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My Browser is not a Billboard: Experimental Evidence on Ad-blocking Adoption and Users' Acquisition of Information

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Abstract

Ad-avoidance technologies such as ad-blocking devices in browsers have become mainstream tools in recent years and escaped their role as niche applications that are only for the technically savvy. While technical impacts of those tools are well researched, their effects on actual consumer behavior is not. In an experimental setting this study provides first evidence on the effect of ad-blocking on users' ability to acquire information in the form of an online reading task. We find that ad-blocking leads to more effort being exerted and increases social welfare by reducing inefficient searching. Additionally, ad-blocking induces users' visit duration on websites to be more elastic in the experienced intensity of advertisements, making the competitive environment among publishers more intense.

JEL Classification: L82, L86, M37, C91.
Keywords: Ad-blocking, consumer behavior, lab experiment, online advertising, welfare, privacy.

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1 Introduction

Ad-avoidance technologies such as ad-blocking devices in browsers have become mainstream tools in recent years and escaped their role as niche applications that are only for the technically savvy. This development has led consumers to use ad-blocking on over 843 million devices worldwide, 69% of those are mobile devices (Blockthrough, 2021). Especially, mobile browsers which block ads by default have contributed to growth rates of the technology of above 10 % per year.

From a consumer's perspective, the decision to use an ad-blocking technology is a way to cast a vote in a heated debate on the benefits and harms associated to online advertising and especially the targeting of ads. On the one hand this debate is had between industry players who claim that ads lead to better product matching, promote free provision of online content and create jobs and economic growth (IHS-Technology, 2015; IHS-Markit, 2017) and consumer protection initiatives who raise concerns over an increased ad load and consumer privacy (Turow *et al.*, 2009). On the other hand, the debate includes also academic contributions which offer contrasting views on the benefits and effectiveness of online advertising (Chen and Stallaert, 2014; Goldfarb and Tucker, 2011; Jeziorski and Segal, 2015; Lewis and Rao, 2015).

While the majority of the academic research is focused on the effectiveness of specific advertising types in terms of click-through-rates, advertisement's effect on real consumer behavior remains overlooked. Behavioral and experimental studies in this field are scarce and overly narrowed on consumers' shopping decisions and regularly impose ad-blocking exogenously (Bloom and Krips, 1982; Frik *et al.*, 2020). These approaches are not holistic as consumer welfare does not only depend on shopping decisions, but is also created through the acquisition of relevant information which inform decisions beyond the scope of purchasing. Furthermore, the adoption of ad-blocking technologies in reality is a consumer's endogenous choice and neither an imposed state nor is a full market convergence towards adoption the only equilibrium as Anderson and Gans (2011) show.

This paper studies consumers' ad-blocking adoption decision and their ability to acquire relevant information under different intensities and intrusiveness levels of advertising in an online laboratory experiment. We compare endogenous ad-blocking adoption and different performance measures of information acquisition in a reading task within a 2x2 treatment design. Our treatments vary in the availability of ad-blocking and the intrusiveness of the filtered out advertisement. To the best of our knowledge, our experimental study is the first to expand the existing literature in two major ways. First, we implement ad-blocking adoption as an endogenous choice instead of imposing its use ex-ante for participants of a specific treatment. Hence, we are able to examine the factors that drive the selection into the use of the technology. Furthermore, we model ad-blocking to be imperfect in a way that adopters still experience advertisements, but only non-intrusive ads which are also limited in intensity. With this feature, we are able to incorporate realistic features of nowadays browsing experiences in which "Acceptable Ads" are still shown to users of ad-blocking due to default settings of blocking devices not being changed or users giving consent to these ads more frequently (Pujol *et al.*, 2015; Blockthrough, 2021). Second, we measure participants' performance in an incentivized reading task which represents a real-effort task in the sense of Charness *et al.* (2018) while being exposed to advertisements. Reading time is costly to represent opportunity costs present in real world situations.

Given the research objective, there is a strong case to study consumers' ability of information acquisition under online advertising in an online experimental setting. Participants of the experimental sessions are asked to visit fictitious websites to read written content in order to answer subsequent questions. This captures every-day browsing behavior in reality reasonably well and each participant in the experiment is equally an internet user in reality. Further, Horton *et al.* (2011) show that online experimental settings provide consistent results compared to their traditional offline laboratory counterparts. Hence, we are confident that our results do not suffer from a limited external validity.

The analysis of the experimental data provides four main results. First, if advertisement is intrusive, the availability of ad-blocking positively affects the time spent reading during the reading task. However, performance does not increase to a comparable degree, such that efficiency in the reading task is lower if ad-blocking is available. Second, if advertisement again contains intrusive elements, ad-blocking availability reduces consumer switching between available websites. Given that switching needs time, it induces costs which are not recouped by a better performance of switching subjects. Hence, the availability of ad-blocking reduces inefficiencies in this regard and acts welfare enhancing. Third, ad-blocking adoption is not driven by experiences during the experiment but rather by external factors. If participants are also subject to intrusive advertising elements which can be filtered out, ad-blocking adoption rates are higher as the resulting benefits from adoption increase as well. Additionally, the likelihood of adoption depends positively on a subject's age, whether ad-blocking is also used outside of the experiment and negatively on higher education degrees. For our fourth result we conjecture on competition between website publishers and potential profits based on the evidenced browsing behavior in our experiment.[1] The browsing behavior in our experiment suggests, that a website publisher experiences larger marginal losses in visit duration from choosing a higher ad-intensity than rival alternatives if ad-blocking is available. Hence, ad-blocking seem to induce consumer browsing behavior which creates a more competitive environment among publishers which should also translate to a dampening effect on profits.

With these results our study contributes to two strands of the academic literature. First, the ongoing discussion on the efficiency and benefits of different formats of online

[1]Please note that in reality a website publisher actively chooses the ad intensity on her website strategically, whereas it is randomly drawn in our experimental setting. Therefore, we abstract in these analyses on this topic completely from profit maximization motives and strategic responses on other publishers' ad intensity choices, ad-blocking decisions by consumers or the observed reading times (visit duration) exerted by participants on the respective websites during the reading task. Given this caveat, our conjectures are entirely based on subjects browsing behavior during the experiment as response to different exogenous realizations of ad intensity.

advertising and the closely connected strand on the absence of advertising due to ad-blocking. Second, on the very few behavioral studies which investigate how ad-blocking affects actual consumer behavior.

Online advertising accounts for a steadily increasing proportion of the entire advertising mix. One of the main benefits of advertising online as compared to traditional offline formats are more efficient methods of matching advertisers and consumers, that is, targeting (Evans, 2009). However, gathering and analyzing the necessary data for efficient targeting involves an intrusion of consumers' privacy, a trade-off inherent to the entire online advertising environment which is dominated by large, intermediary multi-sided platforms (Evans, 2008; Tucker, 2012; Goldfarb and Tucker, 2011).

Given that online advertising is not always welcomed by consumers, it exerts nuisance costs similar to traditional offline settings (Anderson and Coate, 2005; Anderson and Gabszewicz, 2006). The phenomenon of ad avoidance technologies (AAT) is not new and AAT have been used in the past already as countermeasures to TV commercials. The employed mechanisms range from simple human actions in the form of "going to the bathroom during commercial breaks" studied by Moriarty and Everett (1994) and Speck and Elliott (1997) to the "TiVo" hardware device which made TV ads skippable via a few button presses (Anderson and Gans, 2011). Modern Ad-blocking tools are just the evolutionary next step in consumers' endeavor to reduce their exposure to advertisements.

Ad-blocking is most frequently implemented via additional browser plug-ins to the primary effect of blocking online advertising partially or entirely. Second order effects of ad-blocking are numerous and have been extensively studied in the academic literature. Since ad-blocking interrupts ad-based revenue streams, it is perceived as a threat to existing advertisers' and publishers' business models. In this light, Shiller *et al.* (2017) find that ad-blocking curtails indeed a significant portion of publishers' ad revenues and could endanger the provision of free content in the web. A contrasting view is offered by the theoretical findings of Despotakis *et al.* (2021) which shows that ad-blocking adoption can be interpreted as a user's signal about her individual nuisance costs from ads. This offers publishers an implicit screening method to differentiate between sub-populations with different ad nuisances within their user base and realize higher profits from adapting ad intensities accordingly.

On the opposing side, ad-blocking tools offer consumers a variety of benefits that are associated with a reduced ad load. These include technical aspects of decreased loading times of webpages and higher energy efficiency on mobile and desktop devices (Chen *et al.*, 2013; Mohan *et al.*, 2013; Rasmussen *et al.*, 2014; Simons and Pras, 2010). However, ad-blocking serves also privacy enhancing motives in that it renders the collection of personal data more difficult (Turow *et al.*, 2009), prevents tracking and protects from malware (Singh and Potdar, 2009) and addresses security flaws with respect to malicious advertising (Li *et al.*, 2012; Zarras *et al.*, 2014).

While the more technical consequences of ad-blocking are rather well known, there has been only little research on ad-blocking's influence on actual consumer behavior. Leon *et al.* (2012) investigated the usability of ad-blocking tools from a user's perspective, but studies that focus on effects on consumers in an economic sense are scarce. Among the few behavioral studies, the experiments of Bloom and Krips (1982) and Frik *et al.* (2020) on ad-blocking and advertising's effect on consumers' good purchasing behavior are the most relevant to our study. They derive welfare implications on the basis of paid prices for advertised products, the search costs incurred and the satisfaction levels after the purchasing decisions. Their evidence suggests, however, that neither of the above dimensions are affected by advertising or the absence of it (ad-blocking).

Since welfare from browsing is not only realized through good purchasing decisions, it is reasonable to examine ad-blocking's effect on consumer behavior also in other areas of daily internet usage, that is, the acquisition of relevant information and using it in decision making.[2] However, behavioral evidence in this regard is, as far as we are aware, non-existent. Jacoby (1977) and Van Zandt (2004) conjecture, that information overload due to advertising could indeed negatively impact the acquisition of relevant information. This notion is also supported by results of Burke *et al.* (2005) whose eye-tracking data suggest that users' reading speed suffers from impressions of advertising images. Our experimental study provides the necessary behavioral evidence to complement the predominantly technical findings with an economic perspective on ad-blocking's effect on the acquisition of information.

The remainder of the paper is structured as follows. Section 2 introduces the experimental design and provides the theoretical characterization of participants' decision problem. Based on this and relevant literature findings, Section 3 develops the hypotheses which guide the subsequent analysis of the experimental evidence and derivation of treatment effects in Section 4. Finally, Section 5 concludes.

2 Experimental design & model

In our experimental setting we consider two different roles. First, N as the set of users, to which we subsequently refer to as consumers, who can visit fictitious websites to gather information in the form of an reading task. Second, the set of available websites M. The role of each consumer n, with $n \in N$, is represented by the participants while the design of each website m, with $m \in M$, is computerized. Consumers' choices were incentivized and participants were recruited from the Prolific (2021) academic panel. The duration of the experiment ranged between 30 and 40 minutes. Subjects earned points dependent on their performance in the reading task which were transferred to cash at the end of the experiment at an exchange rate of 400 points : £1. The minimum (maximum) payout was £2.79 (£5.92) which was topped up by a fixed participation fee of £3. The sessions were conducted online between the 29th Oct. and 15th Nov. and each participant connected via their own desktop device and web browser. In total 405 subjects participated in the study.

[2] On a related note, Englehardt and Narayanan (2016) find that users perform worse in an e-mail classification task when being subject to advertising.

Fictitious web pages in the experiment were programmed with the LIONESS toolkit by Giamattei *et al.* (2020) and are based on PHP 7.

In the following, we elaborate on the experimental design features, treatment variations and formalize the consumers' decision problem which is faced by the participants.

Design

In the experimental implementation, a consumer-website group consists of 1 consumer ($|N| = 1$) who has the option to visit 3 ($|M| = 3$) websites to acquire relevant information. This information is presented in the form of written text alongside advertising content on each website m. Afterwards, a consumer n is asked to answer two questions which relate to the content of the websites and, if answered correctly, are rewarded with $r_{pay} = 150$ each. In addition to this, a consumer receives an initial endowment of $E = 200$ at the beginning of each round. The design of this reading task can be characterized as an real-effort task in the sense of Charness *et al.* (2018) which provides high external validity. The written texts on the websites consisted of approximately 500 words for which a consumer had at maximum $S = 180$ seconds time to read. Given an average reading speed of 250 words per minute in adults, the available time was sufficient to acquire all the relevant information (Rayner *et al.*, 2016; Brysbaert, 2019). If the reading time expires and a consumer has not finished the reading task beforehand, the subject is directed to the questions automatically.[3]

In order to incentivize the reading process, a consumer incurs a loss of $d = 1$ for each second s, with $s \in [1, S]$, she spends reading on one of the websites which is subtracted from E. On one hand this successfully implements opportunity costs of the invested time from a real world context while on the other hand is reasonably low such that we can abstract from substantial endowment effects in the sense of Kahneman *et al.* (1991). Thus, ceteris paribus, the less time a consumer needs for reading, the higher her payoff. Although a consumer does not choose s explicitly, it can be interpreted as an implicit decision variable that can be freely distributed between the m websites.

