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The Impact of Ad-blockers on Online Consumer Behavior

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Digital advertising is on track to become the dominant form of advertising but ad-blocking technologies have recently emerged posing a potential threat to the online advertising ecosystem. A significant and increasing fraction of Internet users has indeed already started employing ad-blockers. However, surprisingly little is known yet about the effects of ad-blockers on consumers. This paper investigates the impact of ad-blockers on online search and purchasing behaviors by empirically analyzing a consumer-level panel dataset. Interestingly, the analyses reveal that ad-blockers have a significant effect on online purchasing behavior: online consumer spending decreases due to ad-blockers by approximately $14.2 billion a year in total. In examining the underlying mechanism of the ad-blocker effects, I find that ad-blockers significantly decrease spending for brands consumers have not experienced before, partially shifting spending towards brands they have experienced in the past. I also find that ad-blockers spur additional unintended consequences as they reduce consumers' search activities across information channels. The findings remain robust to different identifying assumptions and robustness checks. The analyses draw timely managerial and policy implications for the digital advertising industry as well as additional insights into the role of online advertising.

Key words: ad-blockers; panel data; online consumers; purchasing behavior; search behavior

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1. Introduction

Digital ad spending is expected to reach $201 billion by 2023 just in the U.S., capturing more than two-thirds of total advertising spending (Shaban 2019). Not coincidentally, digital advertising often serves nowadays as the primary marketing communication platform. This shift towards digital advertising is expected to continue over the next years, as consumers spend an increasing amount of time online and advertising platforms continue to innovate in their use of data and new technologies to improve their effectiveness. While the projections for the growth of digital advertising are promising, ad-blockers have recently grown to become an emerging trend in the digital advertising landscape. Ad-blocking is a digital technology –typically software capability in the form of a free-to-use third-party Internet browser extension– that can prevent advertisements from being displayed on a webpage. Essentially, ad-blockers employ a variety of techniques, such as content denial and hiding elements, to block advertisements on the web. Recently, ad-blockers started gaining remarkable popularity worldwide. Anecdotal evidence shows, for instance, that more than 615 million Internet users utilize ad-blocking software (O'Reilly 2017).

In light of these trends, marketers need to assess the potential of ad-blockers to disrupt the digital advertising ecosystem. Recent academic work has already started to investigate their effects for *online publishers* (Shiller et al. 2018). However, *extant research has not yet examined the effects of ad-blockers for other parties of the digital advertising ecosystem, namely brands and consumers.* Consequently, despite the potential of ad-blockers to disrupt digital marketing strategies and alter consumer behavior, surprisingly little is known to date about the effects of ad-blockers on online purchasing behavior, if any. As ad-blocker adoption rates continue to rise, it is essential to gain a better understanding of the effects of ad-blockers for brands and consumers and address this significant research gap in the literature. Investigating such questions will also draw significant and timely managerial implications for the stakeholders of the advertising industry and additional insights for the role of online advertising.

In this paper, I address this important gap in the literature investigating the research question of *whether and how ad-blockers affect online consumer search and purchasing behavior*. One could argue that the adoption of ad-blockers can *positively affect* consumers' purchasing behavior. This is because digital advertisements can, for example, obstruct the online experience (Goldfarb and Tucker 2011, Todri et al. 2020), inadvertently elicit inferences of manipulative intent (Friestad and Wright 1994), invade users' privacy and feel intrusive (Goldfarb 2014, Goldfarb and Tucker 2011), and slow down the browsing speed. Ad-blockers can alleviate such concerns, enhancing purchase intentions (Tucker 2014, Foss and Grant 2016). One could also argue that ad-blockers *may not have an impact* on the purchasing behavior of consumers. Research studies have shown, for instance, that consumers frequently do not attend to anything that preattentively resembles ads (Dreze and Hussherr 2003) and advertising can be ineffective in driving purchasing behaviors (Blake et al. 2015, Tellis and Weiss 1995). Interestingly, several advertisers contend that consumers who install ad-blockers are not influenced by digital ads either way (eMarketer 2019a). If these arguments hold, ad-blockers may indeed not impact the consumers' online purchasing behaviors. Lastly, ad-blockers could *negatively affect* consumers' online purchasing behavior. Advertising can enhance sales as, for instance, it can reduce the cost of information acquisition for consumers –by directly or indirectly conveying information– and enhance prestige (Nelson 1974, Ackerberg 2001, Ghose and Todri 2016), but ad-blockers can hinder such effects. Hence, investigating the ad-blocker effects on online consumer behavior remains an interesting research question that is empirical in nature.

