take part is completely up to you. Your decision will not be held against you. You can ask all the questions you want before you decide. You can even agree to take part and later change your mind.

Why is this research being done?
We want to better understand the online experience of people like you, how companies obtain user consent for the collection and use of their data, and how this affects user browsing experience. We hope that the results of this research will help inform data privacy policy.

How long will the research last and what will I need to do?
The study will last several days, but we will only ask you for 30 minutes of your time. Everything we ask you to do to participate in this research can be done from the comfort of your home. If you choose to participate, we'll ask you to:

- Complete two surveys:
  - The first survey will ask you some questions about yourself and your online browsing behavior. It will also ask you to visit some websites and make privacy choices.
  - The second survey will ask you about your experience during the study.
- Install the Cookie Manager browser extension, which is an application we developed for this study. We'll have instructions for you. The Cookie Manager extension will record your behavior and may tweak the interfaces through which you make cookie selections.
- Keep the extension installed for seven days, until the extension prompts you to uninstall it.

Will I be compensated for participating in this research?
Yes. You will be paid $7.50 after completing the two surveys and keeping the Cookie Manager extension installed for several days.

Is there any way being in this study could be bad for me?
Since we may collect personal information, there is a risk of breach of confidentiality. We have worked hard to minimize this risk. For example, we will encrypt any data before storing it. Before accessing the data for analysis, we will also permanently delete all personal information that we may intentionally or unintentionally collect.

Will being in this study help me in any way?
We cannot promise any benefits to you or others from your taking part in this research. It

is possible, however, that our tweaks to your online browsing lead to a better (or worse) online experience.

Detailed Information

Withdrawing from the Study.

You can leave the research at any time; your decision will not be held against you. We may use the data you have shared with us prior to withdrawing as part of the study. We will provide simple instructions for how you can withdraw. Researchers can remove you from the research study without your approval. Possible reasons for removal include not complying with instructions to install the browser extension or intentionally avoiding data tracking through the extension.

Privacy.

Data security and privacy are important to us. During the course of the study we may collect personal information. The personal information that we know we are collecting will be deleted immediately. Other personal information that we inadvertently collect will be stored but removed after we finish collecting data.

We cannot promise complete secrecy, although efforts will be made to limit the use and disclosure of your personal information. Data will be encrypted and stored on secure servers and cannot be accessed by anyone outside the research team. At no time will study information be available over any public or private network in an unencrypted state.

In the future, when we publish our research, we will post anonymized data from this study in a data repository so that other researchers can reproduce our results. By then, no information that can identify you personally will be available, to us or others. We will not sell data from the study or share data for any commercial or marketing purposes.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, do not hesitate to reach the research team on Prolific or cookie.manager.study@gmail.com.

Please indicate below whether you agree to participate in the study. Agreeing to participate means you are willing to install Cookie Manager (our web browser extension) for seven days, and complete the two surveys.

I agree to participate

I do not agree to participate

Not consent

Thank you for letting us know you do not want to participate. **Can you please return your submission on Prolific?**

Email

Thank you for your willingness to participate in our study!

Next, we will ask you to install *Cookie Manager*, a browser extension we developed to identify website tracking and to enable simplified privacy consent dialogs.

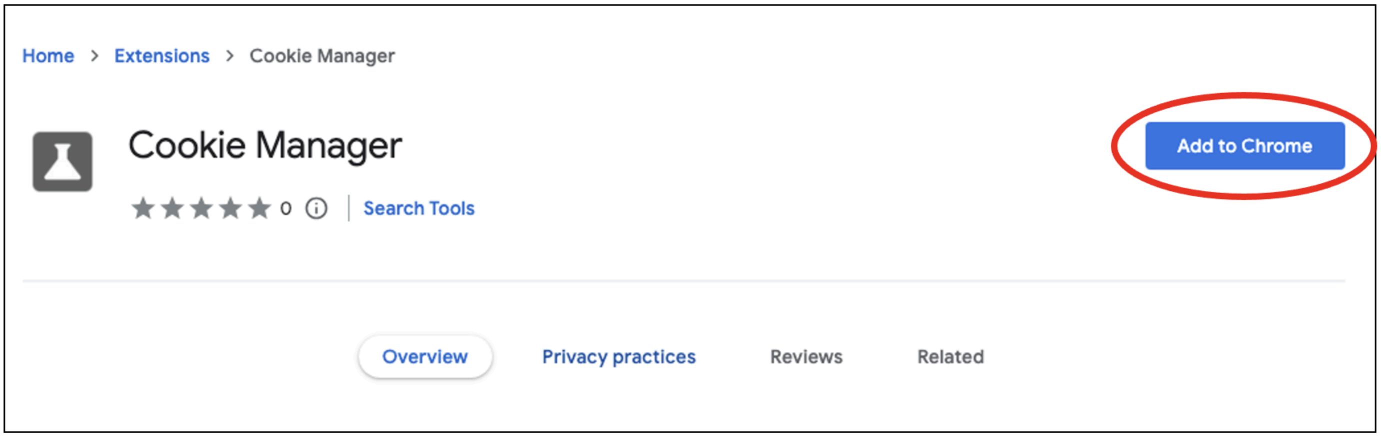
After installing the extension, you will see a consent-request popup window whenever you visit a website for the first time. If you make a choice, the extension will try to pass on your choices to the website. In most cases, if the website has already been collecting consent from users, it will recognize your choice and decide whether to continue tracking you based on your choice.

App Installation

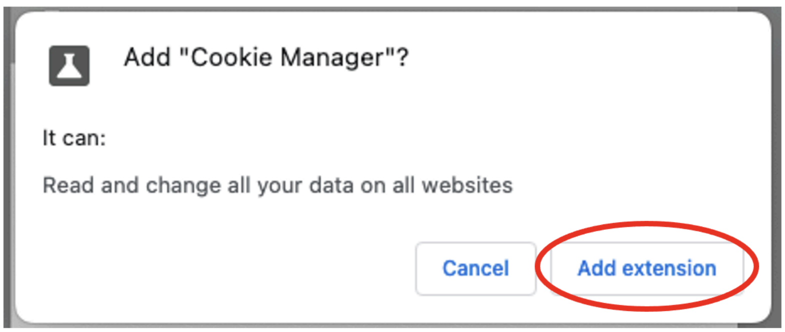
Cookie Manager Installation Instructions.