The relevant information needed to answer the questions can be acquired on any single website m as the textual contents are identical. However, the websites may differ in the graphical advertising displayed.[4] During the reading time, a consumer n is able to switch between the m websites via button-click at any time and as often as she likes. She does not incur any additional costs of switching apart from the amount of time needed for the switch itself since the reading time continues to expire during the loading process of the webpages.

We refer to the differences in the graphical advertising between the sites as the advertising intensity $I_{m,n,p} \sim \mathcal{U}(0, \overline{I} = 100)$ which is i.i.d. for each site, consumer and iteration

[3]The written texts to be read during the reading tasks were of informative nature to avoid any fatigue or disinterest in subjects. The language style was understandable and that of blog- or news articles. Topics of the texts are the following in the order of appearance: Hiking, Art, Health & Food, Financial, Travel.

[4]Please note that the websites only differ in the subsequently introduced ad intensity I, that is, the size of the displayed advertising images. The images themselves are identical across sites.

of the game (period) and is drawn prior to a consumer's visit to a website. The maximum level of ad intensity $\overline{I} = 100$ translates to a width of 700px of the advertising graphic. Ads are placed at the left and right border of the text bodies and were scaled according to I. Since the text size is constant, a higher value of I directly changes the relative proportion of textual content to advertisement on the consumer's screen. As a side effect, the line breaks of the text adapt dynamically to the size of the ads alongside and make the texts more or less well readable.[5]

The experiment consists of multiple periods p, with $p \in \{1, 2, ..., p_K\}$, and the exact number has been determined by a random termination role (RTR) with a continuation probability of $\rho_{continue} = \frac{4}{5}$ and, thus, an expected number of periods of $p_E = 3.1063$. The termination was drawn in advance and the total number of periods are $p_K = 5$ which were identical for all subjects in all treatments. Subjects were informed about the random termination and the continuation process together with the respective draws of each period were presented to the subjects at the end of each period play. The implementation of RTR avoids end-game effects in subject's decision making and secures that theoretical incentives (for ad-blocking adoption) remain identical throughout the entire duration of the experiment which has been found to also be effective on subjects' actual behavior by Bó (2005); Fréchette and Yuksel (2017).

Treatments

While the above fully characterizes the control treatment **NL** ("No-Block Low") we include also 3 other treatments that vary in two dimensions, that is, the intrusiveness of advertising and the availability of ad-blocking and, thus, characterize our 2x2 factorial design structure. In the treatments of **NH** ("No-Block High") and **BH** ("Block High"), advertising on the websites is not only characterized by the intensity I but also by the occurrence O of an advertising pop-up window. O is i.i.d. for each site, consumer and period according to $O_{m,n,p} \sim \mathrm{B}(m \cdot p_K, 0.5)$ which is also independent from I. If a pop-up window occurs, the rest of the website is grayed out with a semi-transparent overlay. Reading the text is not possible while the pop-up is displayed, such that the subject needs to close it first via button-click.[6] Hence, pop-up occurrence causes an implicit reading time penalty of a few seconds and interrupts a subject's reading process and potentially her concentration.[7]

The second variation with respect to ad-blocking is only available in the treatments **BH** and **BL** ("Block Low"). In these treatments, a consumer has the option to adopt an ad-blocking technology B , with $B \in \{0, 1\}$, prior to visiting the websites and starting their reading task.[8] If a consumer decides to use ad-blocking, her endowment gets lowered by

[5] We refer the interested reader to Figures 17 & 16 in Appendix B, which offer website displays of exemplary ad intensities of $I = 14.8, 76.9$, respectively.

[6] Figure 18 in Appendix B displays the occurrence of a pop-up window.

[7] Please note, that the implicit time penalty caused by a pop-up likely depends on a subject's inherent skills, that is, her awareness, reaction time and clicking accuracy.

[8] It was made clear to the participants that the fictitious ad-blocking tool in the experiment is independent

$c = 20$ only in this period while the benefits of ad-blocking remain active for the remainder of the experiment.[9] Once a consumer decides to use ad-blocking, it is not possible to reverse this decision during the experiment.[10]

Ad-blocking technologies are not perfect in reality. Since these technologies depend on curated filter lists, which are maintained based on known advertising publishers, servers and formats, these lists might lag behind the actual rapidly expanding variety of advertisements available on the internet. Moreover, some advertising formats are deemed to be "acceptable" by some ad-blocking providers, as long as they adhere to specific predefined, community accepted criteria, e.g., non-intrusive placement, size and distinctive form site content. Furthermore, Pujol *et al.* (2015) find that the majority of the AdBlock-Plus users does not opt out of receiving acceptable ads. Ad-blocking users are therefore still exposed to some light advertisements that get through the filter, either intentionally or unintentionally.

To account for these facts, the effect of using ad-blocking in the experiment is that it introduces a separate ad intensity only applicable to ad-block users I^B. I^B is again i.i.d. for each consumer, website and period and is drawn according to $I^B_{m,n,p} \sim \mathcal{U}(0, \min(\overline{I}^B = 50, I_{m,n,p}))$. Hence, ad-blocking limits the ad intensity on the websites at least to $\overline{I}^B$, while simultaneously requires that it has to be lower than the realization of I, that is, the relevant ad intensity for consumers without ad-blocking. In the experimental implementation, $\overline{I}^B$ refers to a width of the advertising images of 350px which is also the upper limit of the acceptable ads guidelines. Hence, we model ad-blocking as being imperfect, such that it does not prevent all ads from being shown but rather limits the advertising load. A second effect of ad-blocking is exclusive to the treatment **BH** in that it also prevents pop-ups from being shown and enforces that $O = 0$. Hence, the additional value a consumer gets from using ad-blocking is higher in this treatment compared to **BL** while costs of adoption remain constant at c. Below, Table 1 summarizes the treatment variations while Figure 1 displays the sequence of choices between the Block and No-Block treatments.

from any other real ad-blocking they may have already installed in their browser. Additionally, potential ad-blocking tools they may already have installed are ineffective during our study since advertising images are embedded as image files in the sites' source code and are not associated with any web advertising tag. It was stressed that nothing will be installed on a participant's device during participation and that the ad-blocking option of this study only applies to the websites within this study and does not affect real browsing afterwards.

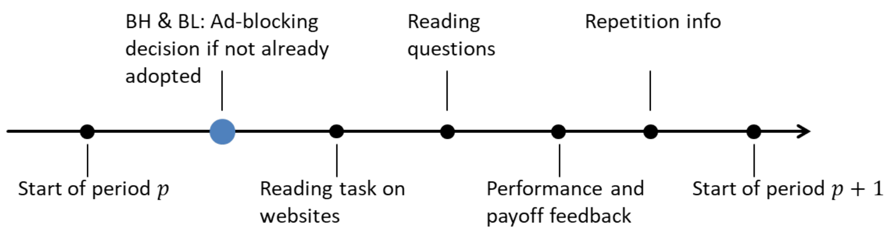
[9]The adoption of ad-blocking technologies, e.g., browser plug-ins, usually involves no direct monetary costs in reality. However, set-up processes usually require costs of a different kind in the form of time and effort on consumers. In the context of mobile operating systems ad-blocking applications might even require monetary transactions. In the experiment the one-time cost of $c = 20$ is equivalent to a loss of 20 seconds in the reading time s. We used the interpretation of c as implicit time delay also as framing in the instructions provided to participants.

[10]As ad-blocking is reducing the intensity of advertising, there is usually no incentive for customers in real-life to reverse their adoption decision after incurring the set-up costs. Furthermore, we abstract from the existence of counter ad-blocking technologies, which have the aim to steer consumers away from disabling their active ad-blocking technologies.

Table 1: Treatment overview

	Ad-blocking	
Pop-up occurrence	No Block	Block
Yes	**NH**	**BH**
No	**NL**	**BL**

Figure 1: Experiment sequence



A consumer's decision problem

A consumer n's decision problem in a given period depends primarily on her two input choices of s, that is, the time needed to read, and her ad-block decision B (in Block treatments). While it is always best to minimize s, ceteris paribus, the decision whether to adopt ad-blocking can be characterized as an investment decision under uncertainty in someone's own capabilities. For the characterization of ad-blocking incentives we define below a consumer n's received period utility (U_p^B) if she adopts ad-blocking in a given period p.

$$U_p^B = E + 2 \cdot r_{pay} \cdot \rho_Q(s(I^B, \theta_n), I^B, \theta_n) - d \cdot s(I^B, \theta_n) - c \tag{1}$$

Since ad-blocking is adopted in Equation 1, I^B applies which can be assumed to influence both the time needed to read s and also the probability ρ_Q that one question of $Q_{1,2}$ is answered correctly. Hence, I^B enters as an argument in both s and ρ_Q. Furthermore, it is a standard feature in economic theory that consumers differ in their nuisance cost from advertisement, that is, the degree to which they are influenced by ads. Usually, it is assumed that a consumer n's nuisance θ_n is uniformly distributed along an unit interval, that is $\theta_n \sim \mathcal{U}(0, 1)$. We account for this also in the formal characterization and include this as an additional argument. [11] Finally, the amount of time spend reading s should, also have an impact on the accuracy of the acquisition of information, which is captured by its influence on ρ_Q. Additionally, it also determines the cumulative costs due to the expiration of reading time while c represents the cost for the adoption of ad-blocking in period p.

The other two states in which a period p can be played is on one hand a situation in

[11] Please note that θ is positive and is usually modeled only as a weighting parameter. Hence, it is neutral with respect to the effect direction of ad intensity and does not impose a relationship of it's own.

which ad-blocking has been adopted in a prior period and is still active, and on the other in which it is not adopted yet. We refer to the utility functions in these scenarios below in which U_p^{PB} (Equation 2) applies to the earlier and U_p (Equation 3) to the latter situation.

$$U_p^{PB} = U_p^B - c = E + 2 \cdot r_{pay} \cdot \rho_Q(s(I^B, \theta_n), I^B, \theta_n) - d \cdot s(I^B, \theta_n) \quad (2)$$

$$U_p = E + 2 \cdot r_{pay} \cdot \rho_Q(s(I, \theta_n), I, \theta_n) - d \cdot s(I, \theta_n) \quad (3)$$

Given these one can characterize a consumer's decision problem with respect to the adoption of ad-blocking. Due to the random termination of the game, profit streams from future periods are not finite but their occurrence becomes more and more unlikely. Endgame effects do not materialize in this setting and a consumer's incentives are identical for any period p. The trade-off of adopting ad-blocking in period p vs. in the next $p+1$ can thus be described by the following inequality.

$$U_p^B + \frac{\delta}{1-\delta} \cdot U_{p+1}^{PB} \geq U_p + \delta \cdot U_{p+1}^B + \frac{\delta^2}{1-\delta} \cdot U_{p+2}^B \quad (4)$$

Ad-blocking is adopted in p if the utility from it on the LHS of (4) exceeds that of a later adoption in the subsequent period (RHS). The profit stream in that case includes the utility and cost of adoption in p (via U_p^B) and the net present value of U^{PB} from $p+1$ onward for the remainder of the game. If ad-blocking is adopted in $p+1$ instead (RHS), the profit stream of U_p^B starts not until $p+2$. Discounting is done via the discount factor δ, with $\delta \in [0,1]$, and is represented in the experimental implementation through the continuation probability of $\rho_{continue}$.[12] Hence, it is especially the random termination rule that secures the adoption trade-off to be theoretically identical in every period. The solution to the inequality in (4) with respect to δ provides the minimum discount factor for adoption δ^* which is presented in Equation 5.

$$\delta \geq 1 - \frac{2r_{pay}\left(\rho_Q(s, I^B, \theta) - \rho_Q(s, I, \theta)\right) + d\left(s(I, \theta) - s(I^B, \theta)\right)}{c} \equiv \delta^* \quad (5)$$

If a consumer is sufficiently patient and δ exceeds δ^* then ad-blocking is adopted. The critical discount factor is thereby determined by the gain-cost ratio of ad-blocking itself (fraction on RHS of (5)). Intuitively, δ^* increases (makes adoption less likely) in the cost of ad-blocking c and decreases (more likely adoption) if the gains from it are large. The gains from ad-blocking can be separated into two sources. First, $2r_{pay}\left(\rho_Q(s, I^B, \theta) - \rho_Q(s, I, \theta)\right)$ as the payoff difference through a change in the likelihood of answering correctly under a reduced ad intensity I^B compared to I. Second, $d\left(s(I, \theta) - s(I^B, \theta)\right)$ as the payoff difference resulting from economies in reading times due to the reduction in the ad intensity.

[12]Please note that it has been shown by Bó (2005) and Fréchette and Yuksel (2017) that the continuation probability as part of random termination schemes in experimental settings has indeed an effect on subjects' play equivalent to a discount factor in economic theory

3 Hypotheses

In this section we lay out different hypotheses and justify them against the background of literature findings or the theoretical characterization of the experimental game. This ex-ante definition of hypotheses serves then as a guideline for the subsequent analysis of the experimental data.

