The Impact of Ad-Blockers on Product Search and Purchase Behavior: A Lab Experiment

Alisa Frik, *International Computer Science Institute / UC Berkeley;* Amelia Haviland and Alessandro Acquisti, *Heinz College, Carnegie Mellon University*

https://www.usenix.org/conference/usenixsecurity20/presentation/frik

This paper is included in the Proceedings of the 29th USENIX Security Symposium.

August 12–14, 2020

978-1-939133-17-5

The Impact of Ad-Blockers on Product Search and Purchase Behavior: A Lab Experiment

Alisa Frik
ICSI, University of California Berkeley

Amelia M. Haviland
Heinz College, Carnegie Mellon University

Alessandro Acquisti
Heinz College, Carnegie Mellon University

Abstract

Ad-blocking applications have become increasingly popular among Internet users. Ad-blockers offer various privacy- and security-enhancing features: they can reduce personal data collection and exposure to malicious advertising, help safeguard users' decision-making autonomy, reduce users' costs (by increasing the speed of page loading), and improve the browsing experience (by reducing visual clutter). On the other hand, the online advertising industry has claimed that ads increase consumers' economic welfare by helping them find better, cheaper deals faster. If so, using ad-blockers would deprive consumers of these benefits. However, little is known about the actual economic impact of ad-blockers.

We designed a lab experiment (N=212) with real economic incentives to understand the impact of ad-blockers on consumers' product searching and purchasing behavior, and the resulting consumer outcomes. We focus on the effects of blocking contextual ads (ads targeted to individual, potentially sensitive, contexts, such as search queries in a search engine or the content of web pages) on how participants searched for and purchased various products online, and the resulting consumer welfare.

We find that blocking contextual ads did not have a statistically significant effect on the prices of products participants chose to purchase, the time they spent searching for them, or how satisfied they were with the chosen products, prices, and perceived quality. Hence we do not reject the null hypothesis that consumer behavior and outcomes stay constant when such ads are blocked or shown. We conclude that the use of ad-blockers does not seem to compromise consumer economic welfare (along the metrics captured in the experiment) in exchange for privacy and security benefits. We discuss the implications of this work in terms of end-users' privacy, the study's limitations, and future work to extend these results.

1 Introduction

In recent years, online advertising and blocking of it using dedicated tools (e.g., browser extensions and mobile apps) have been at the center of a heated debate. The online advertising industry has claimed that online ads benefit all agents in the advertising ecosystem (vendors, publishers, ad companies, and consumers alike), and support the provision of free online content and services [49]. Claimed benefits range from immediate advantages (such as matching buyers to sellers, increasing companies' revenues, and satisfying consumer needs), to broader economic contributions (including creation of jobs and stimulation of the economic growth in digital sectors) [43, 47, 48].

On the consumer side, however, online ads have raised diverse concerns [30], including privacy and security, inducing growing numbers of Internet users to install software blocking online advertising [87]. Concerns relate both to the growing exposure to large volumes of online ads and to the extensive data collection associated, specifically, with ad targeting. For instance, users believe that today ads are more ubiquitous (81%) and intrusive (69%) than 3 years ago [57]. Moreover, 66% of adult Americans do not want to receive targeted ads [105], and 61% believe free access to the websites is not worth the privacy invasion caused by advertising targeting [80].

In response, according to a recent survey [34], Internet users deploy ad-blockers to stop compromises of their online privacy; to avoid too many or intrusive ads, some of which contain bugs and viruses jeopardising security; to prevent customization based on browsing history; and to increase browsing performance in terms of screen space, loading speed, and consumption of data and battery. Ad-blockers have become increasingly popular consumer tools to address different dimensions of privacy concerns. First, some ad-blockers address concerns associated with privacy and security by curtailing online tracking and malware [97] and other security threats posed by malicious advertising [68, 113], thus helping protect user privacy [33]. Second, by reducing the exposure to ads, ad-blockers address broader concerns related to the protection of users' decision-making autonomy, choice and control over browsing experience, and improvement in such experience (via the reduction of visual clutter and of distraction of attention, and increased speed of page loading). Indeed, users believe that ad-blockers protect from intrusion, interruption of attention, and offensive or inappropriate content of ads [42]. In this regard, ad-blockers ameliorate privacy defined in terms of private sphere, inviolate personality, and autonomous decision making [11, 22, 83, 108].

The growing popularity of ad-blockers among consumers has been met with anxiety, and even hostility, by online advertising companies and online publishers [38]. Industry fears have been supported by some recent studies: researchers have used industry data to estimate online publishers' revenue losses due to ad-blockers, and concluded that "ad-blocking poses a substantial threat to the ad-supported web" [94].

Very little is known, however, about the impact of ad-blockers on the economic-relevant behavior and welfare of *consumers*, and on product searching and purchasing, specifically. Therefore, some of the advertising industry's claims about how consumers benefit from online ads (such as matching buyers to sellers and satisfying consumer needs) have been neither confirmed nor disproved by the empirical evidence.

We conducted a lab experiment with real economic incentives to address this gap in the literature. We investigated the effects of blocking ads on individuals' online product searching and purchasing behavior, and the resulting outcomes.

We focus on contextual ads—ads that are targeted to individual, potentially sensitive, contexts related to consumer interests, but not relying on consumers' past online behaviors (i.e., behaviorally targeted ads). For instance, contextual search ads (also known as sponsored search results) are targeted to a search query chosen by the consumer when looking for information or a product online; and contextual display ads can be targeted to the content of a web page visited by the user. As such, our results and discussion focus on one specific set of claims regarding the value of online ads (those pertaining to direct economic consequences for consumers, rather than claimed macroeconomic effects such as the support of free content), and on a specific family of targeted ads (primarily contextual ads on sponsored search results in a specific search engine, Google, and, to a smaller extent, on vendors' landing pages).[1]

Experimental participants (N=212) were invited to search for products online and purchase them using their credit cards. They were randomly assigned to experimental conditions in which ads were displayed, or blocked. We captured the impact of showing or blocking ads on participants' purchase decisions—in particular, on the price of the products they searched for. In addition, and based on research on the psychological and cognitive effects of advertising [40, 51, 52, 54, 107], we captured how showing or blocking ads impacts participants' search costs (time spent on searching) and satisfaction with their browsing experience and product choices.

We find that the removal of contextual ads using ad-blockers did not have a statistically significant effect on how much participants chose to pay for the products, how much time they spent searching for them, or how satisfied they were with the chosen products, prices, and perceived quality. In essence: we do not reject the null hypothesis that consumer welfare stays constant when ads are blocked or are shown. Thus, we do not find evidence that the use of ad-blockers against contextual ads compromises consumer welfare, along the metrics captured in our study, in exchange for privacy and security benefits.

2 Related Work and Hypotheses

2.1 Ad-blockers

In recent years, ad-blockers have become increasingly popular tools of digital self-defense. The global number of consumers adopting technologies to block ads had reached 615 million in December 2016 [87]. The growth in ad-blockers' popularity has likely been fueled by Internet users' resistance to increasing amounts of invasive ads and the associated tracking of personal data.

Ad-blockers are third-party tools that users can install on their machines to block ads from appearing in the browsers. Most ad-blockers are able to block multiple types of ads—including search ads appearing as sponsored search results on search engines and display ads appearing on other sites. Numerous researchers have investigated the technical performance of ad-blockers [81, 95], and have demonstrated that ad-blockers are highly effective in eliminating online ads and limiting web tracking [5, 28, 50, 72, 74, 75, 109], and in reducing energy consumption on smartphones [20, 79, 92] and laptops [96]. As discussed in §1, users often deploy ad-blockers to counter privacy and security concerns. When configured properly, ad-blockers are shown to be effective in protecting some aspects of user privacy and security [33].

A few user studies on ad-blockers have primarily focused on the usability of these tools [64]. Pujol et al. [91] found that the majority of the users of a popular ad-blocker, AdBlock Plus, did not opt out from a default list of "non intrusive ads," and did not enable the filter that blocks web trackers. Similarly, another popular ad-blocker, Ghostery, does not protect from privacy risks with its default settings [33]. One study [77] investigated the effect of ad-blockers on user engagement with the Internet. That study, however, used observational data (compared to experimental data in our study), and focused on browsing (not on online shopping) behaviors.

[1] The usage of a lab experiment and the focus on contextual search ads allow us to control for potential confounding factors and obtain internally valid, conservative estimates of the effects of that specific type of advertising. Capturing the effects of behaviorally targeted ads would likely require much larger sample sizes and different experimental designs, due to the challenges of developing realistic online consumer profiles for behavioral targeting in a lab setting, and controlling for the larger set of factors behavioral targeting relies on (e.g., idiosyncratic online behaviors, user profiles, device specifications). In future field experiments we plan to explore the effects of eliminating behaviorally targeted ads, and of displaying non-targeted ads.

In summary, while a few studies have explored the privacy implications of online advertising tracking [114] or the economic impact of fraudulent ads on the companies' revenues [98], and have quantified ad-blockers' privacy implications [33, 109], none have estimated the impact on ad-blocker *users'* economic welfare and satisfaction. To our knowledge, our study—investigating the impact of ad-blockers on actual Internet users' purchasing behavior, outcomes, and satisfaction—is the first to attempt to bridge the gaps in the existing research on ad-blockers' technical aspects of security, human factors, economic impact, and privacy implications. How end-users react to the usage of ad-blockers (and, therefore, to the presence or absence of online ads) is critical to the analysis of industry claims on the negative effects of ad-blockers, and to the understanding of the broader effects of ad-blocking on the society.

