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The Impact of Ad-Blockers on Consumer Behavior: A Lab Experiment

This is a preliminary draft. Please contact the authors for the most recent version.

Abstract: Ad-blocking applications have become increasingly popular among Internet users. Ad-blockers have known privacy- and security-enhancing implications, such as improvement in browsing experience due to reduction of visual clutter and increased speed of page loading; protection of users' decision-making autonomy, choice and control over browsing experience; and decrease in exposure to malicious advertising. Some ad-blockers also attempt to reduce online tracking. However, little is known about their impact on consumer behavior, particularly in the context of online shopping. The online advertising industry has claimed that targeted ads help consumers find better and cheaper deals faster. Following the logic of this claim, using ad-blockers should deprive consumers of these benefits. We designed a lab experiment (N=212) with real economic incentives to vet those claims. We focus on the effects of blocking contextual ads on participants' online purchase behavior. Contextual ads are targeted to specific contexts, such as search query or webpage content. We find that blocking contextual ads did not have a statistically significant effect on the prices of products participants chose, the time they spent searching for them, or how satisfied they were with the chosen products, prices, and perceived quality. Thus, we do not reject the null hypothesis that consumer welfare stays constant when those ads are blocked or are shown. In other words, we do not find evidence that the presence of contextual ads or their removal using an ad-blocker decreases (or increases) consumer welfare in terms of prices paid, search costs, or product satisfaction. Hence, the use of ad-blockers does not compromise privacy and security benefits in exchange for consumer welfare. We discuss the implications of this work in terms of end-users' privacy, its limitations, and future work to extend these results.

Keywords: Ad-blockers, consumer behavior, welfare, economic impact, privacy, lab experiment.

1 Introduction

In recent years, online advertising and blocking of it using special tools (e.g., browser extensions and mobile apps) have been at the center of an heated debate. The online advertising industry has maintained the economic benefits of online advertising, claiming that online ads (and in particular targeted 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 [38]. 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) [32, 36, 37].

On the consumer side, however, the large volumes of ads and the extensive data collection associated with many of them have raised diverse concerns [22, 58, 75], inducing growing numbers of Internet users to install software blocking online advertising content altogether, or countering online tracking [64]. This suggests that ad-blockers do address important users' needs, such as protect from online tracking and malware [72], and from other security threats posed by malicious advertising [49, 82]. Users believe that ad-blockers also improve user experience, due to increased page load speed, and decreased bandwidth usage, and protect from intrusion, interruption of attention, and offensive or inappropriate content of ads [30], therefore guarding privacy defined

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in terms of private sphere, inviolate personality, and autonomous decision making [7, 14, 60, 77].

On the other hand, the growing popularity of ad-blockers among consumers has been met with anxiety, and even hostility, by online advertising companies and online publishers [27]. 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" [70].

Very little is known, however, about the impact of ad-blockers on the economic welfare of consumers, and on shopping behavior specifically. Thus, some of the advertising industry's claims about the consumer benefit of online ads (such as matching buyers to sellers and satisfying consumer needs) have been neither confirmed nor disproved. We present the results of a lab experiment with real economic incentives investigating the effect of blocking ads on individuals' online purchase behavior. We focus on contextual ads — ads that are targeted to specific contexts. For instance, search ads, also known as sponsored search results, are targeted to a search query, and display ads are targeted to the webpage content. Specifically, we study some of the downstream economic consequences of contextual advertisements either being shown, or being blocked via a popular ad-blocker, on the webpages and results pages of a popular search engine following queries for several consumer products. We consider, first, the impact of showing or blocking contextual ads on participants' purchase decisions — in particular, the price they will end up paying for products they searched for. Second, and based on research on the psychological and cognitive effects of advertising [29, 40, 41, 43, 76], we consider how showing or blocking contextual, and especially search, ads impact participants' search costs and their satisfaction with their browsing experience and product choices.

We invited 212 participants to a lab to use a popular search engine to search online for 10 product categories and purchase the product they liked the most in each category. We randomly assigned participants to two experimental conditions. The treatment group performed their searches on laptops instrumented with popular browser plug-ins that blocked advertising content on visited web pages. Therefore, participants in that group were only exposed to organic search results. In the control group, ads on web pages visited by participants (including both search engine pages and vendors' pages) were not blocked. Thus, control participants were exposed to both "organic" and sponsored search results in the search engine, and to other forms of advertising (e.g. display ads) on the websites they ended up visiting. At the end of the experiment, participants completed the purchase of one of the products they had chosen using their own bank cards and filled out an exit survey. Few weeks after the experiment, participants responded to a follow-up survey designed to elicit their satisfaction with the purchased products. We find that removal of contextually targeted advertising 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 their chosen products, their prices, and their perceived quality. In essence: we do not reject the null hypothesis that consumer welfare stays constant when ads are blocked or are shown. In other words, we do not find evidence that the use of ad-blockers compromise privacy and security benefits in exchange for consumer welfare.

The study is, to our knowledge, the first attempt at addressing a significant gap in the literature on online advertising and ad-blockers. Previous behavioral work on ad-blockers has focused on their usability [46, 67]. And previous studies on online ads (e.g., [47, 80]) have 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 constrained by a narrow focus on consumers' response to a specific ad campaign (or a set of ad campaigns). Our experiment goes in a different (and somewhat broader direction): it was designed to track participants' behavior across an array of vendor sites and capture their response to the presence or absence of an array of ad campaigns from different vendors. Essentially, we attempt to investigate a critical counterfactual currently underexplored in the literature: what happens (to consumer behavior, to their choices, to their economic outcomes) when 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.