The few behavioral studies that focus on advertising's influence on actual consumer behavior predominantly produce null results. Frik *et al.* (2020) who examine online shopping decisions find that contextual ads (or the lack thereof) has no influence on prices paid for the chosen products, search costs or the satisfaction with the chosen product. In a similar offline setting Bloom and Krips (1982) also find null effects. Their advertisement treatments produce comparable search times and exerted effort in their shopping task. However, since our study focuses not on shopping behavior but the acquisition of information, the application of these findings may be limited. If we turn to the seminal literature on the economics of online advertising, we find that advertising acts as an implicit price component for consumers and creates nuisance costs (Gabszewicz *et al.*, 2004; Anderson and Coate, 2005). A similar argument is also raised by Van Zandt (2004) and Jacoby (1977) who raise concerns that a high intensity of online advertising may impede the identification of relevant information and use of it in decision-making. Since these findings apply more closely to the reading task in our experimental setting, we formulate our first hypotheses with respect to the effect of ad intensity and ad-blocking availability as follows:

Hypothesis 1.1 & 1.2: *The intensity of advertising I negatively influences the acquisition of information with respect to probability of correctly answered questions ρ_Q (1.1) and the time spent reading s (1.2). Given that ad-blocking reduces I, ad-blocking availability's effect on the same measures is the inverse.*

Ad-avoidance in the experiment is on one hand directly implemented through ad-blocking availability in treatments BH and BL. On the other hand, subjects can avoid high realizations of ad intensity also imperfectly by switching between the M alternative websites and decide for the best option. However, switching takes time during the reading task and every second expired is penalized by d which can be characterized as search costs in the economic sense. Given that both Bloom and Krips (1982) and Frik *et al.* (2020) do not find differences in search times and search costs in their effort tasks, we formulate start in a similar manner with the h_0-hypothesis and formulate our second hypothesis below as:

Hypothesis 2: *Consumers do not engage in any other ad avoidance behavior if ad-blocking is not present, that is, ad-blocking availability has no effect on the number of website switches w.*

Previous behavioral studies which studied advertising's or ad-blocking's effect on consumer behavior, imposed the presence (absence) of advertisements and the usage of ad-blocking exogeneously as treatment variation. Hence, treatment selection determined whether a specific subject used ad-blocking or not. To the best of our knowledge, our behavioral study is the first which endogenizes the ad-blocking adoption decision in treatments in which the technology is available (BH, BL). Thus, we do not have any prior basis to formulate a testable hypothesis, but rather formulate a exploratory research question below:

Exploratory research questions 1: *How fast and when is ad-blocking adopted during the experiment? Who adopts ad-blocking and what are other drivers in the adoption decision?*

A publisher's decision of the ad intensity on her website, I is not an endogenous variable in the experimental and is not strategically chosen. Hence, in our analyses concerning the potential effects for the competition among publishers, we have to abstract from any strategic response a publisher might undertake as reaction to observed consumer behavior. Any conjecture on possible implications for publishers based on our experimental data comes, thus, with a major caveat. Therefore, we are not in the position to define a testable hypothesis ex-ante but rather pose our second exploratory research question to be the following:

Exploratory research question 2: *What is the potential effect of ad-blocking availability on publishers? Based on the experimental data, are there any systematic implications derivable on an arbitrary publisher's profit function* $\pi_{Pub}(I, s)$*?*

4 Data Analysis

In this section we first provide information on the necessary filtering operations of the experimental data. Secondly, we provide insights into the composition of our participant sample before we turn to the descriptive statistics of subjects' input variables. Finally, we test our previously defined hypotheses and carve out the treatment effects.[13]

Data filtering

Prior to any analysis, we need to filter out any data associated to subjects' strategies that is not within the intention of the experiment and, thus, not reflective of any real world behavior. To be precise, in the present experiment we observe that a fraction of subjects intentionally skip the timed reading task on the websites in order to forego any decay of their endowment due to reading time. After this, they then take the gamble on the reading questions with a chance of $\frac{1}{4}$ to answer correctly given the four available answering

[13]Please note that all statistical tests and hypothesis testing employs non-parametric methods which are assumption free on the distribution of the underlying data. If we depart from non-parametric statistics in our analyses, we will indicate this in the text.

options. Although this a valid strategy for the incentivized experiment, it is not reflective of typical browsing behavior in reality. Hence, if these observations would remain in the data set, any analysis would be biased and the external validity of derived effects would suffer.

Given that we anticipated this strategy of gaming the experimental design, we chose to put comparably more payoff weight on the two questions $(2 \cdot r_{pay} = 300)$ than on the amount to be maximally saved due to skipping the reading task $(d \cdot S = 180)$. As a result, subjects that followed this strategy of "skip-and-gamble" save indeed on reading time but exhibit consequently lower correct answer ratios. In this way, "skip-and-gamble" players do not manage to realize higher payoffs than those who participate in the reading task.

To effectively filter out those "skip-and-gamble" observations, we use a cut-off of 25 seconds reading time for at least 3 periods. Specifically, we exclude all participants who finish the reading task under 25 seconds in three or more periods. We feel confident that this cut-off is for one effective in identifying those participants who really do not read the written articles and for another is not too restrictive and excludes participants who either only cross-read or accidentally finish the reading task early and continue to the questions. Please note that the main results of the analysis are qualitatively robust to a more or less restrictive filtering. Employing the above cut-off filter eliminates 49 observations across all treatments such that we continue with $88, 88, 94, 86$ observations $(356$ in total$)$ in treatments BH, BL, NH and NL, respectively.

Participant sample

Participants were recruited from the Prolific (2021) Academic Panel which provides the options to filter the subject pool according to a variety of indicators. We used this feature and only allowed participation of subjects that are of EU27 +UK nationality and residence, exhibit English language proficiency, have no reading and literary difficulties and were able to connect via a desktop computer device.[14] Given these pre-filters, Prolific sends out invitations to eligible subject in their pool randomly.

The assignment of participants to treatments can be assumed to be at least as random as in traditional offline lab experiments. Typical experimental studies are based on offline sessions which take place in the geographical location of usually one, seldom two laboratories. This implicitly filters the participant pool to contain predominantly subjects of the nationality in which the lab is located and ensures that participants do not lack the necessary literary skills to understand the experimental material. We replicate these features by using the nationality filter which is less narrow in comparison while the requirement of English literacy ensures the understanding of the experimental tasks.

The distribution of nationalities in our sample is displayed in Table 2. It becomes ap-

[14]Countries of EU27+UK countries include: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom .

parent that one consequence of employing no further filtering is that nationalities are relatively skewed towards those of Portugal, Poland, Italy, Greece and Spain which seems to be reflective of Prolific's EU27 participant panel.

Table 2: Nationalities of sample

Nationality	**Proportion**	**Nationality**	**Proportion**
Portugal	0.2219	Netherlands	0.0112
Poland	0.1657	Finland	0.0112
Italy	0.1264	Denmark	0.0112
Greece	0.0758	Belgium	0.0112
Hungary	0.0702	Switzerland	0.0084
Spain	0.0674	Germany	0.0084
United Kingdom	0.0449	Croatia	0.0084
Estonia	0.0421	Romania	0.0056
Slovenia	0.0393	Czech Republic	0.0056
Latvia	0.0308	Austria	0.0056
France	0.0140	Bulgaria	0.0028
Sweden	0.0112		
No. Obs. $= 356$			

While the assignment to the treatments may be random, registration into the Prolific Academic panel is not. This selection into panel registration, however, lies outside our control and is not different to the selection into recruitment pools traditional offline experimental studies draw upon. Usually, participant pools from university laboratories are almost exclusively made up of students who registered voluntarily. It is likely that more dedicated and interested students or those who rely financially more on the experiments' payoffs, sign up more frequently. The same argument applies to online experimental settings which are not perfectly free from endogenous selection into participation. However, this is not problematical as long as selection between treatments is not structurally different for which we do not find any evidence. Interestingly, the distribution of nationalities, and with that registration to the Prolific panel, seems to be positively correlated to the youth unemployment rate. According to Eurostat (2021) Spain, Greece, Italy and Portugal all exhibit the highest unemployment rates among youths below 25 years with all ratios well above 25%.

To further characterize the participant sample beyond nationality, Table 3 provides statistics on socio-demographic factors while Table 4 displays sample distributions across education, employment and digital device usage.

The sample is equally distributed across males and females and is exhibits a majority of students (62.9%). Consequently, the average age is approx. 25.96 years and the average maximum yearly income is around 28.51 thousand euros. If one looks at the highest completed education degree, the most pronounced are degrees of completed high school, undergraduate and graduate studies. Hence, our sample pool is also comparable to samples

Table 3: Socio-demographic statistics

Variable	**Type**	**Mean (Std. Dev.)**	**Min**	**Max**	No. Obs.
Female	Binary	0.4699			349
Age	Discrete	25.96 (8.07)	18	58	356
Children	Binary	0.1180			356
Income (in k)	Continuous	28.51 (24.23)	10	150	356
Student	Binary	0.6292			356
Programming	Binary	0.3655			342
Ad-Block.ext	Binary	0.7061			347

Table 4: Socio-demographic statistics II

Highest Education	**Proportion**	**Employment status**	**Prop.**	**Device usage (weekly)**	**Prop.**
Doctorate degree (PhD,...)	0.0169	Full-time	0.2669	Multiple times per day	0.4073
Graduate degree (MA,MSc,MPhil,...)	0.2191	Part-time	0.1629	Every day	0.4354
Undergraduate degree (BA,BSc,...)	0.2781	New job	0.0281	2-6 times a week	0.1292
Community college	0.0393	Not working	0.0618	Once a week	0.0225
Secondary education (GED,GCSE,...)	0.0393	Unemployed	0.2219	Never	0.0028
High school diploma /A-levels	0.3820	Other	0.2556	Other	0.0028
No formal qualifications	0.0140				
Other	0.0112				
No. Obs.= 356					

of traditional offline lab experiments which are comprised predominantly of students.[15]

Against the background of a relatively younger, student orientated sample, it is not surprising that also digital skills and the frequent use of corresponding devices is higher compared to population averages. This is reflected by 36.6% of the sample having programming skills and over 84% use digital devices at least once per day. Noteworthy is that more than 70% also state that they use some form of ad-blocking when browsing the web.

Given all these points, we are confident in that the sample selection into treatments

[15]Concerns over external validity of predominantly student comprised experimental samples can be rejected by the results of Bolton *et al.* (2012) who find that students and managers behave similarly in laboratory environments. Additionally, our sample does not purely consist of students but includes also members of the active workforce. Hence, we are confident that our results do not suffer on the grounds of limited external validity due to our sample composition.

is random and is at least comparable to the standards of traditional offline experimental settings. More so, the sample indeed consists of a majority of students, but is not exclusively comprised of them. Hence, external validity of the results should be higher due to a more heterogeneous participant group.

Descriptive statistics

To accommodate the previously discussed socio-demographic statistics, Table 5 displays descriptive statistics of experimental variables. These include on one hand the computerized elements of the websites I, I^B, O in the form of *AdInt.1X*, *AdInt.2X* and *AdPop.X*, respectively, with $X \in A, B, C$ relating to each of the three available websites. On the other hand, variables that are determined by subjects' inputs are B, s, w, ρ_Q and are represented by *BlockAdopt*, *ReadingSecs*, *Switches* and indirectly *QCorrect* as the number of correctly answered questions in a given period.

Table 5: Descriptive statistics by treatment

	BH	**BL**	**NH**	**NL**
Variable	Mean (Sd)	Mean (Sd)	Mean (Sd)	Mean (Sd)
AdInt.1A	50.42 (28.34)	48.83 (28.02)	49.48 (29.03)	49.30 (28.81)
AdInt.1B	49.67 (29.62)	48.13 (30.32)	51.74 (28.73)	52.01 (28.42)
AdInt.1C	49.75 (28.73)	52.40 (28.59)	49.35 (28.35)	49.15 (28.08)
AdInt.2A	19.68 (14.14)	18.19 (14.44)	-	-
AdInt.2B	18.12 (13.77)	17.83 (14.17)	-	-
AdInt.2C	19.13 (14.26)	19.35 (13.73)	-	-
AdPop.A	0.49 (0.50)	-	0.51 (0.50)	-
AdPop.B	0.45 (0.50)	-	0.51 (0.50)	-
AdPop.C	0.49 (0.50)	-	0.51 (0.50)	-
BlockAdopt	0.43 (0.50)	0.31 (0.46)	-	-
ReadingSecs	92.17 (43.89)	90.97 (46.53)	81.25 (44.29)	85.65 (39.31)
Switches	0.58 (1.14)	0.80 (1.26)	1.25 (1.45)	1.12 (1.51)
QCorrect	1.65 (0.57)	1.64 (0.57)	1.60 (0.57)	1.60 (0.58)
PeriodProfit	353.83 (87.78)	355.23 (87.73)	360.39 (86.58)	356.04 (85.44)
Earnings	4.42 (0.6)	4.44 (0.57)	4.51 (0.54)	4.45 (0.53)
No. Obs.	440	440	470	430

Although the expected values of the randomly drawn ad intensities and pop-up occurrences are identical for each and every subject, it is reasonable to conduct a "sanity check" and ensure that actual realizations are comparable across treatments. This is the case here, as *AdInt.1X*, *AdInt.2X* and *AdPop.X* are not significantly different (**Enter P-value**).