Analyzing a web behavior and ad-blocker panel dataset containing detailed consumer information, the empirical analyses reveal that ad-blockers have a statistically and economically significant negative effect on both online consumer purchase and search behaviors. Specifically, I find that ad-blockers decrease consumers' online spending by 1.45% on average. Given that about 615 million users have adopted an ad-blocker (O'Reilly 2017), these estimates suggest that online consumer spending decreases by approximately $14.2 billion a year in total due to the adoption of ad-blockers. Interestingly, when examining the *underlying mechanism of the ad-blocker effects*, I find that the effect is heterogeneous as ad-blockers disproportionately affect online consumer spending for some brands. In particular, ad-blockers significantly decrease spending for heavy online advertisers as well as for brands consumers have not experienced in the past, partially shifting spending towards brands consumers have experienced before. Moreover, I find that ad-blockers have additional unintended consequences as they significantly reduce consumers' tendency to engage in search activities across various information channels, as captured by the search engine sessions consumers initiate and the visits they make to e-commerce websites. These findings remain robust to various identification strategies, that account for self-selection to treatment, such as instrumental variables and propensity-score matching, and a variety of robustness checks.

This research contributes to the burgeoning stream of literature that has started to examine the effects of ad-blockers. There is a gap in the extant literature as current work has focused on the effect of ad-blockers for website content providers (e.g., publishers). In this stream of work, Shiller et al. (2018) examine the impact of ad-blockers on the website quality, using site-level data. They note that ad-blocking software allows Internet users to obtain information without generating ad revenue for publishers and this can undermine investments in content. Their analysis reveals that sites with a high proportion of ad-blocking visitors experience deterioration in the traffic ranks (a signal of website content quality). In the context of an advertisement avoidance technology for television advertising, Wilbur (2008) shows that ad-blockers tend to decrease content provider revenues. While these research questions have continued to garner attention, due to the scarcity of the empirical data, much of the extant literature has relied on developing theoretical models to study the impact of ad-blockers. For instance, focusing on the publishers' side again, Anderson and Gans (2011) build an analytical model to study the impact of the adoption of ad-blockers and demonstrate that ad-blockers may discourage investment in content quality, or skew content toward the "mass market." Similarly, several other analytical papers (e.g., Aseri et al. 2018, Despotakis et al. 2020, Gecer et al. 2019), have examined optimal strategies for content providers and publishers in an effort to mitigate the impact of ad-blockers. To the best of my knowledge, while prior research has examined the ad-blocker effect for online content providers, this is the first paper to investigate the impact of ad-blockers for consumers and advertisers.

The findings have important *managerial and policy implications* for the digital advertising ecosystem and yield insights for the role of online advertising. These implications are timely as they can inform the mounting debate over ad-blockers and, importantly, enable the stakeholders of the digital advertising industry to assess the overall economic impact of ad-blockers and potentially negate their adverse effects. For instance, in showing that ad-blockers have a significant effect on online purchasing and search behavior of consumers, the present work demonstrates that ad-blockers can have detrimental effects for other parties of the digital advertising ecosystem as well. Put simply, contrary to the popular belief that publishers alone bear the ruinous implications of ad-blockers, this research shows there are implications for advertisers and consumers as well, highlighting the need for a more holistic strategy to mitigate the adverse consequences of ad-blockers. Hence, the digital advertising stakeholders may take industry-wide initiatives and engage publishers, firms, and consumers to collectively form policies that delineate what constitutes acceptable advertising practices to tackle the need for ad-blockers. Such coordination is particularly important since a publisher (or advertiser) who engages in questionable advertising practices contributes to the adoption of ad-blockers, imposing negative externalities on the rest of the advertising ecosystem. In addition, although it is believed that consumers who utilize ad-blockers do not like ads and are not influenced by them (eMarketer 2019a), the analyses reveal that ad-blockers do have a significant effect on online consumer spending, highlighting that the economic impact of ad-blockers is not confined to the financial impact on publishers. Furthermore, when investigating the underlying mechanism of ad-blockers, the analyses reveal that ad-blockers significantly decrease spending for brands consumers have not experienced before, partially shifting spending towards brands consumers have experienced in the past. This finding highlights that, in an ad-blocking environment, consumers rely more heavily on their own past experiences with the brands and, hence, ad-blockers could potentially make the markets more concentrated. This finding has also important managerial implications for the business-expanding efforts of firms as it demonstrates that it might be more challenging to acquire new online customers as ad-blockers continue becoming more mainstream. Lastly, the finding that ad-blockers have additional unintended consequences reducing consumers' search activities across various information channels suggests that advertisers cannot simply rely on organic channels of conveying information. This finding also draws important insights since it demonstrates that digital advertising and search are complementary information channels while they have often been presumed to act as substitutes in providing information to consumers (Fong 2017).