Our study only focused on a subset of industry claims (those pertaining to direct economic consequences for consumers, as opposed to macroeconomic effects, such as the support of free content), and on a limited family of targeted ads (contextual ads on webpages and sponsored search results in a specific search engine, Google). Within that context, we did not find support for much of the industry's claims. In fact, the null findings arising from the experiment provide a countervailing context to the advertising industry's claims about the direct benefits of online ads (and associated purported harms of ad-blockers) to consumers. Users deploy ad-blockers primarily to limit exposure to invasive advertising and protect their privacy and security [30, 72]; and our study did not find evidence of their detrimental counter-effects on consumer welfare. The null results for several of the outcomes are accurately estimated, allowing us to rule out any large, and in some cases even moderate, improvements in consumer welfare with *versus* without ad-blockers. Our current research agenda focuses on both vetting and expanding these results in an ongoing field experiment that will include other types of online ads.

2 Related Work

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 has reached 615 million in December 2016 [64]. The growth in ad-blockers popularity has been likely fueled 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 download and install on their machines to block ads from appearing on their browsers. Most ad-blockers allow users to select the types of ads they want to be blocked, or the sites where they would like to allow, or block, ads. Some ad-blockers are able to block multiple types of ads - including contextual ads appearing as sponsored search results on search engines and display ads appearing on other sites. The growing popularity of ad-blockers has lead entities in the advertising industry to see it as an "existential threat" [70]. Numerous researchers have demonstrated that ad-blockers are highly effective in eliminating online ads and limiting web tracking [4, 20, 39, 52, 54, 55, 78], and reducing energy consumption on smartphones [13, 57, 68] and laptops [71]. Only a few user studies on ad-blockers have been carried out. Those studies primarily focus on the usability of these tools [46]. For instance, Pujol et al. [67] argue that while many Internet users deploy ad-blockers, the default settings without proper configuration do not always ensure the expected level of protection. The authors 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.

To our knowledge, no prior study has investigated the impact of ad-blockers on actual Internet users' purchasing behavior, outcomes, and satisfaction. 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 those technologies. As noted, online advertising companies and online publishers have reacted with concern and fear to the rise of ad-blockers [27]. Some researches have stated that "ad-blocking poses a substantial threat to the ad-supported web" [70]. Understanding how end-users react to the usage of ad-blockers is also critical to vetting industry claims about the benefits that consumers themselves are supposed to gain from exposure to online ads [31].

2.2 The impact of online (targeted) advertising

Internet advertising is the main business model for most online publishers and a fast-growing sector of the global economy. Online advertising revenues have reached USD 48 billion in Europe and USD 88 billion in the U.S. in 2017 [33, 34]. 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. 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: ads on a web page are targeted based on the content of that particular page, which in turn is based on generalised 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 clickstream behavior across multiple sites. Our analysis focuses on contextual targeting, not behavioral.

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 (especially behavioral targeting) on advertising campaigns effectiveness, such as click-through and conversion rates, website visits, and sales [12, 23–25, 42, 79]. On the other hand, other researchers and even some advertisers [73] argue that the effect of targeted ads on consumers' likelihood to purchase may be overestimated due to methodological issues [23, 47, 62] and "activity bias" [48]. Indeed, some evidence suggests a limited technological efficiency in correctly targeting consumers based on their behaviors [35, 45, 53]. From the consumer perspective, targeting is claimed, on the one hand, to decrease searching costs [11, 19, 63], but on the other hand, to potentially reduce consumer surplus (which is absorbed by the advertisers) through application of price and offer discrimination [2, 15],[1] and to raise privacy concerns and related psychological discomfort [22, 58, 75]. While focused on the business outcomes, those studies did not consider the implications for consumers' welfare.

The current tension between the interests of different stakeholders in the online advertising ecosystem is mirrored by a theoretical tension between different schools of economic thought on the economic impact of advertising in general (for review see [3]).

The body of theoretical knowledge about the impact of advertising on economic markets is only in part complemented by limited empirical evidence about the impact of advertising on consumer behavior: the time they spend on product searching, their choices of products and resulting prices, and satisfaction. These are the main variables that we focus on in our study. For instance, a lab experiment in [9] showed that the availability of traditional (offline) advertising did not reduce searching time or effort. However, other researchers argue that due to information overload [76], exposure to a large amount of online advertising may hinder the identification of relevant information and use of this information in decision-making [40], increasing the time required to make a choice [29, 41], and decreasing levels of satisfaction [41, 43]. Eye-tracking data in Burke et al. [10] showed that online banner ads decreased visual search speed. Moreover, distraction by advertising may decrease the quality of decisions. For instance, exposure to ads in Goldstein et al. [26] decreased the ability of participants to perform an email classification task. Subjects in the lab experiment of Bloom and Krips [9] 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, which 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. In contrast, when prices between advertised and non-advertised goods were similar, participants chose advertised services with slightly lower prices. Empirical evidence in Bloom and Krips [9] demonstrated that subjects exposed to advertising reported that they received higher quality for higher expenditures, suggesting a higher level of satisfaction with their purchasing decisions.

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 [17, 18, 59, 65, 66]. Some research also suggest 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, 16, 21]. Bart et al. [5] 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 [28, 50, 81]. In addition, product involvement positively correlates with product satisfaction [28].