2.2 The impact of online advertising

Internet advertising is a popular business model among online publishers and a fast-growing sector of the global economy. Online advertising revenues reached USD 48 billion in Europe and USD 88 billion in the U.S. in 2017 [44, 45]. However, on the consumer side, the proliferation of online ads has caused growing dissatisfaction and adoption of ad-blockers. Users report blocking online advertising because they find ads excessive (48%), annoying and irrelevant (47%), intrusive (44%) and personalized based on browsing history (20%), sometimes containing bugs and viruses (39%), occupying too much screen space (37%), decreasing page loading speed (33%), and compromising online privacy (25%) [34]. Thus, targeting is one of the users' concerns with online ads, but not the only or most common one.

Nevertheless, the ability to target advertising to individual consumers is one of the crucial factors responsible for the generation of large revenues in the online advertising market [19, 32, 35, 36, 53, 110]. Targeting refers to advertisers' ability to match ads to Internet users in the attempt to meet their preferences and interests. Targeting can take place in a number of ways, all ultimately dependent on some knowledge, or inference, of users' information or behavior. One way is *contextual* targeting of ads based on the content of that particular page, which in turn is based on generalized and aggregated information about consumers' preferences. Another way is *behavioral* targeting based on the prediction of consumers' individual preferences, which are typically inferred through monitoring of click-stream behavior across multiple sites. While our analysis focuses on contextual targeting, rather than behavioral, the theoretical predictions and results of empirical research about targeted ads presented in this section apply to both types of targeting.

Across policy and academic circles, contrasting propositions have been offered regarding the effects of online advertising (including targeted advertising) on the welfare of different stakeholders (consumers, online publishers, advertising vendors, and data companies). One the one hand, some studies show a positive impact of targeting on advertising campaigns' effectiveness, such as click-through and conversion rates, website visits, and sales [19, 32, 35, 36, 53, 110]. On the other hand, other researchers (and even some advertisers [101]) argue that the effect of targeted ads on consumers' likelihood to purchase may be overestimated due to "activity bias" [67], and methodological issues [32, 66, 85] such as large confidence intervals and (sometimes) absence of comparisons with a randomly selected control group. Some evidence suggests a limited technological efficiency in correctly targeting consumers based on their behaviors [46, 58, 73].

Users express privacy concerns regarding targeted advertising [30, 65, 70, 80, 105, 106]. From the economic perspective, targeting is claimed, on the one hand, to decrease search costs [18, 27, 86], but on the other hand, to potentially reduce consumer surplus (which is absorbed by the advertisers) through application of price and offer discrimination [2, 23, 76, 88].[2] While focused on the business outcomes, those studies did not consider the implications for consumers' welfare.

Our study attempts to address a gap in the literature on ad-blockers and online advertising. Previous behavioral work on ad-blockers has focused on their usability [64, 91], and effectiveness and performance [33]. Previous studies on online ads (e.g., [66, 111]) have also typically focused on ad "effectiveness," which is captured through click-through rates or conversion metrics. Those studies often rely on rich field data, but are focused on consumers' response to a specific ad campaign (or a set of ad campaigns). Our experiment goes in a subtly but importantly different (and somewhat more expansive) direction: it is designed to track participants' behavior across an array of search results and vendor sites, thus capturing their response to the presence or absence of an array of ad campaigns from different vendors. In so doing, the study attempts to investigate a critical counterfactual currently underexplored in the literature: what happens (to consumer behavior, to their choices, and to their economic outcomes) when certain ads are blocked? Rather than investigating online ads' effectiveness by testing whether a consumer will click on a certain ad or end up buying through it, we investigate broader consumer behavior in the presence and absence of contextual ads.

2.3 Hypotheses

Theoretical and practical research has offered contrasting claims, predictions, and evidence regarding the impact of advertising on search costs in terms of time, prices paid for a product, and satisfaction. Accordingly, hypotheses about the effect of ad-blocking on those variables are mixed.

[2]The actual prevalence of first degree price discrimination on the Internet is the object of some debate [84].

Search time. While advocates of the informative role of advertising argue that advertising *reduces* consumers' search costs and therefore search time [18, 86, 99], some empirical evidence shows that advertising may *increase* search time due to distraction, information overload, and increased cognitive effort [37, 40, 51, 52, 107]. Specifically, eye-tracking data showed that online banner ads decreased visual search speed [16]. Additionally, ad-blockers may increase web page loading speed [42], further decreasing the search time.

Product prices. Advocates of the persuasive advertising school predict *increase* in prices and consumption quantities (therefore increasing the overall spending) due to advertising [6, 8, 13, 21, 103], and some empirical evidence supports that prediction [14]. However, the same empirical study shows that participants chose advertised services with slightly *lower* prices, when advertised and non-advertised goods were similarly priced. Subjects in another lab experiment [14] on average chose services with *higher* prices when advertising was available than when it was not. The presence of price information in those ads had an effect on its own: when ads were promoting services that had lower prices compared to non-advertised services, subjects chose higher-priced non-advertised services, because they suspected lower quality of advertised services and preferred to avoid them. Yet, when prices between advertised and non-advertised goods were similar, participants chose advertised services with lower prices.

Satisfaction. Consumer satisfaction largely depends on the perceived product quality and price–quality balance. While some theoretical works predict higher quality of advertised goods due to "quality-guarantee effects" and competition [4, 17, 56, 100], others warn that brand and reputation—which play a primarily persuasive role—may mislead consumers' judgment about the high quality of the advertised products [15], and encourage manufacturers to advertise low-quality goods [63]. Experimental evidence demonstrates an inverted-U shape relation between the perceived product quality and advertising: when a company exerts reasonable efforts in advertising, consumers perceive higher product quality because the firm seems to be sure about the quality of its products [14], whereas when the amount of advertising is excessive, consumers tend to associate it with lack of producers' confidence [41, 60, 61, 62]. The perceptions of quality further guide consumer satisfaction. In addition to the product quality perceptions, ad-blockers may improve satisfaction with the browsing experience itself, by reducing annoyance, clutter, and distraction caused by ads.

Moderators. Some studies show that the effect of advertising is moderated by product and individual consumers' characteristics, such as durability, product involvement, frequency of purchasing, and utilitarian *vs.* hedonic nature. For instance, some researchers argue that advertising has a more powerful effect on rate of return and profit for non-durable and convenience goods, which are usually lower priced, and frequently purchased [25, 26, 82, 89, 90]. Some research also suggests that prior experience and previous purchases (so-called loyalty, or inertia effects) are more predictive of purchasing decisions than advertising, whereas ads influence more inexperienced consumers [1, 24, 29]. Bart et al. [7] found that mobile display advertising had a bigger positive effect on purchase intent for high-involvement and utilitarian goods, consumption of which is characterized by goal-oriented, practical functionalities. Product involvement has also been shown to affect price acceptability: price plays a smaller role on purchasing decisions of highly involved consumers than on the decisions of consumers less involved with a product category [39, 69, 112]. Product involvement also positively correlates with product satisfaction [39].

As results of prior research are mixed, we believe our study offers an important empirical contribution.

3 Method

We designed a lab experiment to test the effects of ad-blockers on consumers' searching and purchasing behaviors and resulting outcomes. We focused on the impact of the presence or blocking of contextual ads—primarily sponsored search results following queries for consumer products on a popular search engine, and to a smaller extent display ads on the visited web pages.[3] We captured participants' product choices (including the price they would ultimately pay for products), time spent on product searching, and satisfaction with the products and browsing experience.

Prospective subjects answered an entry survey about their Internet and online shopping experiences. We screened out participants who were younger than 18 years old, who had not made any online purchases in the last 12 months, and who could not use a debit/credit card in the experiment.All participants who completed the entry survey entered a raffle for a 1:50 chance to win a $50 Amazon gift card. Eligible respondents were invited to participate in the lab experiment.

In the lab, participants sat in front of a laptop and used it to search via Google search engine for products to buy online. On Google, alongside organic search engine results, sponsored search results appear in two forms: *sponsored links* and *sponsored Google Shopping listings* (which are usually found on the top of the search engine result list, before organic and sponsored links). Participants had 40 minutes to use a search engine to search for 10 product categories, using search terms specified by the experimenter (Table 1), and to choose, in each category, the product and online vendor they intended to purchase from. To account for idiosyncratic product characteristics, prior to the experiment we conducted a separate online survey to assess the characteristics of various products, and included in the study 10 diverse product categories with

[3] While display ads were blocked, and their impact is reflected in the main treatment effects, we do not analyse in detail the impact of particular types of display ads (e.g., by placement on a page, or format) because we focus on the impact on consumer economic welfare, not ad effectiveness.

Table 1: Product categories and search queries.

Product	Query	Search	Durable
Winter hat	Winter hat	generic	yes
Wall poster	Wall poster	generic	yes
Headphones	Headphones	generic	yes
Book	Book	generic	yes
Votive candles	Votive candles	generic	no
Juice	"Ocean Spray" juice 10oz. 6 pack	specific	no
Flash drive	"Cruzer" flash drive 8Gb	specific	yes
Body wash	"St. Ives" body wash 24oz.	specific	no
Teeth whitening	"Plus White" teeth whitening kit	specific	no
Key chains	Key chains	generic	yes

average price under $25 that vary along different dimensions (e.g., durable *vs.* non-durable, hedonic *vs.* utilitarian, etc.).