To install Cookie Manager, please **use Chrome** on the computer that you are using for online shopping:

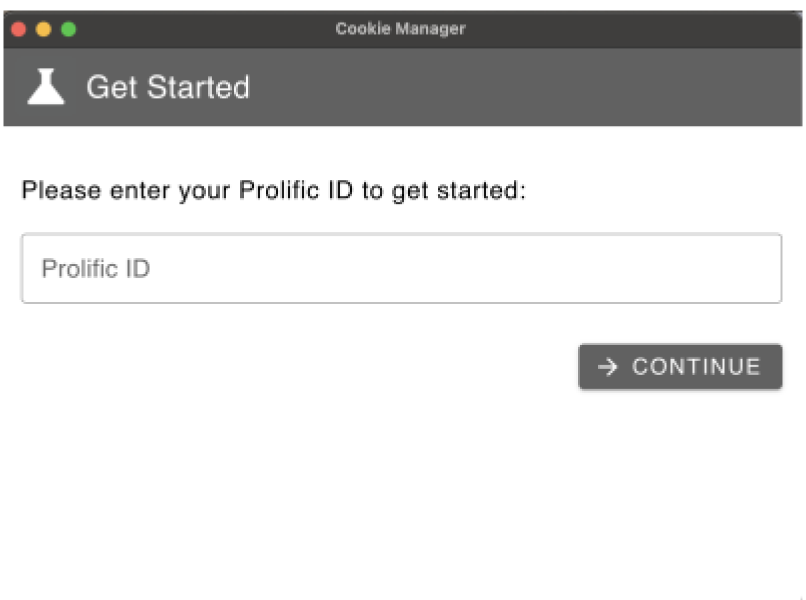
- Click here.
- Click “Add to Chrome.”



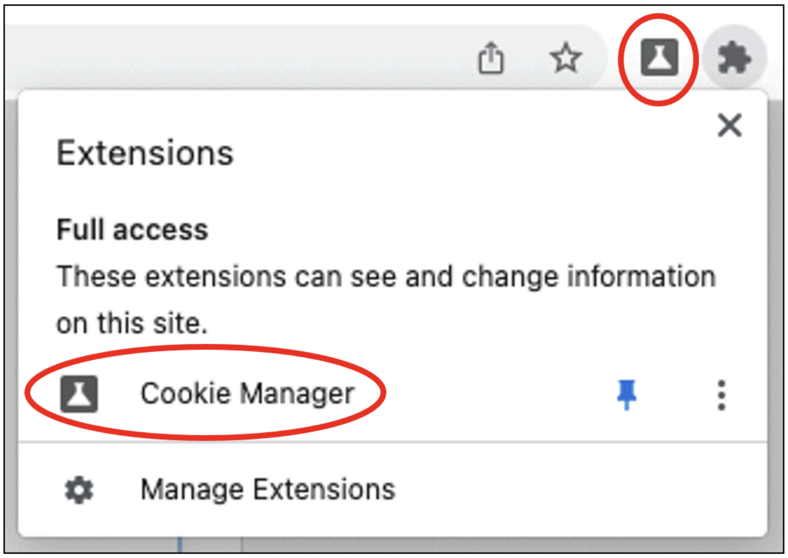
- When prompted, click “Add Extension.”



- You will be prompted to add your prolific id.



- You should now see the Cookie Manager icon on the top right corner of your browser. If you don’t see it, it may be hidden under the puzzle icon, which is visible in the upper right corner of the screenshot below.



- You are all set.

If you have trouble installing Cookie Manager, email us at cookie.manager.study@gmail.com and we will help you with additional instructions.

Were you able to successfully install the extension?

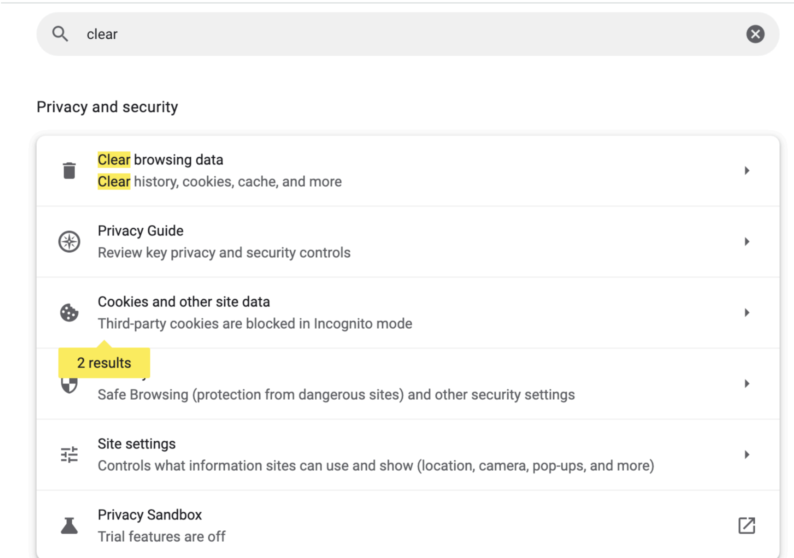
Yes

No

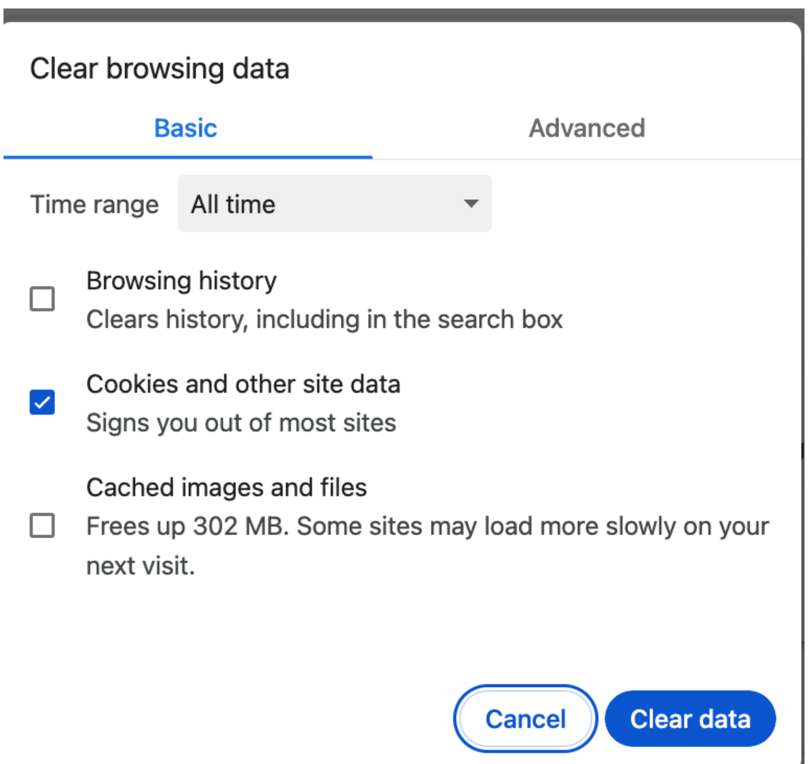
What difficulties have your encountered when installing the extension?

Clear Browsing History

Next, we will ask you to clear your cookie data. Please navigate to chrome://settings/privacy?search=clear (copy and paste the address directly on your search bar), and click on "Clear Browsing Data". Then select **only 'cookies and other site data'**, and click clear data.