To summarize, theoretical and practical research has raised questions about welfare allocation among various stakeholders in the advertising arms race and offered contrasting claims, predictions, and evidence. Empirical economic research has been called upon to explore subtle, nuanced, and non-monotonic effects that advertising can have on consumer welfare, and whether such consumer welfare effects offset privacy and security benefits of ad-blockers. Especially understudied are the effects of online advertising on *consumers*, as most previous research has focused narrow attention on the effectiveness of advertising campaigns in terms of companies' revenues and conversion rate growth [47, 80] or on the effectiveness and usability of the ad-blockers [4, 46, 54, 67], but not on individual purchasing behavior, economic outcomes for consumers, and their satis-

1 The actual prevalence of first degree price discrimination on the Internet is an object of debate [61].

faction. In this paper we present the empirical evidence from a lab experiment to contribute to the growing body of literature on the broader economic impact of online ad-blockers on consumers.

3 Methodology

We designed a lab experiment to test the effects of ad-blockers on consumers' purchasing behaviors and outcomes. We focused on the impact of the presence or blocking of sponsored search results following queries for consumer products on a popular search engine. We captured participants' product choices (including the price they would ultimately pay for products), their time spent on product searching, and their satisfaction with the products and browsing experience.

Prospective subjects were invited to answer an entry survey about their Internet and online shopping experiences. Participants who completed the survey were invited to participate in the lab experiment. In the lab, participants were invited to sit in front of a laptop and use it to search for products to buy online. All searches were conducted using Google search engine. On Google, alongside organic search engine results, sponsored search results appear in two forms: sponsored links and Google shopping sponsored 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. Inspired by the Becker-deGroot-Marschak (BDM) mechanism, 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. Thus, the purchase design was incentive compatible as participants had 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.

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

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 the search engine result pages; in addition, ads appearing on sites that the participants visited during the study (for instance, shopping websites) were also blocked; 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 display contextually targeted 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,[2] configured to block ads at the maximum state-of-the-art effectiveness rate, laptops in the NoBlock condition were not. While even the best ad-blockers do not always guarantee complete removal of all ads, prior research [4, 20, 52, 54, 55] and our own testing demonstrated that participants in the Block condition were exposed to significantly fewer online ads (tending to zero) than participants in the NoBlock condition.

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

2 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/.

to the experiment we saved locally the first 10 pages of search engine results (SERPs) for each product category, fully preserving their original visual appearance, and presented those to the subjects as the results of their searches. Figure 1 shows how SERPs for the same product category differ across conditions. By clicking on the organic or sponsored search results subjects were directed to the correspondent "live" online websites and continued browsing in the Internet in real time.[3]

Anecdotal evidence suggests that longer keywords associated with goal-oriented searches for specific products result in larger rates of clicking on organic links [80]. Moreover, consumer response (in terms of click-through and conversion rates) is higher for branded keyword searches in [69], although Blake at al. [8] 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 search query, we used both generic and specific searches. In other words, out of the 10 searches each participant was expected to complete, five search terms were generic, unbranded product categories, *e.g.*, "a book," while five 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. To account for idiosyncratic product characteristics, we included in the study product categories that vary along different dimensions (*e.g.,* durable *vs.* non-durable, hedonic *vs.* utilitarian, *etc.*).

The order of product searches was randomized across participants. To prevent contamination of search results via browsing activities across product categories and participants, subjects searched each product in an independent browser profile, and all the browsing history, cache, cookies, and temporary files were automatically deleted after each participant.

At the end of the 40 minutes, they were allocated to complete their searches and choose products to buy, 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 that included questions 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

In regressions 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 to estimate other metrics of satisfactions measured on a 7-point Likert scale. The model specifications with interaction effect between the condition and prior experience with ad-blockers revealed no such interaction effects for either of the variables, hence we did not include them in the manuscript.

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).[4]

In addition, we control for the following covariates:

– "Specific branded search query" defined as 1, and 0 otherwise (Table 1);

3 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.

4 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 3 standard deviations away from the mean (price_mean_outliers). The significance of regression coefficients in sensitivity checks are similar to the one of price_log, confirming the robustness of our results.

- "Durable product" — consumer good that is not consumed immediately but gradually worn out during use over an extended period of time — defined as 1, and 0 otherwise (Table 1);
- "Hedonic product" defined by the participants' responses on a 9-point Likert scale, where 1 defines utilitarian product (purely useful, practical, functional) and 9 defines hedonic product (purely fun, enjoyable, appealing to the senses);
- "Order of the product searching" defined by an ordinal number between 1 and 10, representing the order in which the participant searched for a specific product (e.g., if the participants first searched for a book, then for key chains, the order would be 1 for the book, and 2 for the key chains);
- "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 [56];
- "General online shopping frequency" defined as an index, computed using structural equation modelling 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" defied by the participants' responses on a 6-point Likert scale to a question about how often do you buy products from each of the product categories, where 1 is "Never" and 6 is "Once or several times a day";
- "No exposure to the ads of 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 answered that 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 [51].

4 Results

Two hundred and twelve individuals participated in the experiment over the course of four months 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. We screened out participants younger than 18 year old, and who have not done any online purchases within 12 months prior to the experiment. Participants were grouped into sessions. There were up to 5 participants per session, each of whom was randomly assigned to one of the 2 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 non-student population. The majority (59%) had a Bachelor's degree or higher. About half (49%) specified their ethnicity as Asian (out of which 31% however reside in the US for most of their lives), 36% as White, and 7% as Black.