More variation can be anticipated in the endogenous variables. In the block treatments BH & BL, 43% and 31% decided, respectively, at some point to use ad-blocking. The time needed to read the web articles ranged from approximately 92 to 81 seconds and subjects answered on average 1.6 to 1.65 questions correctly of the available two each period. Besides this, there seems to be a larger variation in subjects' activity between websites and the amount of switching. Across all treatments the average number of website switches per period ranges from 0.58 in BH to 1.25 in NH.

As an enhancement to the mere statistics, Figure 2 displays the evolution of subjects' input variables over all periods. Interestingly, the amount of correct questions seem to be inversely U-shaped such that the questions in $p = 1, 4, 5$ seem to be less frequently answered correctly compared to those of periods $p = 2, 3$. Please note that this does not necessarily have to be already indicative of a relationship with other variables but could just be that the written texts or questions themselves are perceived as more complex or difficult than that of other periods. This could also be supported by the line-graph of reading times which show an U-shaped pattern or at least increasing slope. Hence, subjects spend on average less time reading on the website in periods $p = 2, 3$ compared to later periods.[16] Although the level of some line-graphs might already foreshadow a treatment effect, we postpone this analysis for the subsequent testing of hypotheses.

The pattern of ad-blocking adoption is similar in both block treatments in that the majority of adoptions take place in the first period $p = 1$. Hence, if a subject expects that ad-blocking is beneficial, it is adopted right from the start before any of the websites and ad intensities are encountered. This is totally in line with the theoretical trade-off and critical discount factor laid out in Equation 4 which is identical in each period. Hence, if the condition is fulfilled for an individual subject, ad-blocking should be adopted in the first period which is exactly what we observe in the data. After the first period, ad-blocking is only adopted occasionally by only a few subjects. What precisely drives the ad-blocking adoption of the first-movers in $p = 1$ and the laggards in $p \geq 2$ will be subject to the analysis concerning our exploratory research question 1.

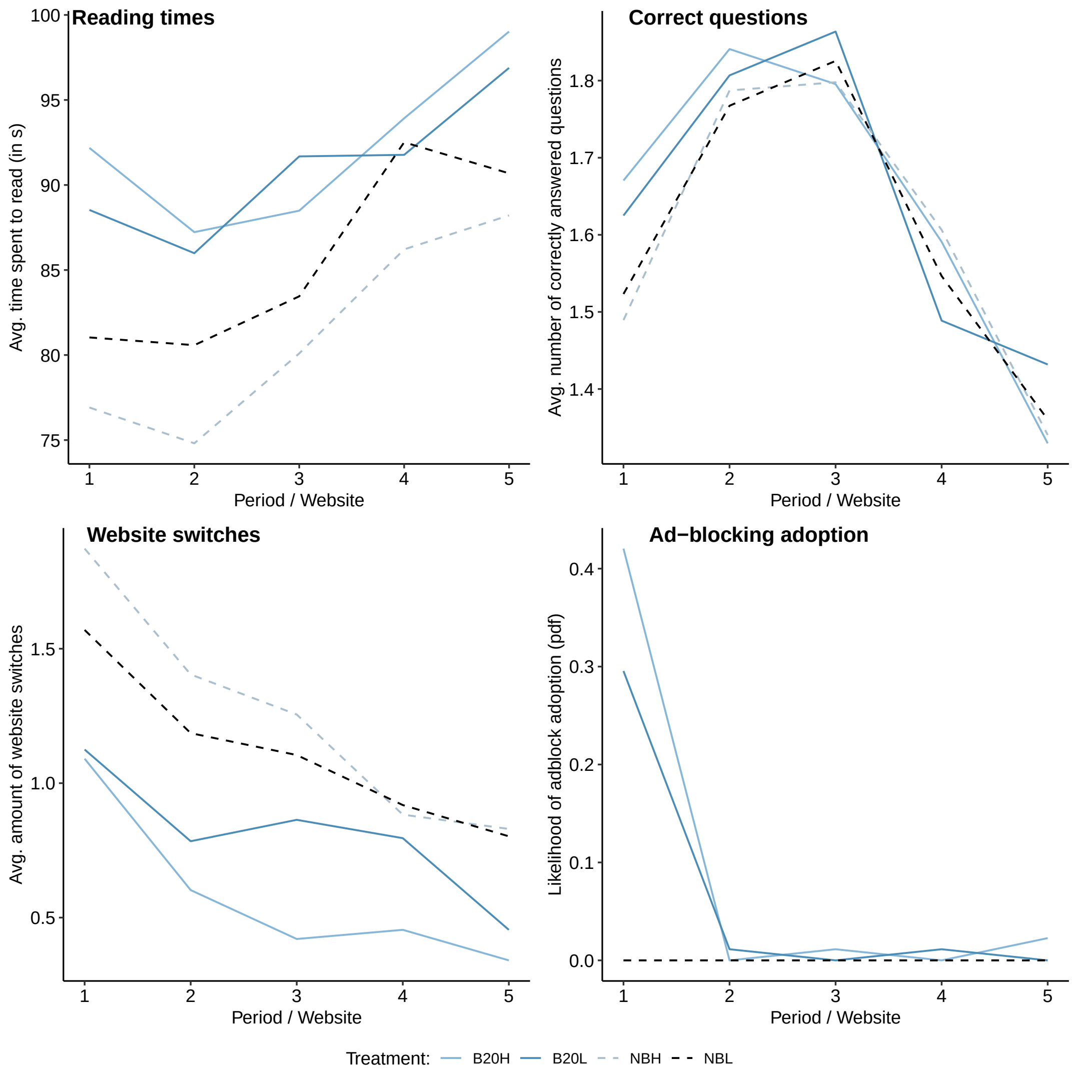
Website switches as a means to explore the ad intensity on other websites are decreasing over time in all treatments. While the main motivation of switching is to find the website which provides the best readability for an individual subject, more frequent switching in the first periods may also be explained by simple curiosity at the beginning of the experiment. After a few iterations, subjects are better able to judge the ad intensity realization of their first choice against the other two unknown alternatives such that switching rates drop as a consequence. Although, the line-graphs already suggest a potential level effect between treatments, we postpone this discussion for the testing of Hypothesis 3.

Ad intensity and ad-blocking effect

We examine the effect of the ad intensity I on the acquisition of information with respect to the reading time s and the probability of answering correctly ρ_Q. Naturally, a subject's decisions during the experiment are only influenced by the individual ad intensity she experiences. This experienced ad intensity I^E is, thus, a subset of the drawn ad intensities

[16]For these reasons, and to cover other potential website/ period specific confounding factors, it might be reasonable to include period fixed effects for any later regression designs on period level.

Figure 2: Timelines of decision variables



on all sites since not all websites are necessarily visited. Additionally, in the block treatments this experienced ad intensity is also dependent on a subject's ad-blocking choice and whether I or I^B is relevant on a given site.

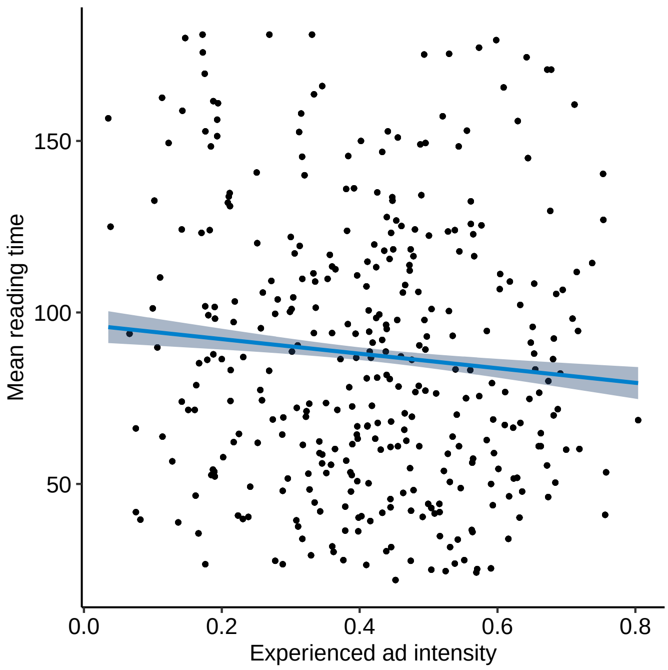
If a subject switches websites, she experiences more than one ad intensity in a given period. Hence, we calculate the experienced ad intensity I^E as the reading time weighted average ad intensity across all websites according to Equation 6.

$$I^E = \begin{cases} \frac{1}{\sum_{m=1}^{M} s_m} \sum_{m=1}^{M} s_m \cdot I_m^B & if B = 1, \\ \frac{1}{\sum_{m=1}^{M} s_m} \sum_{m=1}^{M} s_m \cdot I_m & else. \end{cases} \tag{6}$$

Subsequently, we focus first on the direct relationship between the experienced ad intensity and the two variables of interest, that is, the reading time and correctly answered questions as a measure for speed and accuracy of information acquisition. Please note that the following analyses are not derived by a treatment comparison but across treatments and are correlational and not causal effects. The main reason for this is, that the selection of subjects into different ad intensities is not exogenous. Since subjects can switch websites, they can at least imperfectly decide their own ad intensity among the available realizations.[17]

The direct relation between the experienced ad intensity and the reading time on subject level and across treatments is displayed in Figure 3. As the scatter-plot and the linear regression trend suggests, we find the relation to be weakly negative but significant. The magnitude ranges from -0.051 (Kendall's τ, $p < 0.01$) to -0.078 (Spearman's ρ, $p < 0.01$). Hence, the higher the experienced ad intensity, the less time is spent reading on the websites. This result may seem counter-intuitive at first, but could potentially be explained by subjects being more anxious to leave the reading task earlier in order to escape the more intense advertising.

Figure 3: Relation exp. ad intensity and reading time



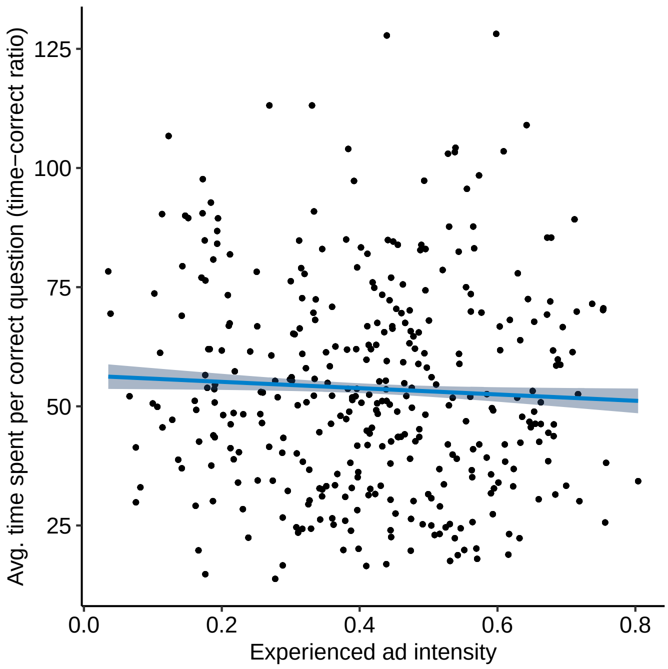
Similarly, the relation between the experienced ad intensity and the number of correctly answered questions is also negative and significant. The size of this relation ranges from -0.073 (Kendall's τ, $p < 0.001$) to -0.098 (Spearman's ρ, $p < 0.001$). Hence, the control questions are less likely answered correctly if the intensity of the experienced advertisement is larger. However, based only on this direct relationship between the two variables, one cannot qualify whether the negative effect of the experienced ad intensity on the likelihood of a correct answer is direct or works indirectly through the previously

[17]Although the expected value of the random variable of I (ad intensity) is exogenous and identical for all subjects, the actual realizations might not. However, we checked the full support of these realizations for each treatment and period and find sufficient realizations of ad intensities over the full support of $I \in [0, 100]$ for subsequent estimation procedures. The Appendix Figure 12 displays the realizations of I by treatment and period.

established negative effect on reading times.

The variables of reading time and the likelihood of answering correctly can be interpreted as measures of absolute performance with respect to the acquisition of information. While both of these exhibit a negative relation to the intensity of experienced ads, the effect on a relative metric of efficiency in the form of the average time spent per correctly answered question remains unclear. If we introduce this time-correct ratio t as $t = \frac{s}{2 \cdot \rho_Q}$, it becomes apparent that the combined effect of the two negative influences remains ambiguous since both the nominator and denominator is negatively influenced. For this, Figure 4 sheds light into the relationship of the experienced ad intensity and the time-correct ratio.