The incentive mechanism used in the study is based on the Becker-deGroot-Marschak (BDM) method [10], but is modified to preserve the realism of the online shopping scenario. We informed participants that, before the end of the experiment, they would have to complete the purchase (using their debit/credit card and personal information) of one of the products they had chosen, picked at random among the 10 product categories. Therefore, participants were encouraged to select every product carefully, as each of them had equal chances to be eventually chosen for purchase. Participants were informed that they would receive a fixed $25 compensation for the purchase, regardless of the money spent. In addition, participants were informed that they would receive $15 for participation in the experiment. Thus, the BDM mechanism, coupled with the payment protocol, creates realistic incentives to shop for desirable prices (as participants would received a fixed amount of money for their purchases) and provided an adequate level of compensation (as average prices for each product category were below $25—see Table 2). Participants were free to buy a more expensive item and pay the difference from their own money if they wanted to.[4] Thus, the purchase design was incentive-compatible, as participants faced realistic conditions for making economically rational decisions within the limits of a given budget, optimizing (or minimizing) the difference between the value of the product and its cost. Prior research shows that moderate monetary incentives and low-involvement goods (e.g., batteries and mugs) are enough to generate economically rational choice behavior [55, 104].

Participants were randomly assigned to two experimental conditions, which we will refer to as "Block" and "NoBlock." In the Block condition, contextual ads were blocked on sites that the participants visited during the study (e.g., shopping websites), and on the search engine result pages (thus, participants in this condition were only exposed to organic search engine results). In the NoBlock condition, no ads were blocked; thus, participants were exposed to contextually targeted display ads, and could choose the products from both organic and sponsored search results.

The laptops used by participants for their searches were instrumented differently according to the experimental condition a participant was randomly assigned to. While laptops in the Block condition were instrumented with ad-blocking extensions,[5] laptops in the NoBlock condition were not. The ad-blockers were configured to the highest rate of effectiveness feasible at the time [5, 28, 33, 72, 74, 75]; our own testing confirmed that participants in the Block condition were exposed to nearly zero ads.

Because search engines' algorithms run in real time, search results are dynamic. To account for that (and show consistent results to the participants), just prior to the experiment we saved locally the first 10 pages of search engine results for each product category, fully preserving their original visual appearance, and presented those to the subjects as the results of their searches. The figure in supplemental material S1[6] shows how search engine result pages for the same product category differ across conditions. By clicking on the organic or sponsored search results subjects were directed to the corresponding live websites and continued browsing on the Internet in real time.[7]

Anecdotal evidence suggests that longer keywords associated with goal-oriented searches for specific products result in larger rates of clicking on organic links [111]. Moreover, consumer response (in terms of click-through and conversion rates) is higher for branded keyword searches in [93], although Blake at al. [12] found no measurable short-term evidence of such effect. To account for the degree of specificity and the presence of brand names among keywords in the search query, we used both generic and specific searches. Out of the 10 searches each participant was expected to complete, 6 search terms were generic, unbranded product categories, e.g., "a book," while 4 others were specific and branded products, e.g., "Cruzer flash drive 8Gb" (Table 1). Participants were instructed not to modify search terms or to type vendors' URL directly in the address bar.

The order of product searches was randomized across participants. To prevent contamination of search results via browsing activities across product categories and participants,

[4] Indeed, one participant paid $40 for a keychain, and was satisfied with it, although the average price for keychains was $6. In total, participants chose a product with the price above $25 only 1.7% of the time.

[5] Simultaneously, Ghostery 5.4.10: `https://www.ghostery.com`, AdBlock Plus 2.6.13: `https://addons.mozilla.org/en-US/firefox/addon/adblock-plus/`, and uBlock Origin 1.10.4: `https://addons.mozilla.org/en-US/firefox/addon/ublock-origin/`.

[6] Available at `https://osf.io/wfv72/`.

[7] This methodology preserves only the order of search results, while the websites can still vary in their content over time. However, the expected fluctuations of price, product availability, and display on the vendors' websites are small; we controlled for that *ex-post* using the data recorded through screen-capturing software and saved web pages of visited websites.

subjects searched each product in an independent browser profile. Browsing history, cache, cookies, and temporary files were automatically deleted after each participant.[8]

At the end of the 40 minutes, participants were informed that one of the product categories they had been searching for would now be selected at random. Participants were then asked to complete the actual purchase of the product they had selected under that product category, using their credit cards and personal information. After completing the purchase, participants responded to an exit survey about satisfaction with the product selection and browsing experience.

During the experiment, in addition to their survey answers, we collected participants' complete browsing history logs with time stamps, visited web pages in HTML format, screenshots of the chosen products' pages, and URLs and shipping cost of the chosen products using a custom desktop application. All browsing activity during the experiment was recorded using a screen-capturing software. Some weeks after the experiment (after the estimated delivery date of the product they had purchased), participants answered a follow-up survey. Through that survey, we collected participants' *ex-post* satisfaction with the purchased product.

Statistical analysis. We conduct the analysis in two ways: univariate statistical tests of means or proportions, and multivariate regression analysis. The main results (estimating the average impact of the treatment) are consistent across the two approaches. However, the regression analysis allows more precise investigation by controlling for explanatory factors. In regression analysis of the prices of chosen products, search time, and satisfaction with the browsing experience, we use linear mixed models with individual participant random effects, fixed effects for all other covariates, and robust standard errors. We use ordered logit regression models for other metrics of satisfaction measured on a 7-point Likert scale.[9]

While in the descriptive analysis we analyze product prices in absolute terms (as inferred from the screenshots of chosen products), in the regressions we compare the relative (rather than absolute) differences in these prices across product categories, so as to account for heterogeneity in product categories. Specifically, we subtract means of log prices for each product category from individual products' log prices and use the resulting metrics as the main dependent variable (price_log).[10]

In addition, we control for the following covariates:

- "Specific branded search query," binary (Table 1);
- "Durable product"—product that is not consumed immediately but gradually worn out during use over an extended period of time—binary (Table 1);
- "Hedonic product" defined by the participants' responses on a 9-point Likert scale, with 1 for utilitarian product (purely useful, practical, functional) and 9 for hedonic product (purely fun, enjoyable, appealing to the senses);
- "Order of the product searching," between 1 and 10;
- "Perceived difficulty of the study" defined by the participants' responses on a 7-point Likert scale to a question about how difficult it was for them to make the decisions about products in the experiment;
- "Home computer ad-blocker user" defined as 1 for the participants who reported using ad-blocker on a personal home computer, and 0 otherwise;
- "Index of purchase-decision involvement"—"the extent of interest and concern a consumer brings to bear on a purchase decision task"; measured using Purchase-Decision Involvement scale [78];
- "General online shopping frequency" defined as an index, computed using structural equation modeling with varimax rotation (Cronbach $alpha = 0.65$), based on participants' responses about how often they buy products and services online from a computer or mobile device that cost less than \$10, \$11–100, and more than \$100;
- "Frequency of product purchasing," on a 6-point Likert scale (between never and every day);
- "No exposure to the ads of the purchased product's brand" in the 30 days prior to the experiment as self-reported by the participants and defined as 1, 0 otherwise;
- "Internet usage skills" defined by a score from 1 to 5 as a sum of positive responses about whether they are able to perform certain activities on the Internet (use a search engine, send emails with attached files, view browsing history, remove temporary files and cookies, create or update a website;
- "Browser" that participants normally use on their home computer (multiple choice between Firefox, Chrome, Safari, and IE);
- "Prefer to buy online" defined as 0 if participants buy products and services "only in physical stores," 1 if they buy from "both physical and online stores, but prefer to buy from physical ones," 2 if they buy from "both physical and online stores, but prefer to buy from online ones," and 3 if they buy "only in online stores";
- "Privacy concerns" measured using Internet Users' Information Privacy Concern (IUIPC) scale [71].

[8] However, we cannot rule out whether the behavioral targeting occurred within, not across, a particular searching session, while the participant was searching for a specific product. While trackers could potentially use IP address or deploy browser fingerprinting, this information is not enough for constructing meaningful user profile for behavioral targeting, without related browsing history and cookies.

[9] The model specifications with interactions between the treatment and prior experience with ad-blockers revealed no significant interaction effects. They are available from the authors on request.

[10] For sensitivity checks, we use two additional measures of price: 1) prices divided by product category means (price_mean), and 2) prices divided by product category means after excluding outliers that are more than 3 SD away from the mean (price_mean_outliers). The significance and similarity of regression coefficients in sensitivity checks confirm the robustness of our results.

4 Results

Before the experiment, we obtained IRB approval and participants' consent. Over the course of 4 months, 212 individuals participated in the experiment in labs at Carnegie Mellon University (CMU). We recruited participants using the CMU Center of Behavioral Decision Research's participant pool, Craigslist, and flyers on CMU campus. Participants were grouped into sessions. There were up to five participants per session, each of whom was randomly assigned to one of the two conditions. Group composition was balanced by gender, with 52% female. Average age of the participants was 26 years old ($SD = 10; min = 18; max = 72$) and included student and non-student population. The majority (59%) had a Bachelor's degree or higher.[11] About half (49%) specified their ethnicity as Asian (of these, 31% have resided in the US for most of their lives) and 36% as White.[12]

Regarding the perceived role of online advertising (see supplemental material S3), the majority of participants agreed that it is distracting (77%) and intrusive (67%), and 46% found it disturbing. On the other hand, many participants agreed that it creates brand awareness (80%) (although only 37% believe it eventually persuades to buy the products), is informative about the available products, their prices, or discounts (62%), and is necessary to enjoy free services on the Internet (58%). Less than half agreed that online advertising helps to find products and services that match one's personality and interests (48%), raising doubts about the perceived benefits of targeted ads. Only about a third of participants agreed that online advertising saves money (33%), time (32%), or helps to buy the best product for a given price (32%).