Note that our manipulation affected both the actual product option space available to participants (through fetching or blocking sponsored search results) *and* participants' 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 this would result in opposite predictions. Finally, exposure to advertising, on the one hand, may distract participants' attention, increasing their product search time, and on the other hand, it may provide a short cut by efficiently matching buyers to the sellers' offers that would satisfy consumer needs and thus save time on searching. 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' *behaviors*, regarding the search, and their subsequent choice of product. The metrics we collect and study in the analysis (prices of selected products, search time, satisfaction with products and browsing experience) should be interpreted as the combined outcome of both processes—potential changes in product option space and participants' purchase behavior.

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 average lower prices than participants in the NoBlock condition ($t(150) = 1.98, p = 0.049$). We also observed that, on average, and for three specific products—Winter hat, Headphones, and Key chains—the variance was 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 SERP 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, marginally, on the 10% level of significance, *lower* than the ones from organic links ($\beta = -1.32$, $p = 0.06$).

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 6). 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 and hence have important practical implications regarding the magnitudes of price differences we can confidently rule out (see §6).

We suspected that participants' previous experience (or lack thereof) 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). To test this premise, we coded participants as users and non-users of ad-blocking technologies based on their responses to the screening survey, and controlled for it in the analysis. We found that subjects who use ad-blockers on their own computer tended to choose about 10-11% cheaper products than non users (Table 6) regardless of which experimental condition they were in.

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 6, model 4). High involvement with the purchasing decision, high frequency of online shopping, and satisfaction with expected product quality measured imme-

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 parenthesis.

	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

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

diately after the experiment have positive associations with prices, while frequent purchasing of the certain product category is associated with lower prices. Self-reported absence of exposure to a product brand's ads in the 30 days prior to the experiment has marginal (on a 10% level of significance) negative associations with prices of the selected product. More time spent on product searching has small marginal (on a 10% level of significance) positive associations with prices. Finally, specificity of search query, durability, and hedonic nature of the product have no significant effect on prices of the chosen product.

4.2 Effect on Searching 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 7) and statistical tests, the absence of ads did not substantially increase or decrease the search costs for participants: across conditions the difference in product searching 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 searching time ($t(1682) = -0.86, p = 0.39$), but users of ad-blocker on home computers inspected slightly more search results ($t(1682) = -2.34, p = 0.02$) in our experiment.

Statistically significant and negative order effect suggests that closer to the end of the experiment participants were spending less time on product searching (Table 7). 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 searching time.

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

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

4.3 The Effects 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*).

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,[5] participants in the NoBlock

5 To obtain these predictions, we transformed the 7-point Likert scale responses on satisfaction with web page loading speed into a simplified categorical variable with 3 levels, whereas Extremely dissatisfied, Somewhat dissatisfied, and Dissatisfied indicate "Dissatisfaction"; and Extremely satisfied, Somewhat sat-

Table 5. The measures of satisfaction, based on Likert scale responses.

Aspect of satisfaction	NoBlock condition			Block condition		
	Unsatisfied	Neutral	Satisfied	Unsatisfied	Neutral	Satisfied
With browsing experience:						
- Overall pleasure from browsing experience	24 (23%)	17 (16%)	65 (61%)	18 (17%)	19 (18%)	69 (65%)
- Speed of webpage load	20*** (19%)	14 (13%)	72*** (68%)	44*** (42%)	13 (12%)	49*** (46%)
- Relevance of the search results to the query	27 (25%)	9 (9%)	70 (66%)	21 (20%)	17 (16%)	68 (64%)
- Selection of the products on the visited websites	23 (22%)	9 (8%)	74 (70%)	14 (13%)	14 (13%)	78 (74%)
- Quality and professionalism of the visited websites	8 (8%)	6 (5%)	92 (87%)	4 (4%)	17 (16%)	85 (80%)
- Ease of navigation on the visited websites	21 (20%)	8 (7%)	77 (73%)	11 (10%)	13 (13%)	82 (77%)
- Technical functioning level	20 (19%)	11 (10%)	75 (71%)	14 (13%)	16 (15%)	76 (72%)
With product choices:						
- *ex-ante*	176 (21%)	125 (15%)	535 (64%)	145 (17%)	152 (19%)	534 (64%)
- *ex-post*	19 (25%)	11 (14%)	46 (61%)	19 (24%)	14 (17%)	47 (59%)
With product prices:						
- *ex-ante*	170 (20%)	117 (14%)	549 (66%)	138 (17%)	147 (17%)	546 (66%)
- *ex-post*	28 (37%)	6 (8%)	42 (55%)	17 (21%)	8 (10%)	55 (69%)
With perceived product quality:						
- *ex-ante*	109 (13%)	124 (15%)	604 (72%)	84 (10%)	176 (21%)	571 (69%)
- *ex-post*	9 (12%)	15 (20%)	52 (68%)	11 (14%)	12 (15%)	57 (71%)

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

condition have a 17% probability of being dissatisfied with the speed of web page loading compared to a 39% probability in the Block condition. In contrast, 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 [6]. Our own auxiliary experiment of computer performance (§E) showed that the web page speed was indeed slower in the Block condition, because ad-blocking extension usage utilized additional computational resources, which provided taxing for mature laptops available in the lab.[6] 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 searching, but had a negative impact on their satisfaction with that speed.

We computed an index of overall browsing experience satisfaction using a single-factor measurement model (Cronbach α=0.85). Overall browsing experience satisfaction (Table 8) was not different across experimental conditions ($t(210) = -0.71; p = 0.48$) but was lower for previous ad-blocker users ($t(210) = 2.75; p = 0.01$). 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.