Select the time range to be **"All Time"** and select the cookies and other data check box, as seen below. Then click "Clear Data."



Were you able to clear your cookie data?

Yes

No

Intro to website navigation

Now that you have *Cookie Manager* installed, we will ask you to visit a list of 20 websites. Please wait until a banner shows up for each site and interact with the banner as you normally would. We will ask you to answer a few questions after each visit. After you finish the survey task, the frequency of pop-ups will drastically decrease.

Note: for your browsing action to be correctly registered in our database, please directly left-click on the link on the survey page to navigate to the website. If instead you right-click on the link and select "open on a new tab", a warning will continue showing up, meaning that our database has not recognized your click action.

YouTube

Please use Chrome to navigate to youtube.com. Please wait until a banner shows up. Search for a video of your choice.
You haven't clicked on the link

Do you normally visit Youtube?

Yes
No

Have you ever heard of Youtube?

Yes
No

How often do you normally visit Youtube?

At least once a day

At least once a week

Less than once a week

Never

New York Times

Please use Chrome to navigate to nytimes.com. Please wait until a banner shows up. Click on an article of your choice.
You haven't clicked on the link

Do you normally visit NYTimes?

Yes

No

Have you ever heard of New York Times?

Yes

No

How often do you normally visit New York Times?

At least once a day

At least once a week

Less than once a week

Never

Apple Insider

Please use Chrome to navigate to appleinsider.com. Please wait until a banner shows up. Click on an article of your choice.
You haven't clicked on the link

Do you normally visit Apple Insider?

Yes

No

Have you ever heard of Apple Insider?

Yes

No

How often do you normally visit Apple Insider?

At least once a day

At least once a week

Less than once a week

Never

Yahoo

Please use Chrome to navigate to yahoo.com. Please wait until a banner shows up. Click on an article of your choice.
You haven't clicked on the link

Do you normally visit Yahoo?

Yes

No

Have you ever heard of Yahoo?

Yes

No

How often do you normally visit Yahoo?

At least once a day

At least once a week

Less than once a week

Never

Amazon

Please use Chrome to navigate to amazon.com. Please wait until a banner shows up. Search for a product of your choice.
You haven't clicked on the link

Do you normally visit Amazon?

Yes

No

Have you ever heard of Amazon?

Yes

No

How often do you normally visit Amazon?

At least once a day

At least once a week

Less than once a week

Never

eBay

Please use Chrome to navigate to ebay.com. Please wait until a banner shows up. Search for a product of your choice.
You haven't clicked on the link

Do you normally visit eBay?

Yes

No

Have you ever heard of eBay?

Yes

No

How often do you normally visit eBay?

At least once a day

At least once a week

Less than once a week

Never

What is 6 divided by 2? Regardless of the correct answer, you should always select the option with the value "one". This is an attention check question.

2

3

1

Target

Please use Chrome to navigate to target.com. Please wait until a banner shows up. Search for a product of your choice.
You haven't clicked on the link

Do you normally visit Target?

Yes

No

Have you ever heard of Target?

Yes

No

How often do you normally visit Target?

At least once a day

At least once a week

Less than once a week

Never

Etsy

Please use Chrome to navigate to etsy.com. Please wait until a banner shows up. Search for a product of your choice.
You haven't clicked on the link

Do you normally visit Etsy?

Yes

No

Have you ever heard of Etsy?

Yes

No

How often do you normally visit Etsy?

At least once a day

At least once a week

Less than once a week

Never

Turro

Please use Chrome to navigate to turo.com. Please wait until a banner shows up. Click on a car of your choice.
You haven't clicked on the link

Do you normally visit Turo?

Yes

No

Have you ever heard of Turo?

Yes

No

How often do you normally visit Turo?

At least once a day

At least once a week

Less than once a week

Never

StockX

Please use Chrome to navigate to stockx.com. Please wait until a banner shows up. Search for a product of your choice.
You haven't clicked on the link

Do you normally visit StockX?

Yes

No

Have you ever heard of StockX?

Yes

No

How often do you normally visit StockX?

At least once a day

At least once a week

Less than once a week

Never

ESPN

Please use Chrome to navigate to espn.com. Please wait until a banner shows up. Click on an article of your choice.
You haven't clicked on the link

Do you normally visit ESPN?

Yes

No

Have you ever heard of ESPN?

Yes

No

How often do you normally visit ESPN?

At least once a day

At least once a week

Less than once a week

Never

Facebook

Please use Chrome to navigate to facebook.com. Please wait until a banner shows up. Scroll down.
You haven't clicked on the link

Do you normally visit Facebook?

Yes

No

Have you ever heard of Facebook?

Yes

No

How often do you normally visit Facebook?

At least once a day

At least once a week

Less than once a week

Never

Funny Or Die

Please use Chrome to navigate to funnyordie.com. Please wait until a banner shows up. Click on an article of your choice.
You haven't clicked on the link

Do you normally visit Funny Or Die?

Yes

No

Have you ever heard of Funny Or Die?

Yes

No

How often do you normally visit Funny Or Die?

At least once a day

At least once a week

Less than once a week

Never

Weather

Please use Chrome to navigate to weather.com. Please wait until a banner shows up. Search for a location.
You haven't clicked on the link

Do you normally visit Weather.com?

Yes

No

Have you ever heard of Weather.com?

Yes

No

How often do you normally visit Weather.com?

At least once a day

At least once a week

Less than once a week

Never

DuckDuckGo

Please use Chrome to navigate to duckduckgo.com. Please wait until a banner shows up. Search for a product of your choice.
You haven't clicked on the link

Do you normally visit DuckDuckGo?

Yes

No

Have you ever heard of DuckDuckGo?

Yes

No

How often do you normally visit DuckDuckGo?

At least once a day

At least once a week

Less than once a week

Never

Truewerk

Please use Chrome to navigate to truewerk.com. Please wait until a banner shows up and navigate to an item.
You haven't clicked on the link

Do you normally visit Truewerk?

Yes

No

Have you ever heard of Truewerk?

Yes

No

How often do you normally visit Truewerk?

At least once a day

At least once a week

Less than once a week

Never

Thomann

Please use Chrome to navigate to thomannmusic.com. Please wait until a banner shows up and navigate to an item.
You haven't clicked on the link

Do you normally visit Thomann Music?

Yes

No

Have you ever heard of Thomann Music?

Yes

No

How often do you normally visit Thomann Music?

At least once a day

At least once a week

Less than once a week

Never

MerrySky

Please use Chrome to navigate to merrysky.com. Please wait until a banner shows up and search for a location.
You haven't clicked on the link

Do you normally visit Merry Sky?

Yes

No

Have you ever heard of Merry Sky?

Yes

No

How often do you normally visit Merry Sky?

At least once a day

At least once a week

Less than once a week

Never

Seattle Times

Please use Chrome to navigate to seattletimes.com. Please wait until a banner shows up and then click on an article.
You haven't clicked on the link

Do you normally visit Seattle Times?