Figure 4: Relation exp. ad intensity and correct-time ratio

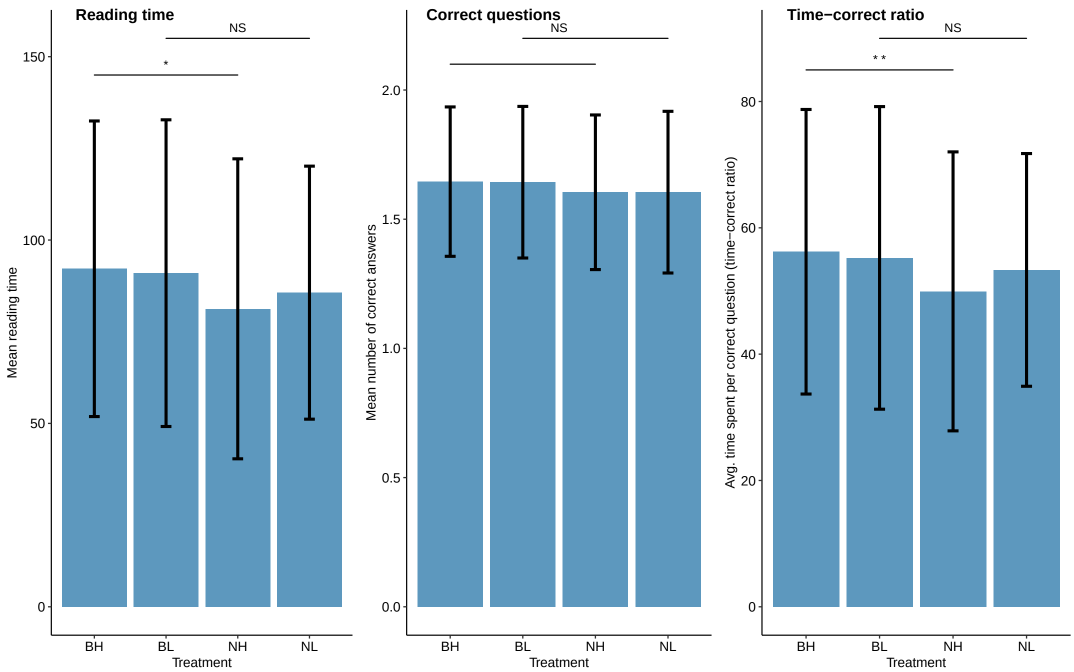


We find that the relation of experienced ads and the time-correct ratio is also negative, less pronounced than the previous two but still significant. The magnitude of this relation ranges from -0.033 (Kendall's τ, $p < 0.05$) to -0.05 (Spearman's ρ, $p < 0.05$). Apparently, the negative effect on lower reading times dominates that on the likelihood of answering correctly such that the ratio overall is negatively affected by higher ad intensities. Although the relation is only weak, this can be interpreted such that higher ad intensities force subjects to be more efficient in their reading or, to put it differently, higher ad loads induce subjects to evasion and be more resourceful with their time as opportunity costs.

Subsequently, we enhance the previous analysis with the pairwise comparisons of our treatment specifications. In this way, we will examine the causal effect of ad-blocking availability on the different performance metrics of information acquisition. Naturally, the main channel of effect that is induced by ad-blocking is through a lower experienced ad intensity which is 0.35, 0.48, 0.37, 0.47 for treatments BH, NH, BL and NL, respectively (Mann-Whitney-U (MWU), all $p < 0.001$).[18] Please note for the following analyses that the interpretation should not be reduced to this channel of lower ad intensity alone. The treatment comparison between blocking treatments (BH, BL) and no-blocking treatments (NH, NL) is not between subjects who adopt ad-blocking, and experience lower ad intensities, and those who do not, but rather between subjects to whom adoption is available and those who do not have that option. This distinction is, of course, important since the active decision to not-adopt is endogenous and fundamentally different to simply not having the choice.

In the following, we expand upon the correlational findings of the previous analyses and examine the causal treatment effect of ad-blocking availability. Variables of main interest are again the performance metrics of information acquisition in the form of reading times, correctly answered questions and the time-correct ratio. Figure 5 displays the corresponding treatment effects.

Figure 5: Treatment effects of ad-blocking on reading performance



The first finding which we observe is that treatment effects are more pronounced and more often significant if advertising is also intrusive, that is, if pop-up windows do occur. Hence, we elaborate in the following mainly on treatment effects of the pairwise comparison between BH & NH.

With respect to the reading time we find a similar effect to the correlational evidence in Figure 3. The mean reading time in treatment BH is 92.2 seconds compared to 81.0 in NH,

[18]All pairwise treatment comparisons are conducted with the relevant Mann-Withney-U non-parametric test for independent samples which is equivalent to the two-sample Wilcoxon rank-sum test. The tested pairwise comparisons that provide the treatment effect of ad-blocking availability are always that of BH & NH and BL & NL.

which is significantly higher (MWU, $p < 0.1$). Hence, subjects are willing to spent more time on the websites when the option of ad-blocking is available to them. This falsifies our Hypothesis 1.1 in that ad-blocking availability does not have a negative effect on reading times s.

Although reading times are higher in a scenario with ad-blocking, we find that differences in the likelihood of answering correctly are not (MWU, $p = 0.36$). On average, only slightly more questions are answered correctly in BH with 1.65 compared to 1.60 in NH. Hence, the availability of ad-blocking induces a longer visit duration which probably improves the gathering of information, but this is not reflected in a higher likelihood of answering correctly compared to a scenario without the option of ad-blocking. Potentially, this could be explained through a level effect in that correct answer probability is already quite high in NH with 1.6 of 2 available questions. There is simply not much room to improve upon and an additional second of reading time at the margin does only little in improving answer probability at that level. Given this, we also have to reject Hypothesis 1.2 since we can not prove a significant effect on the empirical ρ_Q as the likelihood of correct answers.

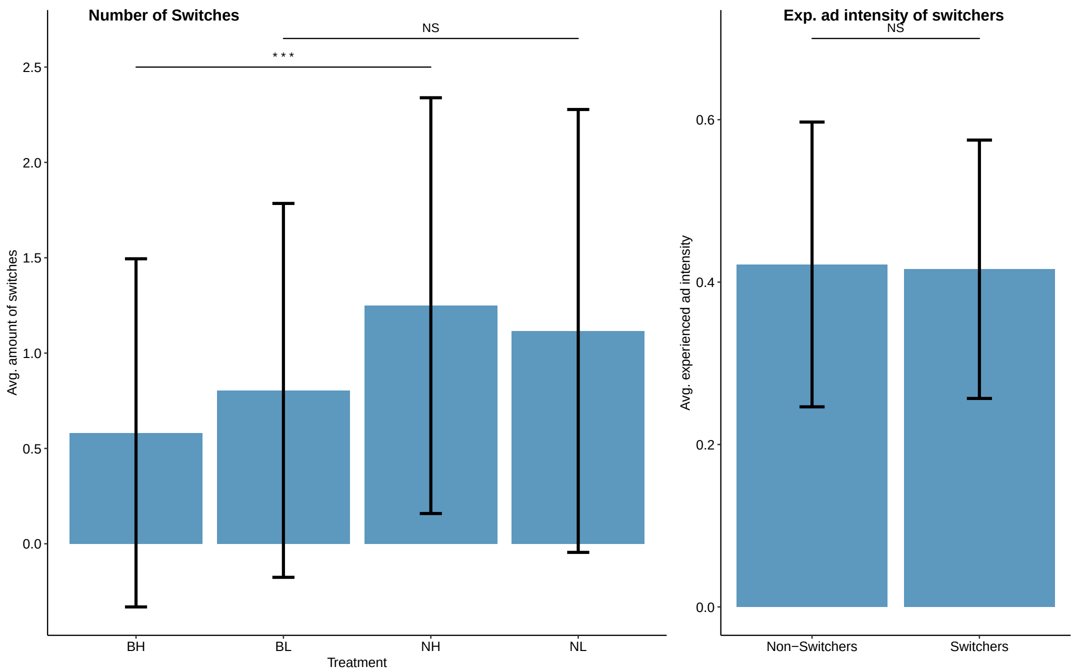
As a logical consequence of this, ad-blocking availability's positive effect on reading times dominates that on answer probability. Hence, we find that subjects need significantly (MWU, $p < 0.05$) less time per correctly answered question in NH (49.9 seconds) than in BH (56.2 seconds). Thus, in a scenario with ad-blocking availability, subjects spent inefficiently more time on the websites. We formulate our first main results as the following.

Result 1.1, 1.2 & 1.3: *If advertisement is intrusive (BH & NH), the availability of ad-blocking induces subjects to spent more time reading s (2.1), does not effect the likelihood of answering a reading question correctly ρ_Q (2.2) and leads to a higher time-correct ratio t (2.3). Thus, the acquisition of information is less efficient if ad-blocking is available.*

Ad avoidance behavior

In the blocking treatments of BH and BL, the option of ad-blocking offers a direct solution for subjects to influence the intensity of advertising they encounter. In NH and NL, where this option is not available, switching and choosing between websites is the only means to influence the ad intensity and how the content is displayed to an individual subject. The left panel of Figure 6 expels the treatment effects with respect to the switching behavior as the most prominent ones. Similar to the treatment effects on reading performance measures, differences in switching behavior are significant if advertisements are intrusive, that is, in the pairwise comparison between BH & NH. Subjects switched on average 0.58 times per period in BH and 1.25 times in NH, which is significantly more (MWU, $p < 0.001$). Thus, we can reject our Hypothesis 3 and find that ad-blocking availability reduces switching between websites.

Figure 6: Website switches as ad-avoidance



The aim of switching websites from a subject's perspective is, naturally, to find the one website which offers the individual the optimal ad intensity or layout among the three options. To shed light on this, the right panel in Figure 6 displays the experienced ad intensity for switchers and non-switchers across all treatments. Apparently, they settle for only slightly lower ad intensities (0.416) compared to non-switching subjects (0.422) as a result of their endeavors. However, these differences among the two groups are not significant (MWU, $p = 0.729$).[19]

While the result of the switching behavior in terms of ad intensity seems neglectable, it for sure is costly as the available reading time continues to expire during the switching process. This time span could have been used prolifically to read the text on the original website.[20] Whether these implicit search costs are recouped through a better reading performance is displayed in Figures 13 and 13 in the Appendix. Especially in BH it becomes apparent that switchers consequently exhibit higher reading times but do not answer significantly more questions correctly. Thus, time-correct ratios are higher and switchers are less efficient.

[19]The experienced ad intensity between switchers and non-switchers becomes more pronounced in specific treatments, especially in BH. Nevertheless, differences remain not significant in all of them. Although the number of observations between switchers (226) and non-switchers (130) is rather asymmetric, we do not think this is a issue of sample size.

[20]Given a standard DSL internet connection, our internal tests produced an average time for one switch of 1.6 seconds. This refers to the duration from the first button click on the original website to the complete pageload of the new one. During this time, the connection to the experimental server is upheld such that the reading timer continues to expire. Hence, one website switch comes with an implicit time penalty of approximately 1.6 seconds.

Based on this, it does not seem to be the case that switchers' search costs are recouped such that the observed switching behavior can be considered excessive from a welfare standpoint. Hence, reducing the incentive to switch through ad-blocking, as a direct way to influence the display of websites, helps to avoid these associated costs. We formulate this as our third main result.

Result 2: *If advertisement is intrusive* $(BH \& NH)$, *the availability of ad-blocking induces subjects to switch less between websites* w. *Since switching is associated with an implicit cost in reading time, the reading times* s *of switchers are higher than those of non-switchers in BH. Similarly switchers are less efficient, that is, the time-correct ratio* t *is higher than that of non-switchers in BH. The availability of ad-blocking reduces the incentive for inefficient switching.*

Drivers of ad-blocking adoption

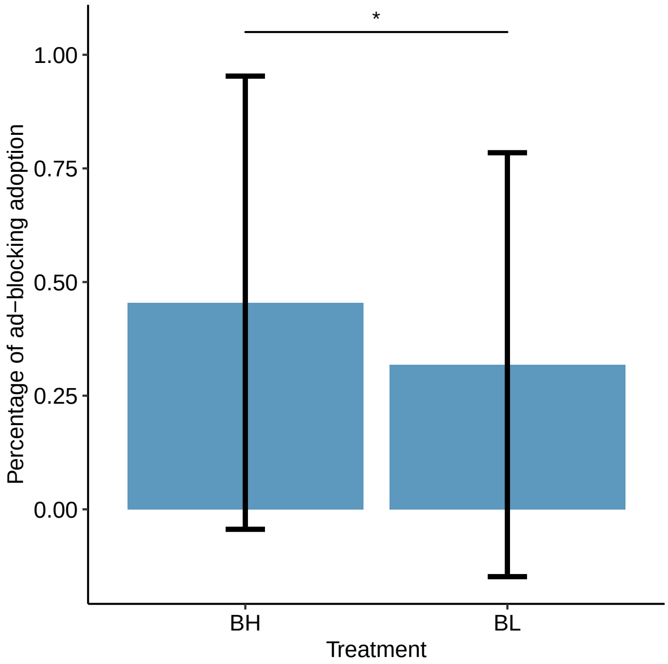
In this subsection we aim at answering the rather exploratory research question of when ad-blocking is adopted and what are other relevant drivers of the adoption decision among subject characteristics, preferences and others. The fourth panel in Figure 2 already provides an answer to the timing of the adoption. In the experiment ad-blocking takes mainly place in period $p = 1$ such that we observe only 5 subjects who adopt at a later stage. Hence, the adoption of ad-blocking is decided before the first reading task and before any of the websites and ad intensities are encountered. The logical consequence from this is, that adoption cannot be driven by experiences during the experiment, but is rather driven by experience outside of it or other subject characteristics.[21]

The two treatment in which ad-blocking is available differ in their ad intrusiveness in the form of occurring pop-up windows. Precisely, in BH ad-blocking not only limits the ad intensity but also prevents pop-ups from being shown $(O = 0)$. Hence, the gains from ad-blocking are different between the two treatment, whereas adoption costs are constant at c. One would expect that these differences in benefits would also affect the decision to adopt. To this end, Figure 7 displays the adoption rates in the two ad-blocking treatments. It becomes apparent that there is indeed a causal effect as adoption rates are significantly higher (MWU, $p < 0.01$) if ads are intrusive in BH (0.454) compared to BL (0.318).