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*). However, in both treatment conditions, for those who use ad-blockers on their home computers, the product satisfaction was marginally lower ($t(1665) = 1.97, p = 0.05$). Regression (Table 9) reveals a marginally statistically significant (on a 10% level of significance) positive ad-blocker treatment effect, while the effect loses statistical

isfied, and Satisfied indicate "Satisfaction." Then we 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.

6 We used Lenovo T460 laptops, which were initially released in 2016, and were running Windows 10 OS.

significance in model 4, after adding controls. 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. Searching time, hedonic nature of the 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 the satisfaction 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 condition 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 10, model 4) found a negative association between home computer ad-blocker usage and satisfaction with the delivered product. Dissatisfaction with the products purchased using specific search queries measured after the experiment persisted after the product delivery according to the bivariate statistical test ($t(154) = 3.46, p = 0.00$) but was not confirmed in the multiple regression model (Table 10). *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 searching time (marginally, on a 10% level of significance) had positive associations with *ex-post* product satisfaction. The types of search results (sponsored or organic) had no significant effect.

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. Regression coefficients reveal that it was marginally (on a 10% level of significance) higher in the Block than in the NoBlock condition after controlling for covariates (Table 11, model 4), although this effect was not confirmed in other regression model specifications or in the bivariate statistical test ($t(1665) = -1.49; p = 0.14$). We found no difference in *ex-ante* price satisfaction between home computer users and non users of ad-blockers ($t(1665) = 0.67; p = 0.5$), but satisfaction was lower for the products chosen using specific search queries ($t(1665) = 9.4; p = 0.00$). Higher prices and searching 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 statistically significant ($t(154) = -1.82, p = 0.07$) and not robust to the inclusion of the full set of controls (Table 12, model 4). The *ex-post* price satisfaction was not different between home computer user and non users of ad-blockers ($t(154) = 0.37, p = 0.71$). Specific search queries were associated with lower *ex-post* price satisfaction ($t(154) = 4.7, p = 0.00$). The negative effect of higher prices was only marginally significant (on a 10% level of statistical significance), while searching time, purchase-decision involvement, frequency of product purchasing, durability, and hedonic nature of the product had no significant association at all. *Ex-post* satisfaction with the product quality and absence of the exposure to brand ads in the 30 days prior to the experiment were associated with a higher degree of *ex-post* price satisfaction. *Ex-post* price satisfaction was also marginally statistically significantly (on a 10% level) lower 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 13). Higher prices and satisfaction with price, product durability, frequent product purchasing, high purchase-decision involvement, and hedonic nature of the product (marginally, on a 10% level of significance) were associated with higher levels of *ex-ante* quality satisfaction. Searching time and prior exposure to brand ads had no significant association with *ex-ante* quality satisfaction. ANOVA demonstrated lower *ex-ante* satisfaction with the quality of the products chosen from sponsored bottom 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 14). The only statistically significant positive predictors of the *ex-post* satisfaction with the quality in the regression (Table 14) 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

Our study has a number of limitations. First, to preserve internal validity of the study (a priority of experimental methodology in a lab environment) we asked participants to search online for specific products or types of products. We did not allow the modification of search queries or the picking of a different product category. Thus, the design does not attempt to achieve the ecological validity of a field experiment (for instance: participants were told what to search for, rather than spontaneously searching for products they were intrinsically motivated to buy). On the other hand, 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. This index demonstrates wide variety in interest for products (mean=.00, SD=1.37, min=-4.38, max=2.64), skewed positively for some, negatively for others, and neutral for the rest of the product categories. Furthermore, behavioral lab research (since endowment-research [44] till today) successfully uses seemingly low-involvement goods (e.g., mugs). Moreover, the study was incentive-compatible and participants had to buy the products using their own credit card and personal details. As the fundamental assumption of experimental economics is that incentives offered in the experiment are analogous to the incentives of real-world consumer economic behaviors, we believe that the results observed in the experiment 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 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 is not important how many products they will eventually search for and that it does not affect the payment, and by showing time elapsed rather than count down 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 in any way. 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 to assess 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 predictors and thus cannot inflate the variance. In contrast, it reduces the model residual and 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, in the lab experiment we explored the effects of removing contextual online ads, as it was not feasible to develop a meaningful and realistic online consumer profile in the laboratory settings and within given time limits. Tightly-controlled lab-experiment allowed us to make conservative inferences about effect of presence and lack of ads on purchasing behaviors and outcomes. In future field experiments we plan to explore the effects of eliminating behaviorally targeted ads and compare the conditions in which all ads are blocked, shown and personalized, or shown but not personalized to the consumers' behavioral profiles. Field experiments have high external and low internal validity, as they are maximally realistic but allow less control over potential confounding factors than lab experiments. Therefore, while validating the effects in an ecological study is indeed the end goal of our research, before we perform a large and costly field experiment, we found it valuable to first explore the phenomena in a controlled experiment. 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). On the other hand, our paper offers a valuable empirical insight that encourage us, and hopefully other researchers, to explore further the impact of hotly debated online 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 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, in the first place), we did not find support for the claims of informative advertising advocates 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 ad-blocking. 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, on the other hand, 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 possible indirect impacts of browsing experience on purchasing behavior is a subject of 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 6 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. On the an individual level, a 10% difference in price, especially for the low-priced goods in our experiment (i.e. \$2.5 difference for a \$25 product), are small for most online consumer's budgets. From a business perspective, a 10% difference in prices of the sold products could produce a large effect in absolute monetary terms (i.e. \$100,000 difference for \$1 million in revenues), and additionally affect the competitive posture of the company. In contrast, if we consider the reported use of ad-blockers outside of the experimental setting, our results imply (as 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 either similar price or are up to 20% cheaper than products chosen by non users of ad-blockers. As this is not experimentally controlled we cannot determine whether using the ad-blocker at home causes them to select lower-priced products or whether more price-conscious consumers are more likely to use an ad-blocker at home.