Yes

No

Have you ever heard of Seattle Times?

Yes

No

How often do you normally visit Seattle Times?

At least once a day

At least once a week

Less than once a week

Never

Semafor

Please use Chrome to navigate to semafor.com. Please wait until a banner shows up and then click on an article.
You haven't clicked on the link

Do you normally visit Semafor?

Yes

No

Have you ever heard of Semafor?

Yes

No

How often do you normally visit Semafor?

At least once a day

At least once a week

Less than once a week

Never

Favorite website

Navigate to your favorite e-commerce website. Please wait until a banner shows up. Search for a product of your choice.

Paste the URL of the product below:

Did you see a cookie consent banner?

Yes

No

Did you make a choice on whether to allow for cookie sharing?

Yes, I allowed my preferred cookies and blocked unwanted cookies

Yes, I chose the default cookie sharing

No, I closed the cookie consent banner

No, I left the website without interacting with the consent banner

Questionnaire

Think about your browsing experiences on a typical day. Overall, how frequently do you encounter cookie consent banners?

Too frequently

A bit more frequently than ideal

Just right

A bit less frequently than ideal

Too infrequently

Overall, how would you rate the ease of navigation of the cookie consent interfaces on the websites you visit?

Very easy to navigate

Moderately easy to navigate

Neither easy nor hard to navigate

Moderately hard to navigate

Very hard to navigate

Overall, how would you rate the ease of making your preferred choices regarding cookie sharing on the websites you visit?

Very easy

Moderately easy

Neither easy nor hard

Moderately hard

Very hard

Which of the following best describes your behavior when deciding whether to share cookies online?

I reject most cookies

I consider both the website that is asking and the types of cookies involved before deciding whether to share them

I accept most cookies

I decide whether to share cookies based on what type of cookies they are

I decide whether to share cookies based on which website is asking

Part1-conclude

Thank you! To finish the rest of the study, we ask you to keep Cookie Manager installed for another seven days. You can continue your browsing activities as usual during this time. The frequency of pop-ups will drastically decrease over time. After the seven days have passed, the extension will prompt you with a survey and the instructions on how to uninstall the extension.

There is no completion code, since our system will detect completion automatically. Please make sure to click the next button below so that we register your response.

TABLE A2. Summary Statistics by Treatment

		10 Minutes			60 Minutes		
		Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
During Survey	Unique Domains in Prior Week	52.28	47.00	40.26	50.68	46.00	38.12
	Domains w. Banner	18.67	20.00	3.71	18.53	20.00	4.16
Post-Survey	Domains w. Banner	28.23	18.00	27.21	15.95	12.00	13.19
	Unique Domains Visited	53.30	36.00	50.32	51.96	36.50	50.38
	Unique URLs	631.21	380.00	724.67	647.74	362.50	838.75
	End Survey Completed	0.84	1.00	0.36	0.86	1.00	0.34
Demographics	Age	38.95	36.00	13.12	37.47	35.00	12.95
	Female	0.48	0.00	0.50	0.44	0.00	0.50
	Bachelor's or Above	0.18	0.00	0.39	0.18	0.00	0.39
Cookie Behavior	Accept-All Rate	0.52	0.62	0.36	0.54	0.66	0.37
	Close-Window Rate	0.27	0.14	0.32	0.29	0.15	0.33
	Reject-All Rate	0.17	0.01	0.29	0.14	0.00	0.26

Number of observations: 653

Notes: Summary statistics for two groups of users, those who experience a pop-up every 10 minutes of organic browsing, and those who experience a pop-up every 60 minutes. "Unique domains in prior week" refers to the number of unique domains visited 7 days before the experiment; we keep the length of the historical visit the same as the post-survey visit for comparability. Number of observations: 656

TABLE A3. Covariate Balance Check for Dark Pattern Randomization

	Age	Female	Bachelor's or Above	Domain Rank (Log 10)
	(1)	(2)	(3)	(4)
Constant	38.720***	0.438***	0.182***	3.579***
	(0.196)	(0.007)	(0.006)	(0.023)
Acc-GrRej-GrSet	0.061	-0.004	-0.009	-0.034
	(0.281)	(0.011)	(0.008)	(0.033)
Acc-Rej-Set	-0.040	0.013	0.005	-0.004
	(0.281)	(0.011)	(0.008)	(0.033)
Acc-Set	-0.023	-0.001	-0.007	-0.023
	(0.280)	(0.010)	(0.008)	(0.033)
Rej-Acc-Set	0.343	0.011	-0.008	0.013
	(0.284)	(0.011)	(0.008)	(0.033)
Rej-Set	0.312	-0.008	-0.011	-0.045
	(0.286)	(0.011)	(0.008)	(0.033)
R^2	0.000	0.000	0.000	0.000
Observations	26,278	26,278	26,773	26,773

Notes: * $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A4. Covariate Balance Check for Banner Frequency Randomization

	# Survey Domains	Age	Female	Bachelor's or Above
	(1)	(2)	(3)	(4)
Constant	18.537***	37.460***	0.443***	0.563***
	(0.222)	(0.703)	(0.027)	(0.027)
10 Min Pop-up	0.123	1.560	0.039	-0.076·
	(0.307)	(1.037)	(0.040)	(0.039)
R^2	0.000	0.004	0.001	0.006
Observations	656	638	638	656

Notes: * $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A5. Choices of "Accept Some" Cookies by Experimental Condition

	Survey	Organic
	Accept Some	
	(1)	(2)
Acc-Set	0.054***	0.023**
	(0.010)	(0.008)
Rej-Set	0.037***	0.036***
	(0.007)	(0.007)
Acc-Rej-Set	-0.003	0.004
	(0.004)	(0.003)
Rej-Acc-Set	-0.005	-0.002
	(0.005)	(0.004)
Acc-GrRej-GrSet	-0.006	0.004
	(0.004)	(0.003)
Benchmark group mean:	0.03	0.03
R^2	0.408	0.491
Observations	12,142	14,163
Participant fixed effects	✓	✓
Domain Cat. fixed effects	✓	✓

Notes: The table regressions of Equation 1, where the outcome is whether the user selects a subset of cookies. Otherwise the table is identical to Table 2. * $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A6. Choices of "Accept Some" Cookies by Dark Pattern

	Survey	Organic
	Accept Some	
	(1)	(2)
Reject Hidden	0.054***	0.023**
	(0.010)	(0.008)
Accept Hidden	0.041***	0.039***
	(0.007)	(0.007)
Accept Top	-0.003	0.004
	(0.004)	(0.003)
Reject Top	-0.005	-0.002
	(0.005)	(0.004)
Highlight Accept	-0.003	-0.001
	(0.004)	(0.003)
Benchmark group mean:	0.03	0.03
R^2	0.408	0.491
Observations	12,142	14,163
Participant fixed effects	✓	✓
Domain Cat. fixed effects	✓	✓

Notes: The table regressions of Equation 2, where the outcome is whether the user selects a subset of cookies. Otherwise the table is identical to Table 3. *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A7. Types of Cookies Accepted among People Making Granular Choices

Cookie Type	Percentage Selected
Preferences and functionality	0.831
Information storage and access	0.630
Performance and analytics	0.600
Content selection, delivery, and reporting	0.388
Ad selection, delivery, and reporting	0.068
Other purposes	0.046

Notes: Percentage of different types of cookies selected among those who selectively accept some cookies but not all.