Our participants chose 53% of the products for purchase from Amazon.com, and 14% of the products from Walmart.com. The rest of the products were chosen from a long tail of 73 other websites (with individual frequency of no more than 5.1%), including popular US retailers (such as Ebay.com, Aliexpress.com, BestBuy.com, Target.com), specific brand vendors' websites (e.g., Zara.com, Ikea.com), and less popular online vendors (e.g., candle-licious.com).

In NoBlock condition, products chosen from the *sponsored Google Shopping listings* were primarily from Walmart.com (25%), Bestbuy.com (20%), and Target.com (10%), and only 1% from Amazon.com. Among the products chosen from the *sponsored links*, 72% were from Amazon.com. Moreover, there is no difference in website and brand familiarity between products chosen from organic and sponsored links, but participants were less familiar with the websites ($\beta = -1.2$, $p = 0.000$) and more familiar with the brands ($\beta = 0.45$, $p = 0.008$) of the products in sponsored Google Shopping listings than in organic links.

Note that our manipulation affected the entire product option space available to participants (through fetching or blocking sponsored search results), and, in turn, participants' actual purchase behavior (e.g., through a potential change of reference point). For instance, if the product prices are lower in sponsored search results than in organic search results, then participants in the NoBlock condition will have a wider product option space with access to lower prices than participants in the Block condition, which could change their reference price, even if they eventually do not buy those lower priced advertised products. Similarly, the exposure to luxury brand products in sponsored search results and display ads could alter the expectations of participants in the NoBlock condition about appropriate product quality, and drive their satisfaction down compared to subjects in the Block condition, who have not seen those ads. If the reverse held, higher prices or lower quality of advertised products compared to organic search results would result in opposite predictions. Finally, exposure to ads, on the one hand, may provide a short cut by efficiently matching buyers to the sellers' offers that would satisfy consumer needs and thus save time on searching; and on the other hand, it may distract participants' attention, increasing their product search time. In this manuscript, we do not focus on price differences across all organic *vs.* sponsored search results and ads. Instead, we focus on analyzing participants' potential changes in search *behaviors* and subsequent product choices.

4.1 Effect on Prices

For most product categories, the average price of the chosen items did not significantly differ between the two conditions (Table 2). Only in the Book category did participants in the Block condition select products with significantly lower average prices than participants in the NoBlock condition ($t(150) = 1.98, p = 0.049$). Additionally, on average, and for three specific products—Winter hat, Headphones, and Key chains—the variance was significantly larger in the Block condition than in the NoBlock condition. This may suggest an "anchoring effect": sponsored Google Shopping listings that contain prices and are shown at the very top of the search engine result page may have triggered participants to rely on this initial piece of information as a reference point in their subsequent product search. We plan to investigate this phenomenon in our future work.

In the NoBlock condition, participants clicked on sponsored search results and chose the products for purchase from them quite often (Table 3). ANOVA suggests that the prices of the chosen products that originated from the top sponsored links ($\beta = 2.84$, $p = 0.01$) were *higher* than the ones originating from organic links. In contrast, the prices of the products chosen following sponsored Google Shopping listings were

[11] This is in line with the fact that people with higher education are more likely to use the Internet[3].

[12] The racial distribution is not representative of the US population as a whole, but reflects the considerable presence of Asian students enrolled at the institution where the study was conducted in 2016: 26.2% White, 17.7% Asian (https://datausa.io/profile/university/carnegiemellon-university/).

Table 2: Prices of chosen products across conditions (in USD).

Product	NoBlock condition			Block condition		
	N	Mean	SD	N	Mean	SD
Winter hat	79	11.26	6.56	86	12.23	10.84
Wall poster	86	9.82	5.57	86	9.17	5.22
Headphones	87	15.72	11.55	84	20.38	40.80
Book	74	11.44*	6.33	78	9.47*	5.97
Votive candles	88	8.33	4.70	88	8.79	5.24
Key chains	81	5.92	3.97	87	7.15	6.19
Juice	82	5.99	3.37	81	5.70	3.24
Flash drive	79	6.92	3.05	79	6.77	2.30
Body wash	82	8.51	3.59	77	8.19	2.85
Teeth whitening	83	5.69	4.01	83	5.08	2.39
Average:	821	8.97	6.55	829	9.33	14.57

Table 3: Average prices (in USD) of chosen products across all product categories, by the type of search engine result and condition. Frequency in parentheses.

	Organic links	Sponsored Google Shopping listings	Sponsored links (top)	Sponsored links (bottom)	Overall
NoBlock	9.09 (79%)	7.77 (14%)	11.93 (5%)	10.44 (2%)	8.97
Block	9.39 (100%)				9.39

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

lower than the ones from organic links but not significantly so ($\beta = -1.32$, $p = 0.06$).

We found no statistically significant treatment effect of ad-blocking on log prices conditional on product type across all model specifications in the regression analysis (Table 2 in S4).

Participants in the Block condition did not choose on average less or more expensive products than in the NoBlock condition. These null results are accurately estimated under the statistical models used in the analysis. Hence, they have direct implications regarding the magnitudes of price differences we can confidently rule out (see §6).

We suspected that participants' previous experience with ad-blockers could have affected the results (e.g., due to habit of being or not being exposed to online ads on their own computer). We found that subjects who use ad-blockers on their own home computer tended to choose about 10–11% cheaper products than non users, regardless of which experimental condition they were in (Table 2 in S4).

We also investigated the effects on prices of products' characteristics and other covariates outlined in §3. We found that the absence of main treatment effects is robust to the inclusion of these control variables (Table 2, model 4, in S4). High involvement with the purchasing decision, high frequency of online shopping, and satisfaction with expected product quality measured immediately after the experiment have positive associations with prices, while frequent purchasing of the certain product category is associated with lower prices. Finally, prior exposure to ads, time spent on product searching, specificity of search query, durability, and hedonic nature of the product have no effect ($p > 0.05$) on prices of the chosen product.

4.2 Effect on Search Time

During the 40-minute-long experiment, participants managed to search on average for 8 out of the 10 products in both conditions and spent about 4 minutes searching per product ($sd = 3.57, min = 0, max = 32$). Subjects spent less time ($t(1682) = 10.41, p = 0.00$) and inspected slightly more search results ($t(1682) = -6.33, p = 0.00$) when searching specific branded products compared to generic ones.

Participants who chose the products from sponsored Google Shopping listings spent less time on their searching (ANOVA: $beta = -1.64, p = 0.00$) than those who chose the products following organic links (Table 4).

According to the results of regression analysis (Table 3 in S5) and statistical tests, the absence of ads did not substantially increase or decrease the search costs for participants: across conditions the difference in product search time ($t(1682) = -0.8502, p = 0.3953$) and total number of inspected search results ($mean = 2.39, sd = 1.83, min = 1, max = 19, t(1682) = 0.24, p = 0.81$) was not statistically significant.

The usage of ad-blockers on home computers did not significantly affect the search time ($t(1682) = -0.86, p = 0.39$), but users of ad-blocker on home computers inspected slightly more search results ($t(1682) = -2.34, p = 0.02$).

Statistically significant and negative order effect suggests that closer to the end of the experiment participants were spending less time on product searching (Table 3 in S5). Participants who reported that the study was difficult spent more time on product searching. On average, participants spent more time searching durable and hedonic products or when they were more involved in the purchase decision. The frequency of product purchasing and self-reported absence of exposure to brand ads in the 30 days prior to the experiment were not significantly associated with the product search time.

4.3 Effect on Satisfaction

We analyzed participants' satisfaction with browsing experience, product choices, prices, and perceived quality. All measures except satisfaction with browsing experience were taken twice—immediately after the experiment, for all chosen products (*ex-ante*), and after physical delivery, for the purchased product (*ex-post*).

Table 4: Average time (in minutes) spent on product searching across all product categories, by the type of search engine result and condition.

	Organic links	Sponsored Google Shopping listings	Sponsored links (top)	Sponsored links (bottom)	Overall
NoBlock	4.36	2.69***	4.72	6.1	4.12
Block	4.27				4.27

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The only significant treatment effect revealed that participants in the Block condition were less satisfied with the web page loading speed than participants in the NoBlock condition. Moreover, home computer ad-blocker users had lower overall satisfaction with browsing experience, and *ex-post* satisfaction with the delivered products, than non-users. The impact of other mediating factors is summarized below.

4.3.1 Satisfaction with browsing experience

Satisfaction with the browsing experience was measured along 7 aspects: overall pleasure from browsing experience, speed of web page load, relevance of the search results to the query, selection of the products on the visited websites, quality and professionalism of the visited websites, ease of navigation on the visited websites, technical functioning level (e.g., presence or absence of broken links, missing/distorted elements of the web page). The majority (between 61% and 87%) of the participants were satisfied with all the aspects of browsing experience in both conditions, except for the speed of web page loading, which satisfied only 46% of the participants in the Block condition, compared to 68% in the NoBlock condition ($t(210) = 3.98, p = 0.00$). Based on the predicted probabilities from the odds ratios in ordered logit regressions,[13] participants in the NoBlock condition have a 17% probability of being dissatisfied with the speed of web page loading compared to a 39% probability in the Block condition. The probability of being satisfied with the speed of web page loading is 72% in the NoBlock condition and only 44% in the Block condition. Previous research has shown that online ads slow down the computer and ad-blockers may not be the most efficient tools in improving the loading speed due to complexity of ad-blocking script execution itself [9]. Our own auxiliary experiment of computer performance showed that the web page speed was indeed slower in the Block condition, because ad-blocking extension usage utilized additional computational resources, which proved taxing for the laptops available in the lab.[14] (See details in supplemental materials S2.) Therefore, we conclude that lower speed of web page loading in the Block condition revealed in the auxiliary experiment did not affect the total amount of time participants spent on product search, but had a negative impact on their satisfaction with that speed.