Second, the confidence interval for the Block condition coefficient in Table 7 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 searching than participants in the NoBlock condition. Although this finding is not statistically significantly different from zero, half an hour of saved time as well as more than an hour of extra time spent on product searching is practically significant on an individual level. Given an average $28 hourly wage,[7] that would translate into loss of up to $35, in the worst scenario case, a loss of $12 on average, and up to $11 in savings in the best scenario case. The $12 is almost half of the budget allocated to our participants in the experiment, while the $35 is 40% more than that budget. 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 may there may even be a decrease in time 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. A similar exercise shows that the correlation between home ad-blocker use and search time implies a smaller lower bound loss ($24 based on 52 minutes longer searching time) and larger upper bound savings ($21 based on 46 minutes shorter searching time) compared to non users.

To summarise, while we did not find the main treatment effect of using ad-blocker in the experiment, we observed that participants who use ad-blockers on their home computers tended to choose products on average 10-11% cheaper 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.

7 The average wage in the US in January 2019 is $27.56 [74].

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 sponsored links payed the highest prices, and participants who chose products from sponsored Google shopping listings paid, on average, lower 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 it again after the product delivery). This suggests that 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 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 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 eventual product choices and their prices. One of the potential explanations for this finding is that specific search queries narrowed down the variations between the products in the search results, therefore saving time due to reduction in dimensions of comparison shopping and practically focusing consumers' attention on the choice of a vendor, price, and shipping conditions rather than on evaluation of product characteristics, thus saving time. On the other hand, limitation of freedom made participants less happy with the chosen products.

Participants spent more time on searching durable and hedonic products. They were also more satisfied (*ex-ante*) with the choices, prices, and expected quality of durable goods. Participants who frequently purchase specific products, chose lower-priced items in these categories and were more satisfied with the respective product choices and expected quality (both *ex-ante* and *ex-post*). This may be related to loyalty effects and reflect consumers' previous experiences with products [1, 16, 21]. In line with previous research, high product involvement made our participants spend more time on product search, choose higher-priced products, and was associated with their *ex-ante* satisfaction with product choices, their prices, and expected quality. Specifically, the choice of higher-priced products confirm the previous findings on the positive correlation of product-purchase involvement with price acceptability [28, 50, 81] and satisfaction [28].

In essence, our experiment does not find the evidence that deployment of ad-blockers, aiming at protecting users' privacy, security, and reducing clutter in online experience, have detrimental effects on consumers' welfare, in terms of priced paid, satisfaction with products, their prices, perceived quality, or time spent on their online searching. Therefore, ad-blockers are ultimately not only privacy- and security-enhancing, but also welfare-preserving for consumers.

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A Search engine result page example.

(a) NoBlock condition

(b) Block condition

Fig. 1. Example of search engine result page for flash drive across conditions.

B Regressions on price

Table 6. Linear mixed model regression on price_log with random individual effects.

	(1)	(2)	(3)	(4)
Block condition	-0.00388 [-0.10,0.10]		-0.00705 [-0.10,0.09]	0.000493 [-0.10,0.10]
Home computer ad-blocker user		-0.111* [-0.21,-0.01]	-0.111* [-0.21,-0.01]	-0.104* [-0.21,-0.00]
Searching time				0.00736+ [-0.00,0.02]
Specific branded search query				0.0268 [-0.07,0.12]
Index of purchase-decision involvement				0.0549*** [0.03,0.08]
General online shopping frequency				0.201* [0.02,0.39]
Frequency of product purchasing				-0.0457** [-0.08,-0.02]
Durable product				-0.0525 [-0.12,0.02]
Hedonic product				0.00921 [-0.00,0.02]
No exposure to the ads of product's brand				-0.0768+ [-0.16,0.01]
Satisfaction with product quality (*ex-ante*)				0.0401** [0.01,0.07]
Constant	0.00124 [-0.07,0.07]	0.0582+ [-0.01,0.12]	0.0619 [-0.02,0.14]	-0.0489 [-0.26,0.16]
sd(Constant)	0.282*** [0.22,0.36]	0.276*** [0.22,0.35]	0.276*** [0.22,0.35]	0.293*** [0.23,0.37]
sd(Residual)	0.627*** [0.55,0.71]	0.627*** [0.55,0.71]	0.627*** [0.55,0.71]	0.620*** [0.54,0.71]
N	1650	1650	1650	1564

95% confidence intervals in brackets. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Regressions on searching time

Table 7. Linear mixed model regression on searching time (in minutes) with random individual effects.