Apart from reasons on cost and benefits from adoption, the decision is likely also driven by inherent subject characteristics such as socio-demographic factors, digital skills and other preferences. For the analysis of these variables and their influence on the binary adoption decision, we conduct a logit regression model. Naturally, these models suffer from over-fitting, that is, the inclusion of to many variables with only limited explanatory power. To augment the crucial variable selection process, we first conduct a Lasso penalized regression whose lambda convergences are displayed in in Figure 15 in the Appendix.

[21] Analyses on the 5 subjects who adopt at later stages is highly restricted due to the limited sample size. However, there does not seem to be any systematic correlation of their adoption decision and lagging (1 and 2 period lags) ad-intensities and performance variables reflecting their experience during the experiment.

Figure 7: Treatment effect of ad intrusiveness



The horizontal lines represent the $+/-1\sigma$ area around the best-penalizing lambda value. Model specifications that include variables which converge in this area towards zero offer a good balance between explanatory power while simultaneously not risking an over-fitting of the model. According to this, the following variables seem to be of importance: The benefits from ad-blocking (adhigh.T - binary pop-up window variable), whether subjects use ad-blocking outside the experiment (q_adblocking), education degree (factors of categorial education variable), income (factors of categorial income variable) and how ads are perceived (factors of categorial perception variable).

Guided by the Lasso variable selection process we proceed and display the regression results of three logit specifications in Table 6. The first specification corresponds to the most complex model and includes all of the above discussed covariates and additional variables of age, time- and risk preferences. The third represents the most reduced form suggested by the lasso only including the ad-blocking usage outside the experiment and the gains from ad-blocking. The second represents an intermediate alternative and excludes covariates of ad perception and income compared to the first. Provided that also the Akaike information criterion is lowest for the second model, we base our further analysis on this specification (Akaike, 1976).

The ad-blocking adoption in period $p = 1$ seems to be driven by an interplay of factors. First, the older the subject, the more likely it is that ad-blocking is adopted. Potentially, these participants expect that their reading performances and/or concentration might suffer more due to advertisement and therefore decide for ad-blocking more regularly.

Second, the strongest predictor for adoption seems to be whether a given subject also uses ad-blocking outside the experiment. If that is the case, adoption in the experiment

Table 6: Drivers of ad-blocking adoption - Logit regressions

	Dependent variable:		
	Ad-blocking adoption (Period= 1)		
	(1)	(2)	(3)
adhigh.T	0.815*	0.798*	0.519
	(0.446)	(0.427)	(0.330)
age	0.109***	0.107***	
	(0.037)	(0.033)	
female	-0.462	-0.354	
	(0.488)	(0.460)	
q_riskq	0.091	0.092	
	(0.112)	(0.105)	
riskswitch	-0.031	-0.045	
	(0.045)	(0.044)	
q_timeq	0.035	0.014	
	(0.109)	(0.105)	
timeswitch	0.028	0.040	
	(0.044)	(0.042)	
q_adblocking	1.355**	1.509***	1.153***
	(0.574)	(0.544)	(0.378)
factor(q_adperception)2	1.231		
	(1.368)		
factor(q_adperception)3	1.144		
	(1.272)		
factor(q_adperception)4	1.178		
	(1.256)		
factor(q06_education)2	-0.544	-1.015	
	(2.404)	(1.957)	
factor(q06_education)5	-1.258*	-1.210*	
	(0.706)	(0.679)	
factor(q06_education)6	-19.149	-18.676	
	(2,399.545)	(1,455.398)	
factor(q06_education)7	-1.475**	-1.716***	
	(0.677)	(0.652)	
factor(q06_education)8	-1.044	-1.208*	
	(0.714)	(0.687)	
factor(q06_education)9	-2.163	-2.200	
	(1.531)	(1.461)	
factor(q05_income)25000	-0.040		
	(0.526)		
factor(q05_income)40000	-0.640		
	(0.735)		
factor(q05_income)55000	-1.356		
	(1.184)		
factor(q05_income)70000	-0.916		
	(1.381)		
factor(q05_income)95000	-16.530		
	(1,655.837)		
factor(q05_income)150000	14.729		
	(2,399.545)		
Constant	-5.317***	-4.262***	-1.632***
	(1.729)	(1.348)	(0.380)
Observations	133	134	172
Log Likelihood	-69.637	-72.901	-106.703
Akaike Inf. Crit.	187.274	175.802	219.406
Note:			*p<0.1; **p<0.05; ***p<0.01

is much more likely.

Third, education categories are also estimated to have a significant negative effect. Please note that categorial covariates such as education can only be interpreted against the left out base category (factor 1) to avoid multicollinearity. In the case of education the base group is that of a student status whereas the included factors of higher numbering are associated to already completed education degrees. Given that covariates are negative, having completed a higher education degree implies a lower likelihood to adopt ad-blocking compared to students. This could be due to a confidence effect in a way that better educated subjects think their reading performance will not suffer from advertisement and ad-blocking adoption is, thus, not a profitable investment.

Lastly, subjects' preferences with respect to time and risk do not seem to be significant. However, it is possible that a major portion of the preferences' influence is already subsumed under the covariate of ad-blocking usage outside the experiment (q_adblocking). In reality, the decision to use ad-blocking technologies should be driven by a plethora of factors, which are all feed into this one variable. Hence, we find it promising to enhance the logit specification with a two-staged estimation procedure with _adblocking as dependent variable of the first stage. We will add to this analysis in future versions of this working paper. We summarize these findings in our fourth main result below.

Result 3: *The decision to adopt ad-blocking is not driven by the experience during the experiment but rather driven by fundamental factors. If the benefits from ad-blocking are high and the intrusiveness of ads is prevented (BH), adoption rates are significantly higher compared to BL. The likelihood to adopt ad-blocking depends positively on age and the ad-blocking use outside the experiment and negatively on higher education degrees.*

Conjectures on publisher competition and profits

In the following subsection we shift the focus away from consumers and conjecture on the competitive environment between publishers based on our experimental evidence. Consequently, also our unit of observation changes from an individual subject to the available websites, that is, the publishers.[22] Please recall that in reality a publisher m chooses the ad intensity on her website strategically, whereas it is randomly drawn in our experimental setting. Therefore, we abstract in our analyses on this topic completely from profit maximization motives and the strategic response incentives on other publishers' ad intensity choices, ad-blocking decisions by consumers or the observed visit duration in the market. Given this caveat, our conjectures are entirely based on subjects browsing behavior during the experiment as response to different exogenous realizations of ad intensity.

Although ad intensity is determined randomly and, thus, not the result of strategic

[22]In the following we use a "website" and a "publisher" synonymous. For the sake of simplicity, we therefore assume that each website is operated by one separate publisher. Consequently m can refer to both a website or a publisher.

optimization, the specific realizations are still implicitly competing for a consumer's visit duration s, that is, reading time. A consumer's switching behavior during the reading task directly determines against how many known alternative ad intensities a given website is evaluated. If we apply this reasoning to a market context, a consumer who visits all $M = 3$ websites and discovers all ad intensity realizations available to her, would create a rather competitive environment among websites (publishers). Contrarily, if a consumer does not switch once, she sticks with her first choice, the other realizations remain unknown and the market environment is rather monopolistic. Hence, it is the consumer who decides the relevant market with her browsing behavior. Since we want to develop implications for competition among publishers, it is reasonable to restrict the subsequent analysis to non-monopolistic markets, that is, consumers who switch at least once. In this way we define V, with $V \leq M$, as the number of visited websites in a given period for a given consumer. Given this, the following analyses include all publisher websites from markets in which $V \geq 2$ is satisfied.

A visited website v, with $v \in [1, .., V]$, competes with the other visited sites through it's ad intensity. To measure a given ad intensity in contrast to the competing alternatives, we introduce ΔI as the mean difference in ad intensity with respect to all visited websites according to Equation 7. Hence, positive (negative) values of ΔI_v indicate that the visited website v exhibits a higher (lower) than average ad intensity compared to it's visited peers.

$$\Delta I_v = \begin{cases} I_v^B - \frac{1}{V}\sum_{v=1}^{V} I_v^B & if B = 1, \\ I_v - \frac{1}{V}\sum_{v=1}^{V} I_v & else. \end{cases} \tag{7}$$

Analogously, we define also Δs_v as a visited website v's mean difference in visit duration according to Equation 8. Again, a positive (negative) value of Δs_v indicates that the visited website v has captured a higher (lower) than average visit duration compared to it's visited peers.

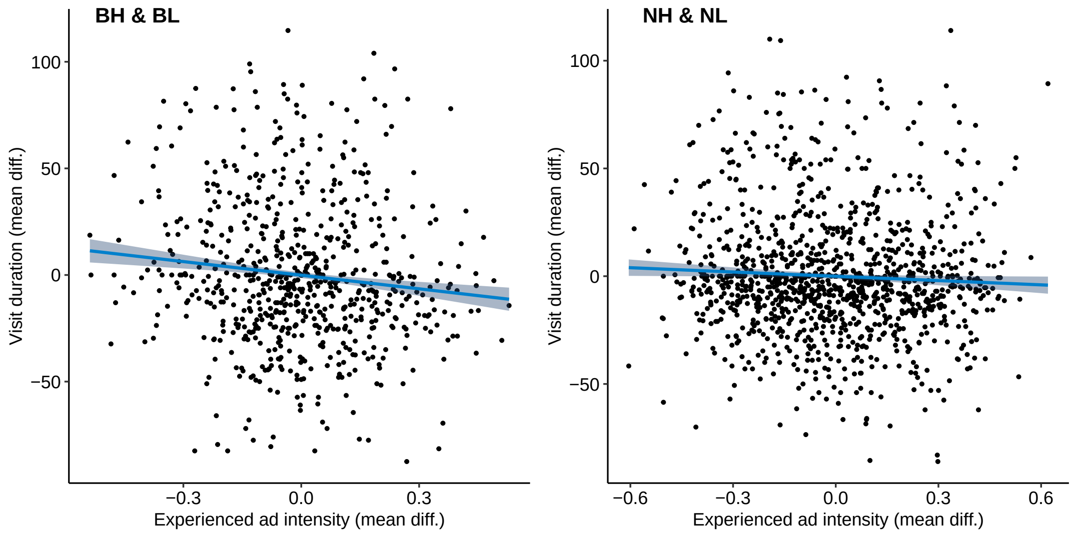
$$\Delta s_v = s_v - \frac{1}{V}\sum_{v=1}^{V} s_v \tag{8}$$

The relationship between these two variables provides insights into the ad intensity competition among publishers for consumers' visit duration, that is, attention. To this end, Figure 8 provides the scatter plots of these two variables. The relation is depicted separately for the ad-blocking (BH & BL) and non-blocking treatments (NH & NL).[23] The first effect which becomes apparent is the negative and significant correlation between the mean differences in ad intensity and visit duration. For the blocking treatments these range from -0.072 (Kendall's τ, $p < 0.001$) to -0.097 (Spearman's ρ, $p < 0.001$). Analogously, for the non-blocking treatments these range from -0.038 (Kendall's τ, $p < 0.05$)

[23]We pool observations here with respect to ad-blocking availability because ad-intensity levels are different between those. Given this, if there is a systematic effect, we expect that it materializes through the availability of ad-blocking. Further, our results do not change qualitatively if we dis-aggregate the analysis and conduct separate pairwise comparisons with single treatments.

to -0.051 (Spearman's ρ, $p < 0.05$). Hence, the higher the ad-intensity difference to the mean, the more visit duration is lost compared to the average. This is an intuitive result if one expects some form of competitive pressure in the ad intensity among websites.

Figure 8: Competition for visit duration by ad-blocking availability



The second noteworthy aspect is that the negative correlation is more pronounced if ad-blocking is available. From a publisher's perspective, there seems to be more downside at the extensive margin, that is, losses in visit duration for an "over-charging" in ad-intensity are higher. Coupled with our Result 2.1 of higher absolute reading times under ad-blocking, this creates a situation in which there are also higher stakes to loose in terms of visit duration. On the flip-side, this provides increased incentives for a visited website v to lower the ad-intensity because marginal returns in visit duration are higher. Therefore, our experimental evidence suggests that ad-blocking leads to a more fierce competitive environment with respect to ad-intensities.