Overall browsing experience satisfaction was not different across experimental conditions ($t(210) = -0.71; p = 0.48$) but was lower for home computer ad-blocker users ($t(210) = 2.75; p = 0.01$).[15] Safari and Firefox users and those who perceived the study to be difficult were less satisfied with the browsing experience. Online shopping frequency, Internet usage skills, preference to buy online (as opposed to brick-and-mortar stores) and privacy concerns were not significantly associated with browsing satisfaction (Table 4 in S6.1).

4.3.2 Satisfaction with product choices

Overall, 64% of participants in both conditions were satisfied with the product choices measured in an exit survey immediately after the experiment (*ex-ante*). Regression (Table 5 in S6.2) reveals a positive but not significant ad-blocker treatment effect. However, in both treatment conditions, product satisfaction appeared lower for those who use ad-blockers on their home computers, but not significantly so ($t(1665) = 1.97, p = 0.05$). Participants were less satisfied with the products they had to search for using specific branded queries ($t(1665) = 11.88, p = 0.00$), likely because they had less freedom of choice in those categories and may have been unhappy about having to purchase the ultimately selected product. High purchase-decision involvement, frequency of product purchasing, product durability, and satisfaction with product price and expected quality had positive associations with product satisfaction. Search time, hedonic products, and absence of exposure to brand ads in the 30 days prior to the experiment showed no significant associations with product satisfaction. Results of the ANOVA suggest that satisfaction with the products chosen from the sponsored Google Shopping listings ($beta = -0.68, p = 0.00$) and bottom sponsored links ($beta = -1.05, p = 0.049$) in the NoBlock condition are lower than with products chosen from organic links.

When we measured participants' satisfaction with the purchased products again a few weeks following the experiment (*ex-post*), after the products had been delivered, we found that 61% of participants in the NoBlock condition and 59% of participants in the Block condition were satisfied with those purchased products; the difference between conditions

[13] To obtain these predictions, we transformed the 7-point Likert scale responses into categorical variable with 3 levels.We then ran ordered logit regression of this simplified metric on treatment ($beta = -1.1, p = 0.00$) and ad-blocker usage ($beta = -1.2, p = 0.00$) dummies. Finally, we computed the odds ratios, and reported the predictions of probabilities.

[14] Lenovo T460, 16 Gb RAM, released in 2016, running Windows 10 OS. Screen-capturing software was deployed in both experimental conditions. Therefore, it equally affected the web page loading speed in both conditions, and cannot cause the difference.

[15] We computed the index of overall browsing experience satisfaction using a single-factor measurement model (Cronbach α=0.85).

is not statistically significant ($t(154) = -0.21, p = 0.84$). Although statistical tests did not reveal a significant difference in *ex-post* product satisfaction between users and non-users of ad-blockers ($t(154) = 1.21, p = 0.23$), the regression with controls (Table 6 in S6.2). The types of search results (sponsored or organic), *ex-post* satisfaction with the product quality and price, absence of brand ads exposure in the 30 days prior to the experiment, frequent purchasing of the product, and longer search time had no significant effect ($p > 0.05$).

4.3.3 Satisfaction with product prices

Immediately after the experiment (*ex-ante*), 66% of the time participants were satisfied with the prices of the chosen products. We found no difference in *ex-ante* price satisfaction between experimental conditions (based on the regressions in Table 7 in S6.3, and bivariate statistical test ($t(1665) = -1.49; p = 0.14$)), and between home computer users and non-users of ad-blockers ($t(1665) = 0.67; p = 0.5$). However, the satisfaction was lower for the products chosen using specific search queries ($t(1665) = 9.4; p = 0.00$). Higher prices and search time negatively affected the *ex-ante* satisfaction with the prices. In contrast, *ex-ante* satisfaction with expected quality, product durability, and purchase-decision involvement were positively associated with *ex-ante* satisfaction with the prices. *Ex-ante* satisfaction with the prices of the products chosen following sponsored Google Shopping listings in the NoBlock condition was lower than for the products from organic links (ANOVA: $beta = -0.33, p = 0.04$).

After the product delivery, 55% of participants in the NoBlock condition and 69% of participants in the Block condition were *ex-post* satisfied with the prices of the chosen product they received. The difference in Likert scale responses is not significant ($t(154) = -1.82, p = 0.07$), and not robust to the inclusion of the full set of controls (Table 8, model 4, in S6.3). The *ex-post* price satisfaction was not different between home computer users and non-users of ad-blockers ($t(154) = 0.37, p = 0.71$). Specific search queries were associated with lower *ex-post* price satisfaction ($t(154) = 4.7, p = 0.00$). Prices, search time, purchase-decision involvement, frequency of product purchasing, durability, and hedonic nature of the product had no significant association ($p > 0.05$). *Ex-post* satisfaction with the product quality and absence of the prior exposure to brand ads were associated with a higher degree of *ex-post* price satisfaction. *Ex-post* price satisfaction was lower, but not significantly so, for the products purchased from sponsored Google Shopping listings (ANOVA: $beta = -1.23, p = 0.08$) than from organic links in the NoBlock condition.

4.3.4 Satisfaction with perceived product quality

Immediately after the experiment (*ex-ante*), 72% of the time in the NoBlock condition and 69% of the time in the Block condition participants were satisfied with the expected quality of the chosen products. There was no statistically significant difference between conditions ($t(1665) = -0.21, p = 0.84$) and between home computer users and non-users of ad-blockers ($t(1665) = 0.96, p = 0.34$). According to a bivariate statistical test, *ex-ante* satisfaction with the expected quality of the products chosen using specific branded search queries was lower ($t(1665) = 7.29, p = 0.00$) than for generic searches; however, this association was not statistically significant in the multivariate regression (Table 9 in S6.4). Price, satisfaction with price, product durability, frequent product purchasing, high purchase-decision involvement, hedonic nature of the product, search time, and prior exposure to brand ads had no significant association with *ex-ante* quality satisfaction ($p > 0.05$). ANOVA demonstrated lower *ex-ante* satisfaction with the quality of the products chosen from sponsored bottom (but not top) links ($beta = -1.01, p = 0.03$) and Google Shopping listings ($beta = -0.68, p = 0.00$) relative to organic links in the NoBlock condition.

After delivery, 68% and 71% of the participants were *ex-post* satisfied with the quality of purchased products in the NoBlock and Block conditions, respectively. This degree of satisfaction did not differ between conditions ($t(154) = -0.25, p = 0.80$), or between users and non-users of ad-blockers on home computers ($t(154) = 0.24, p = 0.81$). A negative association between the specific branded search queries and satisfaction with the quality of purchased products was found in the bivariate statistical test ($t(154) = 2.81, p = 0.01$), but not in the multivariate regression model (Table 10 in S6.4). The only statistically significant positive predictors of the *ex-post* satisfaction with the quality in the regression (Table 10 in S6.4) were product durability, frequent product purchasing, high purchase-decision involvement, and *ex-post* satisfaction with the product price. The types of search results (sponsored or organic) showed no effect.

5 Limitations and Future Work

Before we discuss the findings and their implications, we highlight current limitations in the analysis, and ongoing work aimed at addressing some of those.

First, to preserve internal validity of the study (a priority of experimental methodology in a lab environment) we asked participants to search for specific product types, without modifying the search queries. However, participants were free to explore the websites to choose the product, vendor, and price they liked the most. We also measured and controlled for their purchase-decision involvement with each product category. Based on the answers to the Mittal scale [78], "in selecting from the many types and brands of products available in the market," 89% of our participants "cared which one [they] bought"; for 87% of participants it "was important to make the right choice of the product"; and 87% of participants were "concerned about the outcome of [their] choice." Behavioral lab research (starting with research on the endowment effect [55], and continuing up to the present day) successfully uses seemingly low-involvement goods (e.g., mugs). The study was incentive-compatible, and participants had to buy the products using their own credit card and personal details. As the incentives offered in the experiment are analogous to the incentives of real-world consumer economic behaviors, the experimental results are expected to generalize to the real-world effects, at least to a justified extent.

Second, significant order effect suggests that closer to the end of experiment participants were spending less time on the search, however it did not significantly affect the prices of the chosen products. We tried to mitigate time pressure in our experimental design by informing participants that it was not important how many products they would eventually search for and that it would not affect the payment, and by showing time elapsed rather than a countdown timer. We plan to test ecological validity of the results in the future field experiment, where we will not impose any time pressure, and where participants' purchase decisions will not be restricted by the experimenter.

Third, in this study we did not consider the differences in product quality across conditions and categories, which is a part of our ongoing research efforts.

Fourth, we may have found null treatment effects due to limited sample size, or short experimental period. However, we were able to rule out large effects. Moreover, standard errors on treatment coefficients allow assessing the statistical power, and demonstrate that we were able to detect effects larger than confidence intervals with our experimental design and sample. Due to randomization, the treatment variable is uncorrelated with model covariates and thus cannot inflate the variance. In contrast, including covariates reduces the model residual and hence the treatment variable coefficient's standard error. Thus, our statistical analysis is rigorous, and results are robust and internally valid. In future work we plan to expand both of these dimensions.

Fifth, we focused on contextual ads, rather than behaviorally targeted ads. Running a tightly controlled lab-experiment, with factors other than the treatment manipulation being kept constant across participants, allowed us to make conservative inferences about effect of presence and lack of contextual ads on purchasing behaviors and outcomes.