TABLE A8. Heterogeneity of Dark Pattern Effect by Domain Ranking (Survey Sites)

	Accept All (1)	Reject All (2)	Close Window (3)
Domain Rank (Log 10)	-0.020***	0.015**	0.004
	(0.005)	(0.005)	(0.003)
Domain Rank (Log 10) × Reject Hidden	0.007	-0.013*	0.004
	(0.006)	(0.006)	(0.004)
Domain Rank (Log 10) × Accept Hidden	0.024***	-0.018*	0.002
	(0.007)	(0.007)	(0.006)
Domain Rank (Log 10) × Accept Top	-0.001	0.006	-0.006
	(0.006)	(0.006)	(0.004)
Domain Rank (Log 10) × Reject Top	-0.004	0.006	-0.004
	(0.006)	(0.006)	(0.003)
Domain Rank (Log 10) × Highlight Accept	-0.004	-0.002	0.006
	(0.006)	(0.006)	(0.004)
Reject Hidden	0.059*	-0.131***	0.027
	(0.023)	(0.022)	(0.015)
Accept Hidden	-0.544***	0.243***	0.235***
	(0.030)	(0.030)	(0.025)
Accept Top	0.022	-0.026	0.008
	(0.021)	(0.019)	(0.014)
Reject Top	0.019	-0.007	0.001
	(0.021)	(0.020)	(0.012)
Highlight Accept	0.031	-0.006	-0.022
	(0.021)	(0.018)	(0.014)
R^2	0.655	0.583	0.573
Observations	12,142	12,142	12,142
Participant fixed effects	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓

Notes: * $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A9. Heterogeneity of Dark Pattern Effect by Visit Frequency (Survey Sites)

	Accept All (1)	Reject All (2)	Close Window (3)
Normally Visit	0.103***	-0.091***	-0.015
	(0.015)	(0.015)	(0.009)
Normally Visit × Reject Hidden	-0.046*	0.070***	-0.014
	(0.020)	(0.019)	(0.014)
Normally Visit × Accept Hidden	-0.081**	0.010	0.020
	(0.025)	(0.024)	(0.021)
Normally Visit × Accept Top	-0.015	-0.001	0.006
	(0.018)	(0.016)	(0.012)
Normally Visit × Reject Top	-0.006	0.006	-0.003
	(0.018)	(0.017)	(0.011)
Normally Visit × Highlight Accept	0.007	0.006	-0.006
	(0.020)	(0.018)	(0.011)
Reject Hidden	0.095***	-0.195***	0.043***
	(0.014)	(0.016)	(0.011)
Accept Hidden	-0.441***	0.184***	0.234***
	(0.021)	(0.017)	(0.018)
Accept Top	0.024*	-0.006	-0.012
	(0.012)	(0.010)	(0.007)
Reject Top	0.007	0.011	-0.011
	(0.011)	(0.011)	(0.007)
Highlight Accept	0.015	-0.015	0.000
	(0.012)	(0.011)	(0.006)
R^2	0.658	0.587	0.573
Observations	12,142	12,142	12,142
Participant fixed effects	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓

Notes: "Normally visit" is a binary variable constructed from our question in the survey phase: "Do you normally visit website [X]?" and is available only for the 20 surveyed sites. *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A10. Heterogeneity of Dark Pattern Effect by Prior Site Visits (Survey Sites)

	Accept All (1)	Reject All (2)	Close Window (3)
Has Prior Visit	0.043*	-0.032	-0.014
	(0.020)	(0.018)	(0.013)
Has Prior Visit × Reject Hidden	-0.029	0.052*	-0.014
	(0.028)	(0.026)	(0.017)
Has Prior Visit × Accept Hidden	-0.077*	-0.011	0.049
	(0.032)	(0.031)	(0.029)
Has Prior Visit × Accept Top	0.012	-0.015	-0.005
	(0.028)	(0.025)	(0.021)
Has Prior Visit × Reject Top	0.021	-0.022	0.015
	(0.027)	(0.025)	(0.018)
Has Prior Visit × Highlight Accept	0.011	-0.005	0.004
	(0.028)	(0.025)	(0.020)
Reject Hidden	0.082***	-0.178***	0.041***
	(0.012)	(0.014)	(0.009)
Accept Hidden	-0.458***	0.189***	0.234***
	(0.019)	(0.016)	(0.017)
Accept Top	0.018	-0.005	-0.009
	(0.010)	(0.009)	(0.006)
Reject Top	0.002	0.015	-0.014*
	(0.010)	(0.010)	(0.006)
Highlight Accept	0.016	-0.012	-0.003
	(0.010)	(0.010)	(0.006)
R^2	0.654	0.583	0.574
Observations	12,142	12,142	12,142
Participant fixed effects	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓

Notes: "Has Prior Visit" is a binary variable indicating whether a domain has been visited by the participant two weeks prior to our experiment. *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A11. Heterogeneity of Dark Pattern Effect by Domain Ranking (Organic Sites)

	Accept All (1)	Reject All (2)	Close Window (3)
Domain Rank (Log 10)	0.002	0.002	-0.004
	(0.005)	(0.003)	(0.004)
Domain Rank (Log 10) × Reject Hidden	-0.004	0.000	0.004
	(0.007)	(0.005)	(0.006)
Domain Rank (Log 10) × Accept Hidden	-0.009	0.004	0.009
	(0.008)	(0.006)	(0.008)
Domain Rank (Log 10) × Accept Top	0.004	-0.005	0.000
	(0.006)	(0.004)	(0.006)
Domain Rank (Log 10) × Reject Top	0.001	-0.004	0.001
	(0.006)	(0.005)	(0.006)
Domain Rank (Log 10) × Highlight Accept	0.004	-0.006	0.002
	(0.007)	(0.005)	(0.006)
Reject Hidden	0.073*	-0.093***	0.002
	(0.029)	(0.022)	(0.028)
Accept Hidden	-0.399***	0.056*	0.290***
	(0.035)	(0.027)	(0.035)
Accept Top	0.019	0.020	-0.042
	(0.027)	(0.019)	(0.024)
Reject Top	0.001	0.039	-0.031
	(0.026)	(0.021)	(0.026)
Highlight Accept	-0.019	0.004	0.014
	(0.029)	(0.020)	(0.026)
R^2	0.580	0.522	0.510
Observations	14,163	14,163	14,163
Participant fixed effects	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓

Notes: * $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A12. Heterogeneity of Dark Pattern Effect by Prior Site Visits (Organic Sites)

	Accept All (1)	Reject All (2)	Close Window (3)
Has Prior Visit	0.023	0.002	-0.029
	(0.017)	(0.012)	(0.015)
Has Prior Visit × Reject Hidden	0.018	-0.001	-0.016
	(0.021)	(0.014)	(0.019)
Has Prior Visit × Accept Hidden	-0.007	0.008	-0.025
	(0.026)	(0.018)	(0.025)
Has Prior Visit × Accept Top	0.017	-0.002	-0.005
	(0.019)	(0.013)	(0.018)
Has Prior Visit × Reject Top	0.023	-0.005	-0.004
	(0.022)	(0.015)	(0.020)
Has Prior Visit × Highlight Accept	-0.010	0.002	0.006
	(0.018)	(0.013)	(0.018)
Reject Hidden	0.049***	-0.094***	0.021
	(0.013)	(0.014)	(0.014)
Accept Hidden	-0.434***	0.069***	0.335***
	(0.025)	(0.014)	(0.024)
Accept Top	0.029*	0.003	-0.040***
	(0.012)	(0.008)	(0.011)
Reject Top	-0.002	0.024*	-0.025*
	(0.014)	(0.010)	(0.012)
Highlight Accept	0.001	-0.020*	0.020
	(0.012)	(0.009)	(0.012)
R^2	0.581	0.522	0.512
Observations	14,163	14,163	14,163
Participant fixed effects	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓

Notes: "Has Prior Visit" is a binary variable indicating whether a domain has been visited by the participant two weeks prior to our experiment. * $p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

Intro Page

Thank you for finishing our web browsing task! Now we will walk you through the uninstallation process of the browser extension. To complete the study, we just need to ask you a few more questions about the web browsing and cookie-sharing experiences while using our extension and in general.

Block 1

Think back about your browsing experiences after completing our 20-website visit task while Cookie Manager is installed. Overall, what do you think of the frequency with which cookie consent banners appear during that time?

Too frequent

A bit more frequent than ideal

Just right

A bit less frequent than ideal

Too infrequent

Block 2

Overall, how will you rate the ease of navigation of the cookie consent interface created by our browser extension?

Very easy to navigate

Moderately easy to navigate

Neither easy nor hard to navigate

Moderately hard to navigate

Very hard to navigate

Block 3

Overall, how will you rate the ease of making your preferred cookie sharing choices created by our browser extension?

Very easy

Moderately easy

Neither easy nor hard

Moderately hard

Very hard

Block 4

In the past week, which of the following statement best describes your behavior when deciding whether to share cookies online?

I accepted most cookies

I rejected most cookies

I chose whether to share cookies based on which website is asking

I chose whether to share cookies based on what types of cookie it is

I chose whether to share cookies based on what website is asking and what types of cookie it is

Why choice

Think back to a case when you accepted all cookies during the course of the study. Why did you do so?

Think back to a case when you chose **not** to accept all cookies during the course of the study. Why did you do so?

Block 5

Overall, how do you think the Cookie Manager extension changes your web browsing experience?

It improves my browsing experience by a lot

It improves my browsing experience slightly

It neither improves nor degrades my browsing experience

It degrades my browsing experience slightly

It degrades my browsing experience a lot

Block 12

Consider the cookie consent form below.

One option is to hit the 'x' button in the upper right. If you were to click this 'x', what do you think will happen?

All cookies are accepted.

None of the cookies are accepted.

Other, please explain:

Block 8

During the study period, did you take any actions to change how you browse the internet?

No

Yes, I used a different browser or device.

Yes, I browsed the internet less.

Yes, I did something else. Please specify.

Block 9

As you browse the internet, which information do you think advertisers have about you? Check all that apply.

Your demographic information

Your prior website visits

Your interests

Your prior purchases

Your social media posts

Your address

Your credit score

Block 10

Thinking about privacy polices you might come across online or on your smartphone. Which of the following comes closer to your view, even if neither is exactly right?

Just something I have to get past in order to use a product or service.

A meaningful part of my decision to use a product or service.

Privacy means different things to different people today. In thinking about all of your online browsing, please state how important it is for you to be in control of who can get info about you.

	Not all imporant	Not very imporant	Somewhat Important	Very Imporant
	1	2	3	4
	○	○	○	○

Block 11

What do you think are the benefits of sharing the data listed above with the advertisers?

What do you think are the costs of sharing the data listed above with the advertisers?

Block 6

Do you have any suggestions to help us improve the design of the Cookie Manager extension or the design of our study in general?

Block 14

Consider a tool that that allows you to specify how you would like to answer cookie consent questions online. This tool will then automatically hide all cookie pop-ups and answer them in they way you specified. For example, if you stated that you wanted to accept cookies for all websites, the tool would do so.

Please select how much better or worse the tool is than manually answering the cookie consent form for each website.

Much worse than manual choice	Worse	Somewhat worse	Similar	Somewhat better	Better	Much better than manual choice
○	○	○	○	○	○	○

How much would you be willing to pay for the tool?

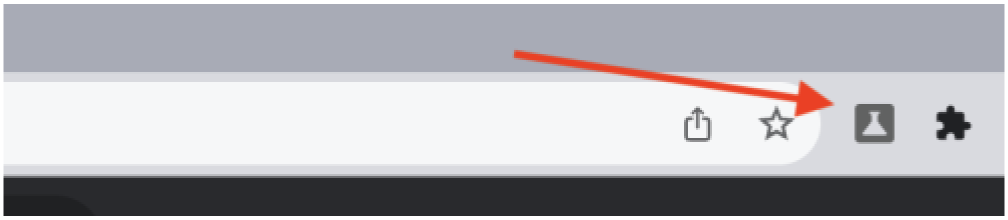
Please enter the price in the text box below.

Instructions for how to download and configure the tool, called Consent-O-Matic, are available here.

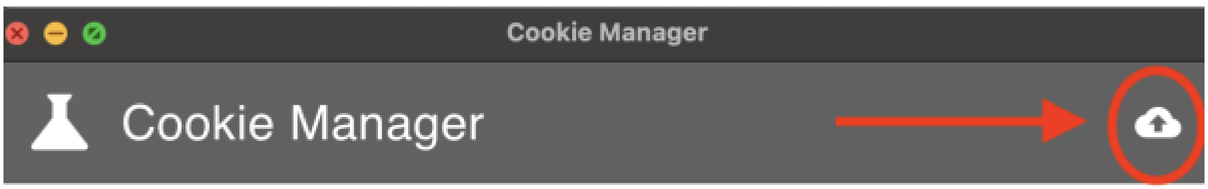
Please click the arrow below to continue the survey.

Block 7

Thank you! We will ask you to upload your data to us prior to uninstalling the extension. Please click on the Cookie Managert extension icon in your Chrome browser.