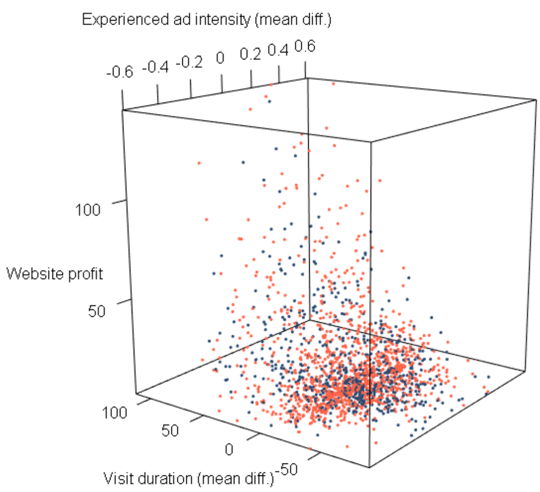
While the visit duration s is a reasonable demand or attention proxy, publisher profits of a visited website π_v should also depend on the intensity of advertising I. The reason for this can be seen in advertisers who are likely willing to pay more for ads which are larger or more prominent. To evaluate possible implications on publishers' profits, we first have to determine how profits depend on experiment variables. In reality, publishers' profits should positively depend on the visit duration a website attracts and the intensity (size) with which advertisement is displayed. While the visit duration of a visited website v is given by the reading time s_v, the latter is given by I_v. Hence, a reasonable profit function $\pi_v(I_v, s_v)$ should satisfy the conditions of $\frac{\delta \pi_v}{\delta I_v} > 0$ and $\frac{\delta \pi_v}{\delta s_v} > 0$. Given this, we model a publisher's profit from a visited website v as the ad intensity weighted visit duration according to Equation 9.

$$\pi_v(I_v, s_v) = I_v \cdot s_v \tag{9}$$

In real world applications, this will be multiplied with some pricing component payed by advertisers which we fix to unity without loss of generality. According to Equation 9, we calculate for each of the V visited websites the respective profits they are realizing given the consumer's visit duration and relevant ad intensity.

To evaluate the potential effect of competition on publishers profits, we again resort to the two mean difference variables already known from the previous paragraphs and Figure 8. However, we now expand the website observations over a third dimension in the form of the calculated publisher's profits which is displayed in Figure 9. Observations from the blocking treatments are displayed as blue dots, while non-blocking observations are colored in orange.

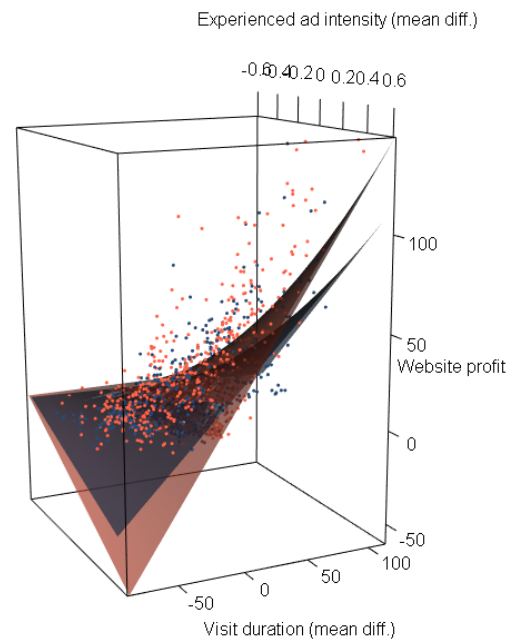
Figure 9: Publisher profits by Δs_v and ΔI_v



In order to improve the interpretation of the point cloud, we enhance this depiction and fit a polynomial regression plane of second degree to the plot which can be seen as a three-dimensional equivalent to the regression line in a two dimensional scatter. Intuitively, the plane is the graphical representation of the systematic combined effect that best explains the calculated profit values. In this way, we can better assess the effect of the mean differences in ad intensity and visit duration on a visited website v's profits. Subsequently, we first elaborate on the influence of visit duration on profits in Figure 10 and follow with the discussion of the ad intensity effect in Figure 11.

Intuitively, the slope of both regression planes is increasing in the mean difference of visit duration. However, the more relevant finding is that profits seem to increase faster in the visit duration in the non-blocking treatments, that is, the slope of the orange plane is larger than the slope of the blue one. This effect can most likely be explained by higher absolute ad intensity levels in the non-blocking treatments. As a consequence of this,

Figure 10: Publisher profits by Δs_v and ΔI_v - Plane view I

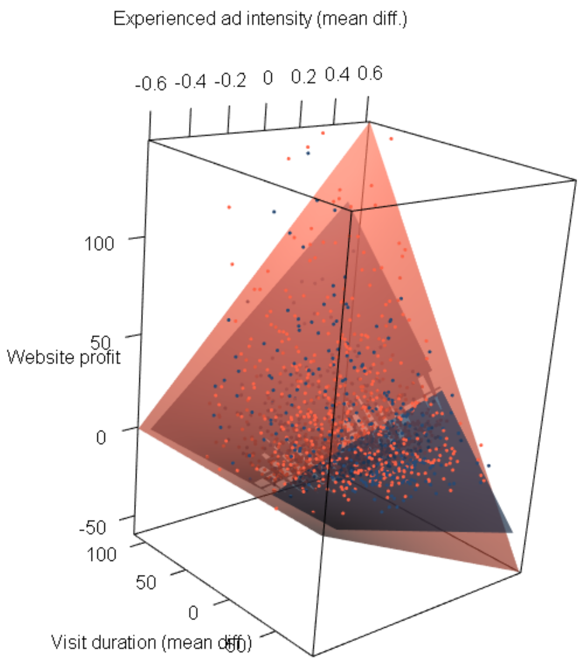


mean differences in the ad intensity materialize on a higher absolute level and provide a higher weighting for a given visiting second in the profit calculation (see Equation 9).

In Figure 11 we elaborate on profit effects due to mean differences in ad intensity. Similar to the visit duration, profit planes of both treatment groups increase in mean differences of ad intensities due to the profit calculation we impose. However, the slope of the planes, that is, the rate of the increase seems to be different between the ad-blocking (blue) and non-blocking (orange) treatments. Although, profits are increasing, they increase at a slower rate if ad-blocking is available. This can be explained by the stronger negative effect on visit duration due to higher ad intensity mean differences already shown in Figure 8. Intuitively, a higher difference to the mean ad intensity reduces the attracted visit duration and thus lowers the weighting factor of ad intensity in the profit calculation. Hence, it is exactly the stronger competitive pressure in ad intensities which dampens the nevertheless positive marginal returns. Therefore, the experimental evidence suggests that ad-blocking applies a dampening effect on publisher's profits. We formulate our fifth main result as the following.

Result 4: *If ad-blocking is available, mean differences in the ad intensity of visited websites ΔI_V are stronger negatively correlated to mean differences in visit duration Δs_v. Hence, the marginal loss in visit duration of increasing ad intensity is higher and competition more intense. Given a publisher v's profit function of $\pi_v(I_v, s_v)$ with $\frac{\delta \pi_v}{\delta I_v} > 0$ and $\frac{\delta \pi_v}{\delta s_v} > 0$, this translates into a lower marginal profit increase in the ad intensity mean difference.*

Figure 11: Publisher m profits by mean differences in s_m and I_m - Plane view II



5 Conclusion

Ad-blocking tools filter out a significant portion of advertisement a user encounters during her journey through the web. Users can harness various additional benefits from these tools which range from increased security, energy efficiency of their devices and being less exposed to tracking activities. However, these benefits likely come at a cost to advertisers and website publishers who see their advertisement based revenue streams decline, spurring a heated debate about ad-blocking between ad-tech industry players, consumer representatives and academic researchers alike.

While the above more direct effects of ad-blocking are typically well understood, the question of how ad-blocking influences users' actual behavior is rather under-explored. Especially unclear in this regard is how ad-blocking affects a consumer's ability to acquire relevant information and use them in decision making. We address this research gap with this study and experimentally investigate consumer behavior in an online reading task, a situation which is common in everyday internet browsing. Based on treatments which differ in the availability of ad-blocking and the intrusiveness of advertising, we derive novel results.

Given that advertisement contains intrusive elements, we find that ad-blocking induces consumers to spent more time during the reading task, which consequences their efficiency to be lower since their decision performance does not increase comparably. However, this result can also be interpreted in another way. Ad-blocking leads to a more pleasant reading experience generally which induces consumers to be willing to exert more costly effort. If one applies this to a real world example in which time is abundant (no opportunity costs), a more thorough and meticulous information gathering process would be welcomed. Furthermore, a consumer's active decision to use ad-blocking is driven by both rational reasoning and personal characteristics. Differences in the intrusiveness of the encountered advertising environment, that is, the gains from ad-blocking, are an influential driver in the adoption decision. This is complemented by the positive impact of a consumer's age.

Additionally, the evidence in this study shows that ad-blocking acts also welfare enhancing in that it reduces inefficient switching between the alternative websites. Since switching implies losses in reading time, search costs are effectively reduced. An intuition for this effect can be found in the homogeneity of the available websites. Given that ad-blocking reduces the intensity of advertising not only on the currently viewed site but also on other sites, websites become, ceteris paribus, more homogeneous. Hence, variations in ad intensity become narrower and incentives to switch sites motivated by the ad load are reduced. A second welfare enhancing effect due to ad-blocking refers to the competition between website publishers. The experiment provides observable consumer browsing behavior as reaction to a variety of experienced ad intensities. Based on this we find that a website's captured reading time, that is, a consumer's visit duration on a website, depends negatively on the own advertising intensity compared to the industry mean. This negative dependence is more pronounced if ad-blocking is available, such that losses in visit duration due to an over-provision in ad intensity are larger. Apparently, ad-blocking availability induces consumers' visit duration (demand or attention) to be more elastic in the ad-intensity which consequences a more intense competition between publishers and the typically associated positive welfare effects.

Our results provide new perspectives on the behavioral effects of ad-blocking, which are currently missing from the debate. Especially, ad-blocking's welfare enhancing effects witnessed in this study cast some doubt on ad-tech's claims of ad-blocking inducing only shifts in economic rents and being welfare-neutral at best. The current discussion of potential ad-tech regulations in the light of the European DMA and DSA initiatives depends on academic insights like ours, such that we hope future research will continue to contribute in this area.

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Appendix A: Graphics figures

Figure 12: Support of first ad intensity realizations (I)