2. Data and Empirical Methodology

2.1. Web Behavior and Ad-blocker Datasets

To study the impact of ad-blockers on online consumer behavior, I combine a web behavior dataset with an ad-blocker dataset. Specifically, the web behavior dataset is an individual panel dataset on consumer browsing and purchasing behaviors from a highly reputable and well-established American media measurement and analytics company.[1,2]

This panel dataset spans a multi-year period, from January 2015 until December 2018, and entails the online web-wide visitation behaviors, transaction behaviors, and demographics for a large sample of U.S. Internet users. Thanks to the data partner's data collection efforts, this panel provides a representative sample of online users that has been utilized in multiple academic publications by various researchers. In particular, the company partners with reputable third-party application providers who offer a vast variety of free software, applications, and utilities (e.g., antivirus software, cloud storage, etc.) to Internet users in exchange for their web behaviors to be passively tracked under a set of shared policy rules; a panelist in the dataset corresponds to a computer and panel measurement is conducted via a monitoring software that resides in the panelists' computer. To ensure the veracity of the data, the majority of the computers in the panel are single-user computers and the users are required to identify themselves periodically; in order for the panel to be representative, multi-user computers are included as well and, in such cases, the vendor also automatically identifies the focal user based on unique user identifiers (e.g., e-mail addresses) and proprietary technology.

Overall, I observe $92,529$ panelists who have made at least one online purchase during this multi-year period, while collectively conducting more than 300 million visits. For each one of these URL visits, I also observe detailed information such as the corresponding website, the referral site (if

[1]This dataset, as well as very similar web behavior datasets, have been leveraged in the past in numerous academic studies on various aspects of consumer behavior published in top-tier journals (e.g., Chiou and Tucker 2012, Liaukonyte et al. 2015, Lambrecht and Misra 2017).

[2]Due to the nature of the NDA, the exact name of the company cannot be publicly disclosed.

any), the duration of the visit, the number of pageviews visited on the website, and whether a transaction occurred. If a transaction took place, I also have access to the total basket value of the transaction, the number of products, and the prices of the corresponding products that were purchased as well as the product categories these products belong to. Hence, the panel monitoring software provides a comprehensive view of the Internet activity (the panelist's web browsing and purchasing behavior) across the web, and it collects all data in a passive non-intrusive fashion.

Along with this web-behavior data, I have access to demographic variables, such as the panelist's zip code, her/his income, age, education level, the size of the household, and whether the household has children. The company collects such demographics data using a variety of methods, including self-reported surveys conducted on an occasional basis.

I augment this web-behavior dataset with the ad-blocker dataset from the aforementioned media measurement and analytics company. In particular, the proprietary ad-blocker dataset provides information on whether and when each panelist has installed an ad-blocker; the installation of an adblocker, if any, on a panelist's computers is recorded by the monitoring software. The matching of the two datasets reveals that approximately 10% of the consumers have installed an ad-blocking technology at some point during the observation window.

The descriptive statistics of the main variables of the dataset are reported in Table 1. As shown, consumers spend on average $38.6 per week. For consumers who end up making purchases in a specific week, the median spending is $52.5 and the median number of products purchased is 2. Moreover, regarding the browsing behavior of consumers, the consumers spend on average 9.4 hours per week online, which is similar to what previous research has documented (Wallsten 2015). The dataset reveals that consumers visit on average 25.6 distinct domains per week and make on average 59.4 visits in total per week. Among the websites consumer visit, they visit more frequently search engine websites with an average number of 7.9 visits per week, while they also visit frequently e-commerce websites with an average number of 2.9 visits per week; I identify whether a website corresponds to a search engine or an e-commerce site based on data from the widely used web analytics company Alexa Internet, Inc.

In addition, I empirically examine whether there are potentially significant differences in characteristics between users who adopt ad-blockers and users who do not adopt ad-blockers by conducting normalized differences tests (Imbens and Rubin 2015), which provide a scale-invariant measure of the size of the difference between the two groups. As shown in Table A.1 of Appendix A, I find that all the normalized differences are well below the suggested threshold of 0.25 (Imbens and Wooldridge 2009), indicating that the groups are not systematically different in observable characteristics. Nonetheless, I have utilized research methods that allow for potential unobserved time-invariant and time-varying confounders, as described in the next sections.

Table 1 Descriptive Statistics of Variables.