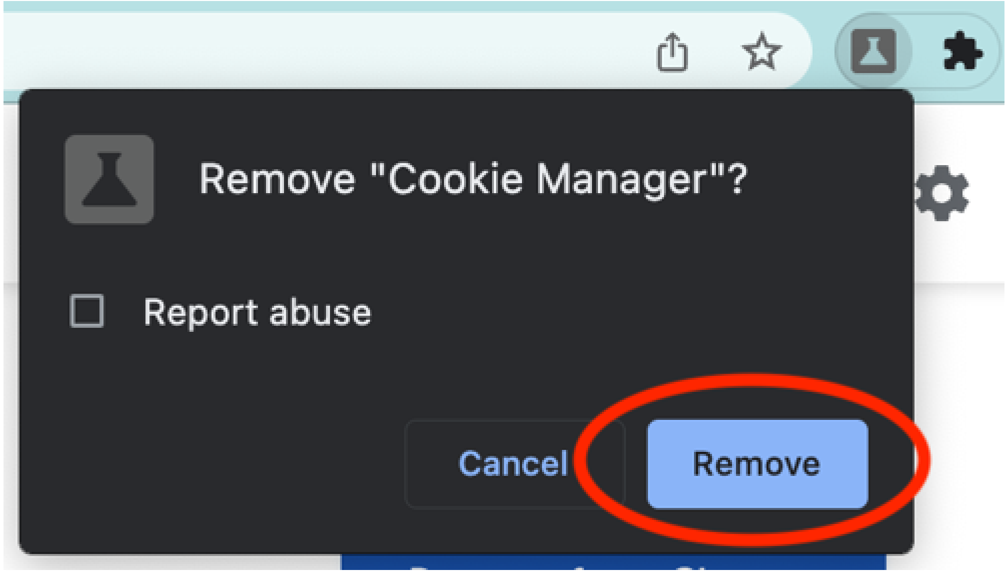
You should see a pop-up. Please click on the cloud button with an arrow. Completing this step ensures that your participation in our study and the associated data are properly recorded.



Now that you've clicked the cloud button, you can now proceed to uninstall the extension. Completing this step ensures that we stop collecting your browsing data going forward.

Here's how you can remove the cookie manager extension:
- Click here.
- Click “Remove from Chrome.”

- Confirm by clicking "Remove" on the pop-up window appearing on the top right corner of your browser.



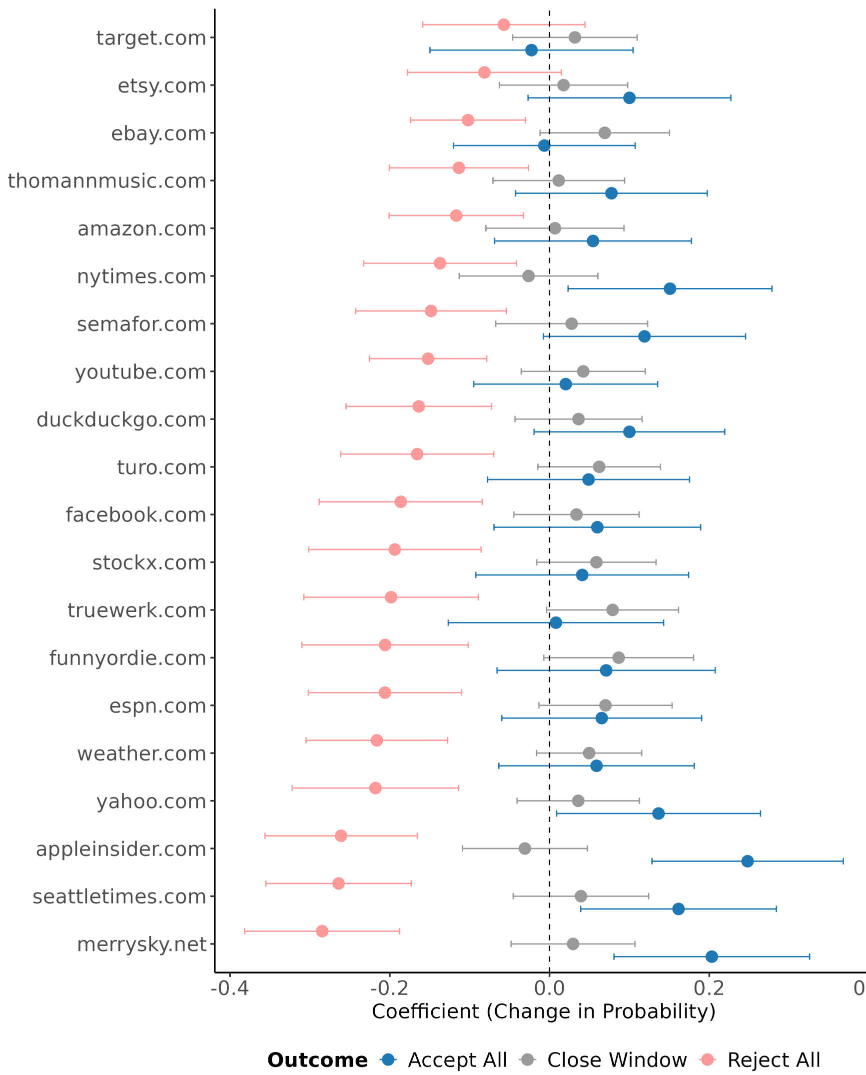
- You're all set.

If you have trouble uninstalling Cookie Manager, email us at cookie.manager.study@gmail.com and we will help you with additional instructions.

Please click the arrow below to finish the survey.