	(1)	(2)	(3)	(4)
Block condition	0.192 [-0.45,0.84]		0.197 [-0.45,0.85]	0.263 [-0.24,0.76]
Home computer ad-blocker user		0.198 [-0.45,0.84]	0.203 [-0.45,0.85]	0.0268 [-0.46,0.52]
Specific branded search query				-1.217*** [-1.58,-0.86]
Order of the product searching				-0.332*** [-0.39,-0.28]
Perceived difficulty of the study				0.529*** [0.36,0.69]
Durable product				0.673*** [0.36,0.99]
Index of purchase-decision involvement				0.297***

Continued on next page

Table7 – continued from previous page

	(1)	(2)	(3)	(4)
				[0.19,0.41]
Hedonic product				0.0817*
				[0.01,0.15]
Frequency of product purchasing				-0.0178
				[-0.15,0.12]
No exposure to the ads of product's brand				0.0167
				[-0.34,0.37]
Constant	4.555***	4.547***	4.445***	4.157***
	[4.11,5.00]	[4.08,5.01]	[3.86,5.03]	[3.17,5.15]
sd(Constant)	2.089***	2.089***	2.087***	1.431**
	[1.71,2.55]	[1.71,2.55]	[1.71,2.54]	[1.10,1.86]
sd(Residual)	3.093***	3.093***	3.093***	2.825***
	[2.82,3.39]	[2.82,3.39]	[2.82,3.39]	[2.56,3.12]
N	1684	1684	1684	1595

95% confidence intervals in brackets. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Regressions on satisfaction

D.1 Satisfaction with browsing experience

Table 8. Linear fixed effect model regression on the index of overall browsing satisfaction.

	(1)	(2)	(3)	(4)
Block condition	0.0878		0.0752	0.0189
	[-0.16,0.33]		[-0.17,0.32]	[-0.22,0.25]
Home computer ad-blocker user		-0.337**	-0.334**	-0.262*
		[-0.58,-0.09]	[-0.58,-0.09]	[-0.50,-0.02]
Perceived difficulty of the study				-0.107*
				[-0.20,-0.01]
General online shopping frequency				-0.218
				[-0.64,0.20]
Internet usage skills				0.0665
				[-0.21,0.34]
Chrome browser user				0.102
				[-0.30,0.50]
Firefox browser user				-0.266+
				[-0.57,0.04]
Internet Explorer browser user				0.156
				[-0.22,0.53]
Safari browser user				-0.358*
				[-0.67,-0.05]
Prefer to buy online				-0.142
				[-0.38,0.10]
Privacy concerns (IUIPC index)				0.109
				[-0.08,0.30]
Constant	-0.0439	0.181+	0.142	0.383
	[-0.22,0.14]	[-0.00,0.37]	[-0.09,0.37]	[-0.98,1.74]
N	212	212	212	212

95% confidence intervals in brackets. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.2 Satisfaction with overall product choices

Table 9. Ordered logit regression on overall satisfaction with the chosen products, measured immediately after the experiment (*ex-ante*), with robust standard errors.

	(1)	(2)	(3)	(4)
Block condition	0.121 [-0.05,0.29]		0.114 [-0.06,0.28]	0.169^{+} [-0.02,0.35]
Home computer ad-blocker user		-0.193* [-0.36,-0.02]	-0.189* [-0.36,-0.02]	-0.131 [-0.31,0.05]
Searching time				-0.00137 [-0.03,0.03]
Specific branded search query				-0.617*** [-0.89,-0.35]
Index of purchase-decision involvement				0.329*** [0.25,0.41]
Frequency of product purchasing				0.188*** [0.09,0.28]
Durable product				0.356** [0.11,0.60]
Hedonic product				0.0195 [-0.02,0.06]
No exposure to the ads of product's brand				-0.0256 [-0.24,0.19]
Satisfaction with product quality (*ex-ante*)				0.840*** [0.74,0.94]
Satisfaction with product price (*ex-ante*)				0.508*** [0.42,0.59]
N	1667	1667	1667	1595

Table 10. Ordered logit regression on overall satisfaction with the purchased products, measured after the product delivery (*ex-post*), with robust standard errors.

	(1)	(2)	(3)	(4)
Block condition	0.0344 [-0.52,0.59]		0.0730 [-0.50,0.64]	-0.0756 [-0.67,0.52]
Home computer ad-blocker user		-0.476 [-1.07,0.12]	-0.483 [-1.09,0.13]	-0.882* [-1.56,-0.20]
Searching time				0.0501^{+} [-0.01,0.11]
Specific branded search query				-0.368 [-1.26,0.53]
Index of purchase-decision involvement				0.160 [-0.10,0.42]
Frequency of product purchasing				0.419* [0.10,0.74]
Durable product				0.512 [-0.14,1.16]
Hedonic product				0.0575 [-0.08,0.19]
No exposure to the ads of product's brand				0.741* [0.01,1.47]
Satisfaction with product quality (*ex-post*)				0.926*** [0.56,1.29]
Satisfaction with product price (*ex-post*)				0.484*** [0.29,0.68]
N	156	156	156	149

95% confidence intervals in brackets. $+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.3 Satisfaction with product prices

Table 11. Ordered logit regression on satisfaction with the prices of chosen products, measured immediately after the experiment (*ex-ante*), with robust standard errors.

	(1)	(2)	(3)	(4)
Block condition	0.125 [-0.04,0.29]		0.124 [-0.05,0.29]	0.159^{+} [-0.02,0.34]
Home computer ad-blocker user		-0.0846 [-0.26,0.09]	-0.0837 [-0.26,0.09]	-0.114 [-0.29,0.07]
Price_log				-0.527^{***} [-0.71,-0.34]
Searching time				-0.0528^{***} [-0.08,-0.03]
Specific branded search query				-0.487^{***} [-0.75,-0.22]
Index of purchase-decision involvement				0.0959^{*} [0.02,0.18]
Frequency of product purchasing				0.0422 [-0.05,0.13]
Durable product				0.476^{***} [0.23,0.72]
Hedonic product				-0.00937 [-0.05,0.03]
No exposure to the ads of product's brand				-0.0746 [-0.28,0.13]
Satisfaction with product quality (*ex-ante*)				0.618^{***} [0.53,0.70]
N	1667	1667	1667	1564

Table 12. Ordered logit regression on satisfaction with the prices of purchased products, measured after the product delivery (*ex-post*), with robust standard errors.