In contrast, field experiments can trade-off internal for external validity: they can be more ecologically valid, but permit a lower degree of control over potential confounding factors compared to lab experiments. While validating the effects of eliminating behaviorally targeted ads in a field study is part of our research agenda, exploring the phenomena in a controlled experiment was a critical first step. Internally valid lab experiments are crucial complements to ecologically valid field experiments, and both methodologies are in fact common in security research [31, 59].

Finally, our study does not address potential second-order effects of online ads on consumer welfare (for instance, the benefits consumers derive from access to free online content that ads may support). Nevertheless, our paper offers an empirical insight that encourages us, and hopefully other researchers, to explore further the impact of ad-blockers on consumers' welfare.

6 Discussion and Conclusions

We have presented the results of a lab experiment investigating the impact of ad-blockers on individuals' online purchase behavior, including the time needed to find products to purchase online, the amounts spent, and the degree of satisfaction with purchased items, when contextually targeted online ads are shown or blocked.

Overall, we found that main treatment effects in our experiment were not statistically significant. Such null results carry an important interpretation and practical implications. Participants who were randomly assigned to use ad-blockers did not lose substantially in economic or temporal terms, but they did not gain either. The findings suggest that the removal of contextual ads does not hurt consumers to any meaningful extent along the dimensions we captured (prices paid, satisfaction, and search costs). In essence, although we did not observe that ad-blockers saved participants time or money during the experiment (but ad-blockers also do not aim to positively affect consumer behavior), we did not find support for the claims about an informative role of advertising either. In other words, we did not find empirical evidence that contextual online advertising improves or speeds up the matching of the consumers' needs with the particular sellers able to satisfy them for a lower price, or that ad-blockers deprived users of potential shopping advantages, and privacy and security benefits of blocking ads.

Finally, the use of ad-blockers did not meaningfully alter consumers' satisfaction with products, their prices, or perceived quality. However, participants in the Block condition, where ad-blockers were enabled, reported lower satisfaction with the perceived web page loading speed. The dissatisfaction with web page loading speed may or may not have indirect economic implications on consumer behavior outside of lab conditions. For example, customers annoyed by slow browsing, on the one hand, may abandon shopping sessions before completing the transactions, or they may be less willing to invest time and effort in comparison shopping and purchase more expensive products than they would otherwise do, if they browsed more items. The examination of indirect impacts of browsing experience on purchasing behavior and satisfaction is a subject for future field work.

Although we did not find statistically significant results of the treatment on our main dependent variables, the confidence intervals from the regressions have valuable *practical* implications. First, the confidence interval for the Block condition coefficient in Table 2 (S4) suggests with 95% confidence that people in the Block condition, where ad-blocker was enabled, chose products that are no more than 10% cheaper or more expensive than the average price in a given category compared to people in the NoBlock condition. In contrast, if we consider the reported use of ad-blockers outside of the experimental setting, our results imply (as a correlational and not necessarily causal relationship) that with 95% confidence, the participants who use ad-blockers on their home computers, purchase products that either have a similar price or are up to 20% cheaper than products chosen by non-users. [16]

Second, the confidence interval for the Block condition coefficient in Table 3 (S5) suggests with 95% confidence that people randomized to the Block condition, where the ad-blocker was enabled, spent between 24 minutes less and 76 minutes longer (with an average of 26 minutes longer) on product search than participants in the NoBlock condition. Although this finding is not statistically significant, half an hour of saved time or 1+ hour of extra time spent on product search is practically significant on an individual level. Given an average $28 hourly wage,[17] that would translate into loss of up to $35, in the worst case scenario, a loss of $12 on average, and up to $11 in savings in the best case scenario. We cannot rule out the possibility that the opportunity costs for consumers who deploy ad-blockers may be substantial, although they are not precisely estimated in this study, and there may even be a decrease in search time. Due to the high variance in search times across participants and products, a larger study is needed to determine ad-blocker effects on search time.

To summarize, while we did not find a main treatment effect of using ad-blockers in the experiment, we observed that participants who use ad-blockers on their home computers tended to choose products on average 10–11% cheaper ($p < 0.05$) than people who usually do not use ad-blockers. This finding suggests that long-term use of ad-blockers may influence consumers' shopping choices, or that individuals who choose to use ad-blockers endogenously may have different shopping preferences than those who do not.

6.1 The Effects of Organic and Sponsored Search Results on Consumer Behavior

We found that, in the control condition where ads were displayed, participants who chose products from the top sponsored links paid significantly higher prices ($p = 0.01$), and participants who chose products from sponsored Google Shopping listings paid, on average, lower, but not significantly so ($p = 0.06$), prices than people who chose products from organic links. Moreover, in the control condition, we found that satisfaction with the products, their prices, and expected quality measured immediately after the experiment, was lower, when chosen following the sponsored Google Shopping listings and bottom sponsored links, than when chosen from the organic links (although these differences did not persist when we measured again after the product delivery). Therefore, the welfare implications of being exposed to ads (or blocking them) may ultimately depend to a significant degree on which ads consumers end up following and purchasing from.

Our findings reflect actual participants' *choices*. They do not imply that prices of products in sponsored search results are similar to or different from the product prices in organic search results in general. Even if general differences in prices across various types of search results are a possible explanation of the observed discrepancy, our study does not aim at generalizing that claim. The goal of our experiment was not to specifically test the difference in *all* prices across various types of search results on the Internet, but to examine consumer behavior regarding prices of the products they *chose* in two types of online shopping environments—with and without ad-blocking in place. For instance, underlying differences in prices of the chosen products may or may not attenuate the effect of ad-blocking on purchasing patterns, depending on other factors such as individual participants' characteristics, low purchase-decision involvement, time pressure, or low individual price sensitivity, which could have lead people to pick the most available options without exerting effort on comparison shopping and price seeking. The general difference in prices and the investigation of the potential factors driving that difference are part of our future work plan.

Our observation of higher variance in prices of the chosen products in certain categories in the Block condition (Table 2) may be another illustration of the indirect effect of treatment on consumer behavior through an "anchoring effect." We conjecture that price ads in sponsored Google Shopping box shown at the top of the search results may have influenced the consumers' reference price. Similarly, ads could have anchored participants' expectations about brand, quality, or specific product characteristics (such as model, color, or flavor of the product) that could have influenced participants' subsequent product search. We plan to investigate this phenomenon in more detail and verify the consistency across the product categories in our future work.

6.2 The Effects of Moderators

We found that participants spent less time on searching products using specific branded search queries and were less satisfied (*ex-ante*) with the product choices and their prices. One of the potential explanations is that specific search queries narrowed down the variations between the products in the search results, thus saving time due to reduction in dimensions of comparison shopping. However, limitation of freedom made participants less happy with the chosen products.

Participants who frequently purchase specific products,

[16] As this is not experimentally controlled we cannot determine if using an ad-blocker at home causes participants to select cheaper products or if price-conscious consumers are more likely to use an ad-blocker at home.

[17] The average wage in the US in January 2019 is $27.56 [102].

chose lower-priced items in these categories and were more satisfied with the respective product choices and expected quality (*ex-ante* and *ex-post*). This may be related to loyalty effects and reflect consumers' previous experiences with products [1, 24, 29]. In line with prior research, high product involvement made our participants spend more time on product search and choose higher-priced products, and was associated with their *ex-ante* satisfaction with product choices, prices, and expected quality. Specifically, the choice of higher-priced products confirms the previous findings on the positive correlation of product-purchase involvement with price acceptability [39, 69, 112] and satisfaction [39].

In essence, our experiment does not find evidence that deployment of ad-blockers against contextual ads, aiming at protecting users' privacy and security, and reducing clutter in the online experience, has detrimental effects on consumers' welfare, in terms of satisfaction with products, their prices, perceived quality, or time spent on online searching.

Acknowledgments

Authors would like thank Jeffrey Flagg, Ralph Gross, Aranta Chatterjee, Naveen Kalaga, and Siddharth Nair for assistance in conducting the study. Authors would also like to thank the members of PEEX Lab, reviewers, and audience of the WEIS'19 workshop, who provided valuable feedback on the earlier version of the manuscript. The authors gratefully acknowledge support from the Alfred P. Sloan Foundation. Acquisti also gratefully acknowledges support from the Carnegie Corporation of New York via an Andrew Carnegie Fellowship. For a complete list of Acquisti's additional grants, please visit `https://www.heinz.cmu.edu/~acquisti/cv.html`. Funding for the doctoral scholarship of Alisa Frik was supported by a fellowship from TIM - Telecom Italia.

References

[1] Daniel A Ackerberg. Empirically distinguishing informative and prestige effects of advertising. *RAND Journal of Economics*, pages 316–333, 2001.

[2] Julia Angwin. The web's new gold mine: Your secrets. *Wall Street Journal*, 30(07), 2010.

[3] Christopher Antoun. Who are the internet users, mobile internet users, and mobile-mostly internet users?: Demographic differences across internet-use subgroups in the us. *Mobile research methods: Opportunities and challenges of mobile research methodologies*, pages 99–117, 2015.

[4] Robert B Archibald, Clyde A Haulman, and Carlisle E Moody. Quality, price, advertising, and published quality ratings. *Journal of Consumer Research*, 9(4):347–356, 1983.

[5] Rebecca Balebako, Pedro Leon, Richard Shay, Blase Ur, Yang Wang, and L Cranor. Measuring the effectiveness of privacy tools for limiting behavioral advertising. In *WEB*, 2012.

[6] Bibek Banerjee and Subir Bandyopadhyay. Advertising competition under consumer inertia. *Market. Sci.*, 22(1):131–144, 2003.

[7] Yakov Bart, A Stephen, and Miklos Sarvary. Which products are best suited to mobile advertising? A field study of mobile display advertising effects on consumer attitudes and intentions. *Journal of Market. Research*, 51(3):270–285, 2014.