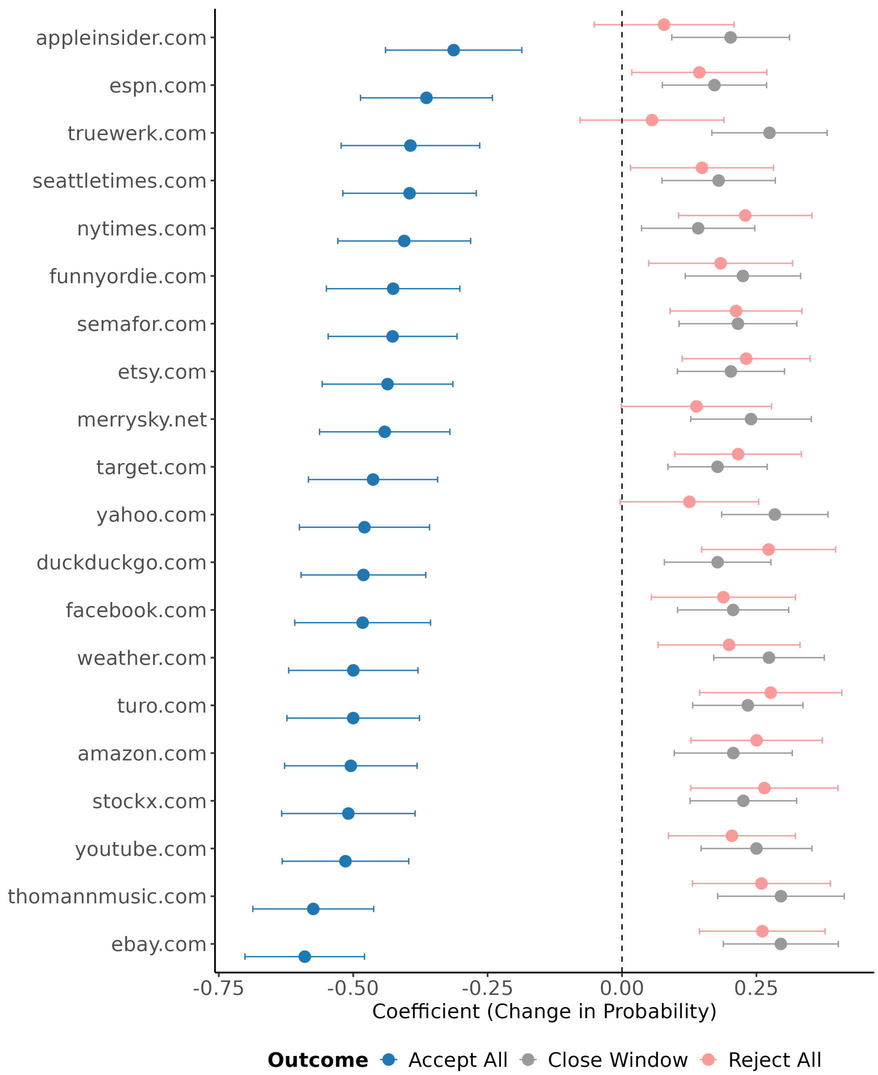
Powered by Qualtrics

FIGURE A2. Treatment Effects by Survey Domain (Acc-Set vs Neutral)



Notes: The figure shows the treatment effects (point estimates and 95% confidence intervals) of 'Acc-Set' vs the no dark pattern interface for each domain featured in the survey visit.

FIGURE A3. Treatment Effects by Survey Domain (Rej-Set vs Neutral)



Notes: The figure shows the treatment effects (point estimates and 95% confidence intervals) of 'Rej-Set' vs the no dark pattern interface for each domain featured in the survey visit.

TABLE A13. Differences Between Participants Who Always Accept, Always Reject, and Make Discerning Choices

Variable	Mean: Never Accept	Mean: Some Accept	Mean: Always Accept	F-value	p-value
Age	37.21	38.33	38.35	0.3	0.74
Female	0.58	0.42	0.45	3.73	0.024
Bachelor's or Above	0.26	0.15	0.18	2.64	0.072
Income > $75,000	0.39	0.45	0.45	0.61	0.545
Prior Domains Visited	54.08	55.89	45.77	4.39	0.013

Notes: "Never Accept" and "Always Accept" indicate the participants who never and always choose "accept all", excluding instances of closing window. Tn this table, all choice probabilities are calculated within the neutral design treatment, thus choice variations in the "Some Accept" group reflect variation across sites, excluding the influence of dark patterns on choice.

TABLE A14. Fatigue in Cookie Choices During Organic Browsing (Additional Fixed Effects)

	Accept All (1)	Reject All (2)	Close Window (3)
Visit Order / 10	-0.017*	-0.002	0.020*
	(0.008)	(0.003)	(0.008)
Time in Study (Days)	-0.001	-0.004	0.005
	(0.005)	(0.002)	(0.005)
R^2	0.476	0.499	0.454
Observations	14,163	14,163	14,163
Domain Cat. fixed effects	✓	✓	✓
Participant fixed effects	✓	✓	✓
Hour fixed effects	✓	✓	✓

Notes: This table estimates a variant of Equation 3, which removes the banner frequency treatment and adds the order of which a domain is visited ("Visit Order") and additional fixed effects. *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

		Survey	Organic
	Intercept	0.699***	0.602***
		(0.017)	(0.015)
	Acc-Rej-Set	-0.017	0.003
		(0.009)	(0.010)
	Acc-Set	0.042***	0.024*
		(0.009)	(0.010)
	Rej-Acc-Set	-0.032***	-0.025*
Effects on Accept All		(0.010)	(0.010)
	Rej-Set	-0.501***	-0.461***
		(0.010)	(0.010)
	Set-Acc-Rej	-0.037***	-0.032***
		(0.010)	(0.010)
	SD (Participant)	0.342	0.334
	SD (Domain)	0.032	0.059
	SD (Residual)	0.294	0.326
	Num.Obs.	12142	14163

Notes: This table presents estimates of a treatment effects model where random effects for participant and domain are included in the regression. Consumer familiarity and trust towards a website is user-domain specific, and choice variation induced by familiarity and trust is captured by the residual term rather than domain random effect.

TABLE A15. Extra Time Spent When Clicking Settings

	Time Spent (Seconds)			
	OLS		Obstruction IV	
	Survey	Organic	Survey	Organic
	(1)	(2)	(3)	(4)
User Clicks Settings	3.700***	2.307***	11.304***	6.732***
	(0.466)	(0.635)	(1.178)	(1.988)
R^2	0.215	0.126	0.192	0.123
Observations	12,247	14,116	12,247	14,116
Condition fixed effects	✓	✓		
Participant fixed effects	✓	✓	✓	✓
Domain Cat. fixed effects	✓	✓	✓	✓

Regression estimates: time spent to make a decision as a function of whether the user's action involved clicking settings. The OLS estimates reflect the average cost across all six treatments, including those always choose granular choices, and those who go to settings to reject or accept all in an obstruction treatment. The IV estimate uses the obstruction treatment as IV, and regression estimates reflect time cost only for those needing to click settings as a result of the deliberate obstruction treatments. *$p < 0.05$, ** $p < 0.01$; *** $p < 0.001$.

TABLE A16. Consumer Surplus Under Counterfactual Policies (Dollar-Value Weekly)

Counterfactual	Pooled Estimate	Accepters	Rejectors	Discerners
US Status Quo	3.19	4.55	-0.81	1.25
CS Maximizing Banner	3.55	4.91	0.97	1.48
EU Norm	3.27	4.30	1.42	1.43
Force Accept All	4.59	6.00	0.07	3.69
Force Reject All	3.07	2.83	3.08	3.30

Notes: The table reports scaled consumer surplus dollar-value estimates under various counterfactual policies, with all values divided by 3 from the original estimates. "US status quo" refers to an accept-settings interface, combined with an accept-all default when consumers close window; "CS maximizing" refers to a neutral interface with an accept-all default when consumers close window; "EU norm" refers to a neutral interface with a reject-all default when consumers close window. "Pooled estimate" refers to the estimate across all subjects, and the other columns correspond to subset-specific estimates.