	(1)	(2)	(3)	(4)
Block condition	0.523^{+} [-0.04,1.09]		0.533^{+} [-0.03,1.10]	0.424 [-0.18,1.02]
Home computer ad-blocker user		-0.187 [-0.76,0.39]	-0.212 [-0.79,0.37]	-0.290 [-0.88,0.30]
Price_log				-0.520^{+} [-1.05,0.01]
Searching time				-0.0340 [-0.10,0.03]
Specific branded search query				-0.947^{+} [-1.90,0.00]
Index of purchase-decision involvement				0.0174 [-0.27,0.30]
Frequency of product purchasing				0.140 [-0.18,0.46]
Durable product				0.537 [-0.32,1.39]
Hedonic product				0.0321 [-0.09,0.16]
No exposure to the ads of product's brand				0.920^{*} [0.21,1.63]
Satisfaction with product quality (*ex-post*)				0.540^{***} [0.28,0.80]
N	156	156	156	147

95% confidence intervals in brackets. $+\ p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.4 Satisfaction with product quality

Table 13. Ordered logit regression on satisfaction with the expected quality of chosen products, measured immediately after the experiment (*ex-ante*), with robust standard errors.

	(1)	(2)	(3)	(4)
Block condition	-0.00763 [-0.18,0.16]		-0.0122 [-0.18,0.16]	-0.0725 [-0.25,0.11]
Home computer ad-blocker user		-0.111 [-0.28,0.06]	-0.112 [-0.29,0.06]	-0.00471 [-0.19,0.18]
Price_log				0.266*** [0.13,0.41]
Searching time				-0.00109 [-0.03,0.03]
Specific branded search query				-0.144 [-0.40,0.11]
Index of purchase-decision involvement				0.400*** [0.32,0.48]
Frequency of product purchasing				0.154*** [0.06,0.24]
Durable product				0.442*** [0.22,0.66]
Hedonic product				0.0371+ [-0.00,0.08]
No exposure to the ads of product's brand				-0.156 [-0.36,0.05]
Satisfaction with product price (*ex-ante*)				0.536*** [0.46,0.61]
N	1667	1667	1667	1564

Table 14. Ordered logit regression on satisfaction with the quality of purchased products, measured after the product delivery (*ex-post*), with robust standard errors.

	(1)	(2)	(3)	(4)
Block condition	0.170 [-0.39,0.73]		0.181 [-0.38,0.75]	0.0298 [-0.66,0.72]
Home computer ad-blocker user		-0.211 [-0.79,0.37]	-0.220 [-0.80,0.36]	0.0831 [-0.54,0.71]
Price_log				0.243 [-0.31,0.80]
Searching time				0.0205 [-0.05,0.09]
Specific branded search query				0.172 [-0.69,1.03]
Index of purchase-decision involvement				0.410* [0.10,0.73]
Frequency of product purchasing				0.346* [0.04,0.66]
Durable product				0.958* [0.12,1.80]
Hedonic product				0.0771 [-0.04,0.19]
No exposure to the ads of product's brand				-0.525 [-1.26,0.21]
Satisfaction with product price (*ex-post*)				0.417** [0.15,0.69]
N	156	156	156	147

95% confidence intervals in brackets. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E Auxiliary experiment on computer performance

On one hand, usage of the ad-blocking extension requires additional resources (such as processing capacity, memory, and network bandwidth), which can increase Central Processing Unit (CPU) usage and thereby reduce computer performance. On the other hand, due to the reduced need to fetch and load the advertising content on a webpage, ad-blocking may save some computational resources and increase computer performance. For instance, Merzdovnik et al. [55] found that blocking extensions in their study did not increase the processing capacity (while Disconnect[8] even decreased it), but increased the memory consumption. Another piece of research showed 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 [6]. These differences may or may not be noticeable by the user.

We ran an auxiliary experiment to check whether the differences in computer performance that affected participants' satisfaction with the browsing experience were objective or just perceived. Using Selenium browser automation our script requested each URL that our participants visited during the experiment. The browser was restarted and all cookies were deleted after each product search to mimic the experimental procedure. We executed two scripts in parallel on the same two laptops (instrumented in the same way) as used during the experiment. One laptop had the ad-blockers enabled and the other did not. We measured memory usage (as percentage of available memory), processor capacity (as percentage of the total CPU capacity), and web page loading time. We took three measurements for each of the metrics: before the browser URL request (T1), after URL fetching (T2), and after automatic scrolling (T3), where the scripted browser scrolled to the end of the document body.

For between 36% to 41% of observations the script was not able to directly download the page. In the vast majority of cases (85.8%) the script encountered page redirects (e.g., page moved permanently or page was removed and browser was redirected to other landing page). In 11.4% of the cases the script encountered client-side errors (e.g., forbidden access to the resource or failed authorization, such as in shopping carts that require login), and in 2.7% of cases the script encountered server errors. Based on the analysis of the remaining 59-64% of the successful requests, we found that the Block condition utilized twice as much CPU capacity as the NoBlock condition ($t(31691) = -86.88, p = 0.00$), used considerably more memory ($t(31658) = -5.1e + 02, p = 0.00$), and had longer web page loading time ($t(30533) = -22.01, p = 0.00$).

8 https://disconnect.me/