[8] M Baye and John Morgan. Brand and price advertising in online markets. *Manage Sci*, 55(7):1139–1151, 2009.

[9] BBC News. Ad code 'slows down' browsing speeds. Accessed 17 February 2019: `https://www.bbc.com/news/technology-47252725`, 2019.

[10] Gordon M Becker, Morris H DeGroot, and Jacob Marschak. Measuring utility by a single-response sequential method. *Behavioral science*, 9(3):226–232, 1964.

[11] Paul Bernal. *Internet privacy rights: rights to protect autonomy*. Number 24. Cambridge University Press, 2014.

[12] Thomas Blake, Chris Nosko, and Steven Tadelis. Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. *Econometrica*, 83(1):155–174, 2015.

[13] Francis Bloch and Delphine Manceau. Persuasive advertising in Hotelling's model of product differentiation. *International Journal of Industrial Organization*, 17(4):557–574, 1999.

[14] Paul Bloom and Jeanne Krips. An experiment in the economics of advertising. *J. Market. & Public Policy*, pages 25–42, 1982.

[15] Dorothea Braithwaite. The economic effects of advertisement. *The Economic Journal*, 38(149):16–37, 1928.

[16] Moira Burke, Anthony Hornof, Erik Nilsen, and Nicholas Gorman. High-cost banner blindness: Ads increase perceived workload, hinder visual search, and are forgotten. *ACM Transactions on Computer-Human Interaction*, 12(4):423–445, 2005.

[17] Richard E Caves and David P Greene. Brands' quality levels, prices, and advertising outlays: empirical evidence on signals and information costs. *International Journal of Industrial Organization*, 14(1):29–52, 1996.

[18] Ramnath Chellappa and Raymond Sin. Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Inform. Technol. & Manag.*, 6(2-3):181–202, 2005.

[19] Jianqing Chen and Jan Stallaert. An economic analysis of online advertising using behavioral targeting. *MIS Quarterly*, 38(2), 2014.

[20] Xiaomeng Chen, Abhilash Jindal, and Y Charlie Hu. How much energy can we save from prefetching ads?: energy drain analysis of top 100 apps. In *Proceedings of the Workshop on Power-Aware Computing and Systems*, page 3. ACM, 2013.

[21] Ioana Chioveanu. Advertising, brand loyalty and pricing. *Games and Economic Behavior*, 64(1):68–80, 2008.

[22] Jean L Cohen. Rethinking privacy: autonomy, identity, and the abortion controversy. *Public and private in thought and practice: Perspectives on a grand dichotomy*, pages 133–165, 1997.

[23] Amit Datta, Michael Carl Tschantz, and Anupam Datta. Automated experiments on ad privacy settings. In *Proceed. on Privacy Enhancing Technologies*, volume 1, pages 92–112, 2015.

[24] John Deighton, Caroline M Henderson, and Scott A Neslin. The effects of advertising on brand switching and repeat purchasing. *Journal of marketing research*, pages 28–43, 1994.

[25] Peter Doyle. Advertising expenditure and consumer demand. *Oxford Economic Papers*, 20(3):394–416, 1968.

[26] Peter Doyle. Economic aspects of advertising: A survey. *Economic Journal*, 78(311):570–602, 1968.

[27] Isaac Ehrlich and Lawrence Fisher. The derived demand for advertising: A theoretical and empirical investigation. *The American Economic Review*, 72(3):366–388, 1982.

[28] Steven Englehardt and Arvind Narayanan. Online tracking: A 1-million-site measurement and analysis. In *Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security*, pages 1388–1401. ACM, 2016.

[29] Tülin Erdem and Michael Keane. Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing science*, 15(1):1–20, 1996.

[30] Eurobarometer. Data Protection. Special Eurobarometer 431, European Commission, 2015.

[31] Sascha Fahl, Marian Harbach, Yasemin Acar, and Matthew Smith. On the ecological validity of a password study. In *Proceed. of the 9th Sympos. on Usable Privacy and Security*, page 13, 2013.

[32] Ayman Farahat and Michael C Bailey. How effective is targeted advertising? In *Proceedings of the 21st International Conference on World Wide Web*, pages 111–120. ACM, 2012.

[33] Arthur Gervais, Alexandros Filios, Vincent Lenders, and Srdjan Capkun. Quantifying web adblocker privacy. In *European Symposium on Research in Computer Security*, pages 21–42, 2017.

[34] GlobalWebIndex. Ad-blocking: A deep-dive into ad-blocking trends. Insight report, GlobalWebIndex, 2018. Accessed 22 July, 2019: https://www.globalwebindex.com/hubfs/Downloads/Ad-Blocking-trends-report.pdf.

[35] Avi Goldfarb and Catherine Tucker. Online display advertising: Targeting and obtrusiveness. *Market. Sci.*, 30(3):389–404, 2011.

[36] Avi Goldfarb and Catherine E Tucker. Privacy regulation and online advertising. *Management Sci.*, 57(1):57–71, 2011.

[37] Daniel G Goldstein, R Preston McAfee, and Siddharth Suri. The cost of annoying ads. *Proceedings of the 22nd international conference on World Wide Web*, pages 459–470, 2013.

[38] Julia Greenberg. Ad blockers are making money off ads (and tracking, too). *Wire.com*, 2016. Accessed 1 May 2018.

[39] Andreas Herrmann, Frank Huber, K Sivakumar, and Martin Wricke. An empirical analysis of the determinants of price tolerance. *Psychology & Marketing*, 21(7):533–551, 2004.

[40] Starr R Hiltz and Murray Turoff. Structuring computer-mediated communication systems to avoid information overload. *Communications of the ACM*, 28(7):680–689, 1985.

[41] Pamela M Homer. Ad size as an indicator of perceived advertising costs and effort: The effects on memory and perceptions. *Journal of Advertising*, 24(4):1–12, 1995.

[42] HubSpot. Why people block ads (and what it means for marketers and advertisers). Accessed 17 May 2019: https://blog.hubspot.com/news-trends/why-people-block-ads-and-what-it-means-for-marketers-and-advertisers, 2018.

[43] IAB. IAB believes ad blocking is wrong. Technical report, IAB, 2016.

[44] IAB. The definitive guide to the European digital advertising market. Technical report, IAB, 2018.

[45] IAB. IAB Internet advertising revenue report, 2017 full year results. Technical report, IAB, 2018.

[46] IAB Canada. Geo-targeting online. Technical report, IAB Canada, 2014.

[47] IHS Markit. The economic contribution of digital advertising in europe. Technical report, IAB Europe, 2017.

[48] IHS Markit. Economic value of behavioral targeting. Technical report, IAB Europe, 2017.

[49] IHS Technology. Paving the way: how online advertising enables the digital economy of the future. Technical report, IAB Europe, 2015.

[50] Muhammad Ikram and Mohamed Ali Kaafar. A first look at mobile ad-blocking apps. In *IEEE 16th International Symposium on Network Computing and Applications*, pages 1–8, 2017.

[51] Jacob Jacoby. Information load and decision quality: Some contested issues. *J. Marketing Res.*, 14:569–573, 1977.

[52] Jacob Jacoby. Perspectives on information overload. *Journal of Consumer Research*, 10(4):432–435, 1984.

[53] Przemyslaw Jeziorski and Ilya Segal. What makes them click: Empirical analysis of consumer demand for search advertising. *American Econ. Journal: Microeconomics*, 7(3):24–53, 2015.

[54] Bodil Jones. Dying for information? *Manag. Rev.*, 86(7):9, 1997.

[55] Daniel Kahneman, Jack L Knetsch, and Richard H Thaler. Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic perspectives*, 5(1):193–206, 1991.

[56] Nicholas Kaldor. The economic aspects of advertising. *The Review of Economic Studies*, 18(1):1–27, 1950.

[57] Kantar Millward Brown. Adreaction global consumer survey. Technical report, Kantar Millward Brown, 2017.

[58] Wreetabrata Kar, Sarath Swaminathan, and Viswanathan Swaminathan. Audience validation in online media using limited behavioral data and demographic mix. *International Journal of Semantic Computing*, 11(01):5–20, 2017.

[59] Patrick Gage Kelley, Saranga Komanduri, Michelle L Mazurek, Richard Shay, Timothy Vidas, Lujo Bauer, Nicolas Christin, Lorrie Faith Cranor, and Julio Lopez. Guess again (and again and again): Measuring password strength by simulating password-cracking algorithms. In *IEEE sympos. on security and privacy*, pages 523–537, 2012.

[60] Amna Kirmani. The effect of perceived advertising costs on brand perceptions. *Journal of consumer research*, 17(2):160–171, 1990.

[61] Amna Kirmani. Advertising repetition as a signal of quality: If it's advertised so much, something must be wrong. *Journal of advertising*, 26(3):77–86, 1997.

[62] Amna Kirmani and Peter Wright. Money talks: Perceived advertising expense and expected product quality. *Journal of Consumer Research*, 16(3):344–353, 1989.

[63] John E Kwoka. Advertising and the price and quality of optometric services. *The American Economic Review*, 74(1):211–216, 1984.

[64] Pedro Leon, Blase Ur, Richard Shay, Yang Wang, Rebecca Balebako, and Lorrie Cranor. Why Johnny can't opt out: a usability evaluation of tools to limit online behavioral advertising. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 589–598. ACM, 2012.

[65] Pedro Giovanni Leon, Blase Ur, Yang Wang, Manya Sleeper, Rebecca Balebako, Richard Shay, Lujo Bauer, Mihai Christodorescu, and Lorrie Faith Cranor. What matters to users?: factors that affect users' willingness to share information with online advertisers. In *Proceedings of the 9th symposium on usable privacy and security*, page 7. ACM, 2013.