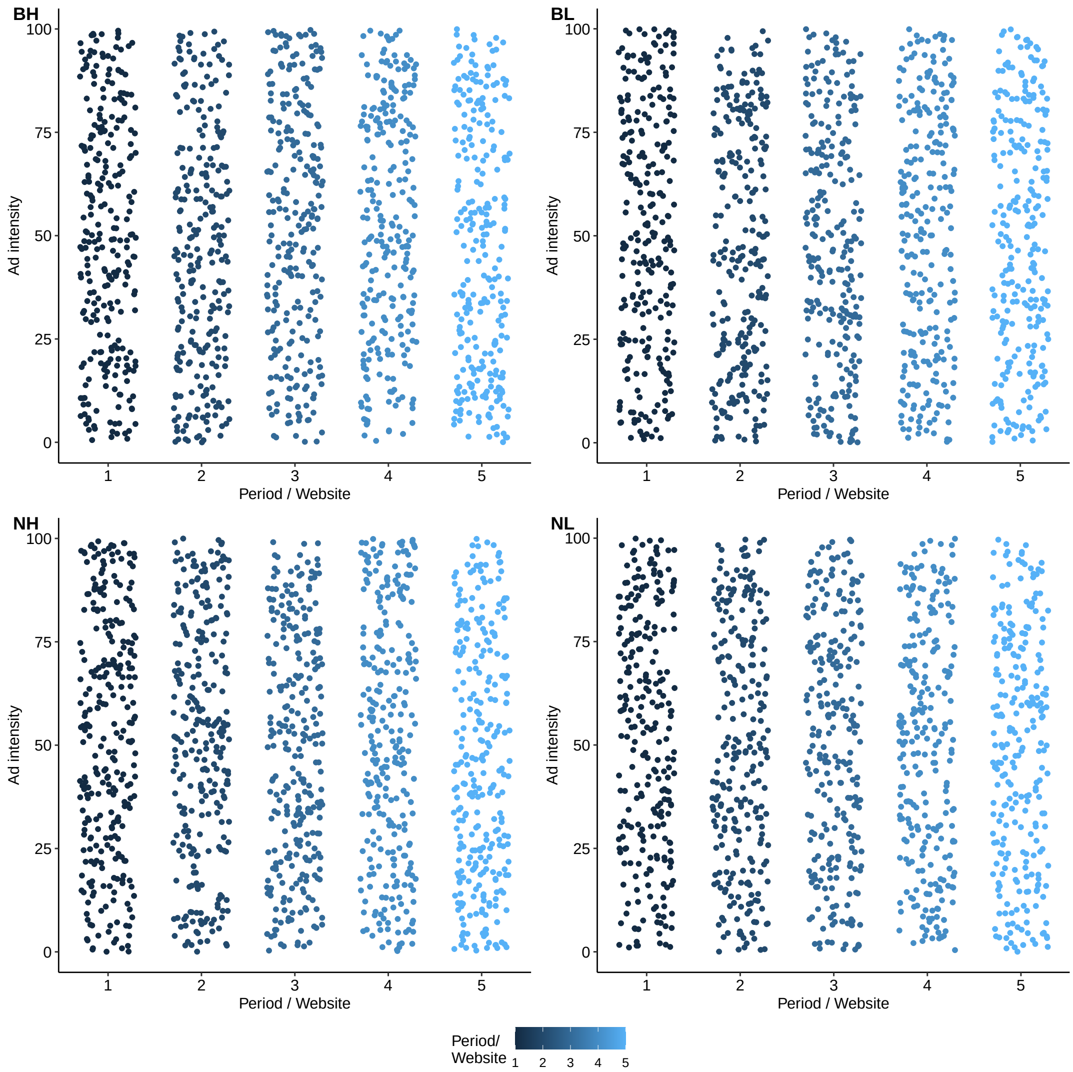


Figure 13: Reading performance for switchers

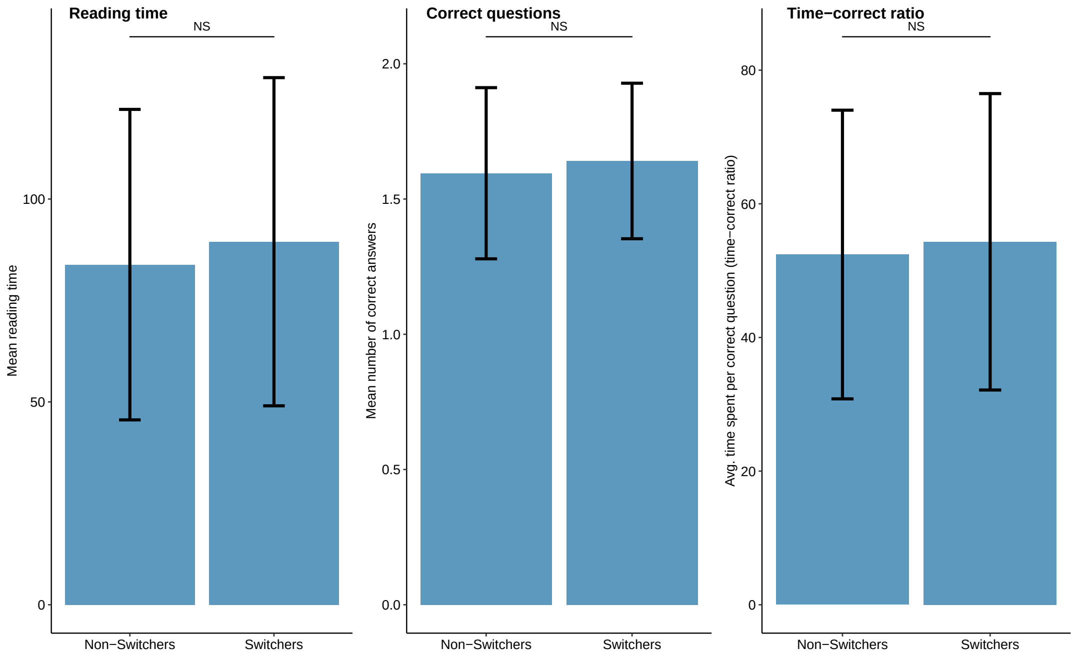


Figure 14: Reading performance for switchers in BH

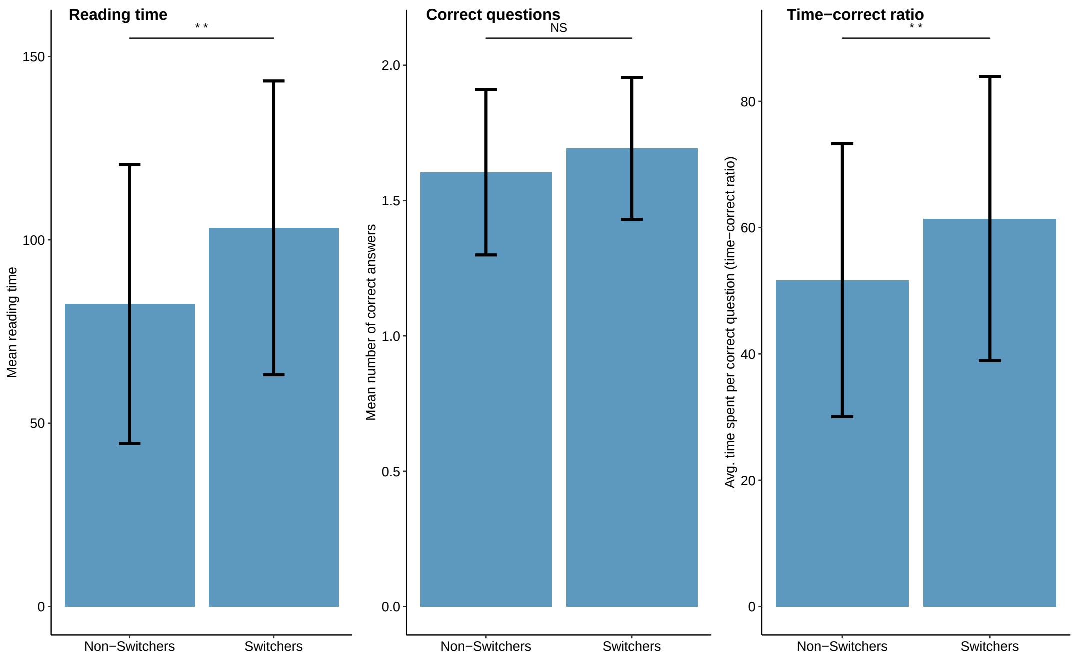
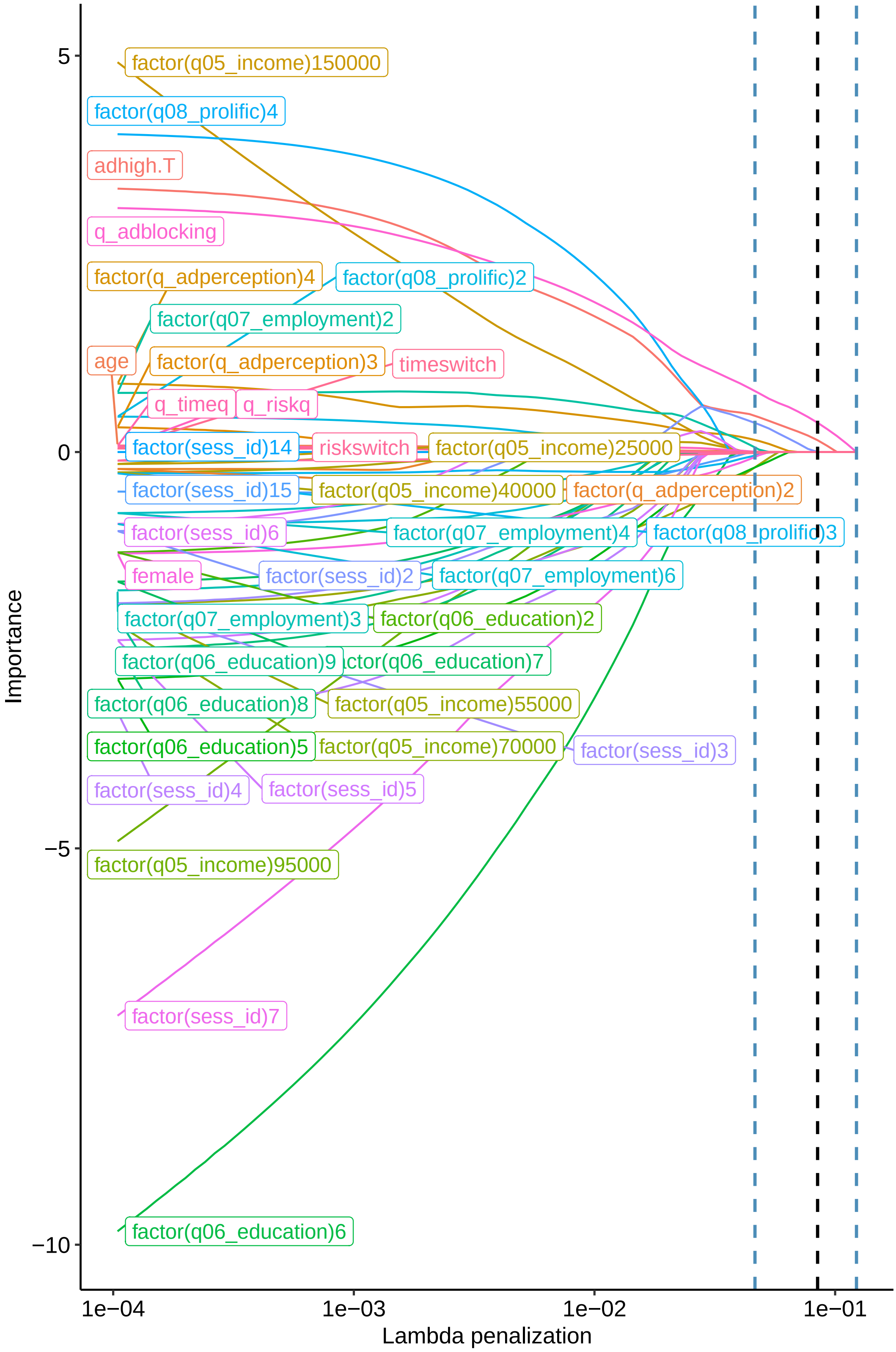


Figure 15: Lasso lambda penalization convergence



Appendix B: Additional experiment materials

Figure 16: Website display in $p = 1$ for $I = 76.9$

Figure 17: Website display in $p = 1$ for $I = 14.8$

Website A

Website C

Currently: Website B

15 seconds left

A Quick & Dirty Guide to the Stubai High Trail

The Stubai High Trail ("Stubaier Höhenweg" in German) is one of the most beautiful treks in the Austrian Alps. Linking together eight characterful mountain huts, this horseshoe-shaped route around the Stubai Valley oscillates between breathtaking passes and enchanting valleys, while affording hikers non-stop views of serrated peaks, shimmering lakes, and magnificent glaciers.

I walked the Stubai High Trail in mid-October 2019, as part of an extended hiking trip in the Alps. It was one of four multi-day high trails I did in Austria during the journey; the others being the Berliner Höhenweg, Schladming Tauern Höhenweg, and the Wormser Höhenweg.

As of 2020, most folks – including the Stubai area's official website – refer to the featured hike as the Stubai High Trail or Stubaier Höhenweg. However, it is also known as the Stubai Rucksack Route or Stubaier Runde Tour in German. For users of the Cicerone Guide books mentioned below, note that in "Walking in Austria" it is referred to as the Hohenweg and listed as 120 km long, whereas in "Trekking in the Stubai Alps" it is called the Rucksack Route and estimated to be about 80 km in length. For the purposes of this article, I'm going to go with "High Trail" or "Hohenweg" and the shorter of the quoted distances, which aligns with GPX data for the route.

Getting There & Away:

The termini of Neder and Neustift are serviced by a regular bus service (multiple times daily / #590) from the nearby city of Innsbruck. The journey takes around half an hour, and the bus stop is located directly outside the entrance to the Innsbruck train station. Click here for bus timetables.

Season:

Hiking season in the Austrian Alps is generally between late June to late September. In an average weather year, September is ideal. The school holiday crowds are gone, the summer thunderstorms (generally short) have subsided, temperatures are cooler, and the mountain huts are less crowded.

Off-season: Depending on the snow levels and experience of the aspirant, the Stubai High Trail can also be done in the late spring or early to mid-fall. When hiking at these times, you may require an ice axe and traction devices. Also, note that the full-service huts closed at these times, so you will need to carry all of your own food and a perhaps a tent/tarp (Note: Most of the huts have small winter rooms ("winterraums") that remain open during the off-season. See Accommodation below for details).

Personally speaking, for someone like myself who has always had an aversion to crowds (especially out in nature), hiking the trail off-season was ideal. I didn't meet a single other person doing the entire route, and the only day-trippers I saw during my three days on trail were around the easily accessible Franz Senn Hut and Dresdener Hut.

Source Text: Cam "Swami" Honan, 2020, The Hiking Life, https://www.thehikinglife.com/2020/09/a-quick-dirty-guide-to-the-stubai-high-trail/.
Source Images: Images have been edited. Original Photos by Alexander Andrews, Karsten Winegeart, Carl Nenzen Loven and Lina Verovaya on Unsplash.

Continue to questions!

Figure 18: Website display in $p = 1$ with pop-up occurrence ($O = 1$)

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