[66] Randall A Lewis and Justin M Rao. The unfavorable economics of measuring the returns to advertising. *The Quarterly Journal of Economics*, 130(4):1941–1973, 2015.

[67] Randall A Lewis, Justin M Rao, and David H Reiley. Here, there, and everywhere: correlated online behaviors can lead to overestimates of the effects of advertising. In *Proceedings of the 20th international conference on World wide web*, pages 157–166. ACM, 2011.

[68] Zhou Li, Kehuan Zhang, Yinglian Xie, Fang Yu, and XiaoFeng Wang. Knowing your enemy: understanding and detecting malicious web advertising. In *Proceedings of the Conference on Computer and Communications Security*, pages 674–686. ACM, 2012.

[69] Donald R Lichtenstein, Peter H Bloch, and William C Black. Correlates of price acceptability. *Journal of consumer research*, 15(2):243–252, 1988.

[70] Miguel Malheiros, Charlene Jennett, Snehalee Patel, Sacha Brostoff, and Martina Angela Sasse. Too close for comfort: a study of the effectiveness and acceptability of rich-media personalized advertising. pages 579–588, 2012.

[71] Naresh K Malhotra, Sung S Kim, and James Agarwal. Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Information systems research*, 15(4):336–355, 2004.

[72] Matthew Malloy, Mark McNamara, Aaron Cahn, and Paul Barford. Ad blockers: Global prevalence and impact. In *Proceed. of the Internet Measurement Conference*, pages 119–125, 2016.

[73] J Marshall. Online data: Cheap, plentiful, inaccurate. Accessed on 15 October 2016: https://digiday.com/media/third-party-datas-accuracy-problem/, 2013.

[74] Jonathan R Mayer and John C Mitchell. Third-party web tracking: Policy and technology. In *Proceedings of the 2012 IEEE Symposium on Security and Privacy*, pages 413–427, 2012.

[75] Georg Merzdovnik, Markus Huber, Damjan Buhov, Nick Nikiforakis, Sebastian Neuner, Martin Schmiedecker, and Edgar Weippl. Block me if you can: A large-scale study of tracker-blocking tools. In *IEEE European Symposium on Security and Privacy*, pages 319–333, 2017.

[76] Jakub Mikians, László Gyarmati, Vijay Erramilli, and Nikolaos Laoutaris. Detecting price and search discrimination on the internet. In *Proceedings of the 11th ACM Workshop on Hot Topics in Networks*, pages 79–84. acm, 2012.

[77] Ben Miroglio, David Zeber, Jofish Kaye, and Rebecca Weiss. The effect of ad blocking on user engagement with the web. In *Proceed. of the World Wide Web Conference*, pages 813–821, 2018.

[78] Banwari Mittal. Measuring purchase-decision involvement. *Psychology & Marketing*, 6(2):147–162, 1989.

[79] Prashanth Mohan, Suman Nath, and Oriana Riva. Prefetching mobile ads: Can advertising systems afford it? In *Proceedings of the 8th ACM European Conference on Computer Systems*, pages 267–280. ACM, 2013.

[80] Lymari Morales. U.S. Internet users ready to limit online tracking for ads. Technical report, Gallup Polls, 2010.

[81] Muhammad Haris Mughees, Zhiyun Qian, and Zubair Shafiq. Detecting anti ad-blockers in the wild. *Proceedings on Privacy Enhancing Technologies*, 2017(3):130–146, 2017.

[82] Phillip Nelson. Advertising as information. *Journal of political economy*, 82(4):729–754, 1974.

[83] Helen Nissenbaum. Privacy as contextual integrity. *Wash. L. Rev.*, 79:119, 2004.

[84] OECD. Personalised pricing in the digital era – note by the European Union. Technical report, Organisation for Economic Cooperation and Development, 2018. Accessed 22 February 2019: https://one.oecd.org/document/DAF/COMP/WD(2018)128/en/pdf.

[85] Paul Ohm. The illusory benefits of behavioral advertising. In *7th Annual Privacy Law Scholars Conference*, 2013.

[86] Shintaro Okazaki, Hairong Li, and Morikazu Hirose. Consumer privacy concerns and preference for degree of regulatory control. *Journal of Advertising*, 38(4):63–77, 2009.

[87] PageFair. The state of the blocked web: global adblock report. Technical report, 2017.

[88] Angelisa C Plane, Elissa M Redmiles, Michelle L Mazurek, and Michael Carl Tschantz. Exploring user perceptions of discrimination in online targeted advertising. In *26th USENIX Security Symposium (USENIX Security 17)*, pages 935–951, 2017.

[89] Michael E Porter. Consumer behavior, retailer power and market performance in consumer goods industries. *Review of Economics and Statistics*, pages 419–436, 1974.

[90] Michael E Porter. *Interbrand choice, strategy, and bilateral market power*. Harvard University Press, 1976.

[91] Enric Pujol, Oliver Hohlfeld, and Anja Feldmann. Annoyed users: Ads and ad-block usage in the wild. In *Proceedings of the Internet Measurement Conference*, pages 93–106, 2015.

[92] Kent Rasmussen, Alex Wilson, and Abram Hindle. Green mining: energy consumption of advertisement blocking methods. In *Proceedings of the 3rd International Workshop on Green and Sustainable Software*, pages 38–45. ACM, 2014.

[93] Oliver J Rutz and Randolph E Bucklin. From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research*, 48(1):87–102, 2011.

[94] Ben Shiller, Joel Waldfogel, and Johnny Ryan. Will ad blocking break the Internet? Technical report, NBER, 2017.

[95] Anastasia Shuba, Athina Markopoulou, and Zubair Shafiq. Nomoads: Effective and efficient cross-app mobile ad-blocking. *Proceed. on Privacy Enhancing Technologies*, (4):125–140, 2018.

[96] RJG Simons and Aiko Pras. The hidden energy cost of web advertising. In *Proceedings of the 12th Twente Student Conference on Information Technology*, pages 1–8, 2010.

[97] Ashish Kumar Singh and Vidyasagar Potdar. Blocking online advertising-a state of the art. In *2009 IEEE International Conference on Industrial Technology*, pages 1–10, 2009.

[98] Kevin Springborn and Paul Barford. Impression fraud in on-line advertising via pay-per-view networks. In *Presented as part of the 22nd USENIX Security Symposium (USENIX Security 13)*, pages 211–226, 2013.

[99] Kar Yan Tam and Shuk Ying Ho. Understanding the impact of web personalization on user information processing and decision outcomes. *Mis Quarterly*, 30(4):865–890, 2006.

[100] Gerard J Tellis and Claes Fornell. The relationship between advertising and product quality over the product life cycle: A contingency theory. *Journal of Marketing Research*, 25(1):64–71, 1988.

[101] Sharon Terlep and Deepa Seetharaman. P&G to scale back targeted Facebook ads. *The Wall Street Journal*, 2016.

[102] Trading Economics. United States average hourly earnings. Technical report, U.S. Bureau of Labor Statistics, 2019.

[103] Victor J Tremblay and Carlos Martins-Filho. A model of vertical differentiation, brand loyalty, and persuasive advertising. *Advertising and differentiated products*, 10:221–238, 2001.

[104] Janice Y. Tsai, Serge Egelman, Lorrie Cranor, and Alessandro Acquisti. The effect of online privacy information on purchasing behavior: An experimental study. *Information Systems Research*, 22(2):254–268, 2011.

[105] Joseph Turow, Jennifer King, Chris Jay Hoofnagle, Amy Bleakley, and Michael Hennessy. Americans reject tailored advertising and three activities that enable it. Working paper. Accessed on 21 December 2017: https://doi.org/10.2139, 2009.

[106] Blase Ur, Pedro Giovanni Leon, Lorrie Faith Cranor, Richard Shay, and Yang Wang. Smart, useful, scary, creepy: perceptions of online behavioral advertising. In *proceedings of the eighth symposium on usable privacy and security*, pages 1–15, 2012.

[107] Timothy Van Zandt. Information overload in a network of targeted communication. *RAND Journal of Economics*, 35(3):542–560, 2004.

[108] Samuel Warren and Louis Brandeis. *The right to privacy*. Litres, 2019.

[109] Craig E. Wills and Doruk C. Uzunoglu. What ad blockers are (and are not) doing. In *4th IEEE Workshop on Hot Topics in Web Systems and Technologies*, pages 72–77. IEEE, 2016.

[110] Jun Yan, Ning Liu, Gang Wang, Wen Zhang, Yun Jiang, and Zheng Chen. How much can behavioral targeting help online advertising? In *Proceedings of the international conference on World Wide Web*, pages 261–270. ACM, 2009.

[111] Sha Yang and Anindya Ghose. Analyzing the relationship between organic and sponsored search advertising: Positive, negative, or zero interdependence? *Market. Sci.*, 29(4):602–623, 2010.

[112] Judith Lynne Zaichkowsky. Involvement and the price cue. *ACR North American Advances*, 15:323–327, 1988.

[113] Apostolis Zarras, Alexandros Kapravelos, Gianluca Stringhini, Thorsten Holz, Christopher Kruegel, and Giovanni Vigna. The dark alleys of madison avenue: Understanding malicious advertisements. In *Proceedings of the Conference on Internet Measurement*, pages 373–380. ACM, 2014.

[114] Sebastian Zimmeck, Jie S Li, Hyungtae Kim, Steven M Bellovin, and Tony Jebara. A privacy analysis of cross-device tracking. In *26th USENIX Security Symposium (USENIX Security 17)*, pages 1391–1408, 2017.