Variable	Description	Obs	Mean	Std. Dev.
Ad-blocker installed	Whether an ad-blocker has been installed during this time period	5,150,760	0.066	0.248
Visits	Number of web visits	5,150,760	59.409	185.696
Purchases	Number of purchases made	5,150,760	0.203	0.818
Domains	Number of domains visited	5,150,760	25.632	162.830
Pageviews	Number of pages viewed across web visits	5,150,760	445.958	1093.685
Duration	Total time spent online (minutes)	5,150,760	566.251	1052.045
Products purchased	Number of products purchased	5,150,760	5.350	8291.490
Purchase spending	Total online spending ($)	5,150,760	38.563	13300.420

Notes: Descriptive statistics of variables at the user-week level.

2.2. Empirical methodology

I use the web behavior and ad-blocker datasets to empirically estimate the impact of ad-blockers on consumers' purchasing and search behaviors. The primary identification strategy relies mainly on the panel structure of the data. Specifically, I use a two-way fixed effects model to compare differences in the purchasing behaviors, before versus after the installation of ad-blocker (i.e., treatment), between panelists who install an ad-blocker and panelists who do not. This *difference-in-differences* (DID) approach effectively controls for time-invariant confounds with ad-blocker adoption using panelist fixed effects, and common time confounds using time fixed effects. I estimate the following DID panel data model across the treated and control groups:

$$Y_{it} = \beta_0 + \boldsymbol{\beta_1 Treat_i \times Post_{it}} + \sum_p \eta_p X_{it}^p + \sum_s \gamma_s User_i^s + \sum_w \delta_w Week_t^w + \lambda Z_{it} + \epsilon_{it}, \quad (1)$$

where Y_{it} denotes the outcome variable (e.g., the online purchase amount, number of search engine visits, etc.) for each individual i at time period (week) t. $Treat_i \times Post_{it}$ is the main variable of interest and becomes 1 when an individual has installed an ad-blocker and enters the post-treatment period at week t, and 0 otherwise.[3,4] Hence, the coefficient $\boldsymbol{\beta_1}$ captures the average treatment effect of ad-blockers on online consumer behavior. The variables X_{it}^p are demographic variables to account for time-varying observed heterogeneity across panelists.[5] The set of dummy variables $User_i^s$ accounts for panelist-specific fixed effects ($User_i^s = 1$ when $s = i$; 0 otherwise) to capture unobserved heterogeneity. Importantly, these consumer fixed-effects control for treatment self-selection on unobserved time-invariant factors. This is important as anecdotal evidence suggests that the decision to adopt an ad-blocker might be affected by the consumer's general tolerance for ads or privacy concerns (eMarketer 2019b), captured by consumer fixed-effects. The dummy variables $Week_t^w$ account for weekly fixed effects ($Week_t^w$=1 when $w = t$; 0 otherwise). The variable Z_{it} accounts for the number of time-paid-off holidays in each user location during the specific time period.[6] I estimate Huber-White robust standard errors to allow for arbitrary serial correlation of residuals within each individual (Bertrand et al. 2004).

In the DID model, the weekly fixed effects that are common across consumers implicitly assume that the treated and untreated consumers follow *parallel trends*. In Section 3.3, I exploit the long time series in the panel data and test for parallel trends during the pre-treatment period (Angrist and Krueger 1999, Bronnenberg et al. 2020). The conducted tests support the parallel trends assumption. Additionally, due to the statistical power in the study, it is unlikely that if any differences in pre-trends existed, they would remain undetected. This evidence in conjunction with

[3]Following the DID panel data specification, I include only the interaction term $Treat_i \times Post_{it}$ as adding either $Treat_i$ or $Post_{it}$ would cause collinearity given that the specification includes user fixed effects.

[4]The lag of the variable $Treat_i \times Post_{it}$ is used to capture entire weeks of post-treatment ad-blocker adoption as users might have installed the software any day of the week. I demonstrate robustness to alternative specifications.

[5]There is within-subject variation of demographics because I often observe consumers over multiple years.

[6]There is variation in the number of time-paid-off holidays as different states officially recognize different holidays.

the individual-specific fixed effects, which allow for self-selection, should ensure the consistency of the average treatment effect estimates. Nevertheless, in Section 3.4, I check the robustness of the estimates using *alternative identification strategies* that relax the parallel trends assumption (Freyaldenhoven et al. 2019).

3. Results

3.1. Effect of Ad-blockers on Purchasing Behavior

Table 2 reports the results of the estimate of the ad-blocker effect on online spending using the DID panel data model.[7,8] The coefficient of $Treat \times Post$ estimated based on Equation 1 is negative and significant, indicating that *ad-blockers decrease online spending of consumers approximately by* 1.45% *(i.e.,* $exp(-0.0146)$). This decrease is also economically significant as ad-blockers collectively lead to a substantial loss of about $14.2 billion every year given that about 615 million users have installed an ad-blocker. These results are robust to using alternative outcomes of purchase behavior, such as purchase frequency. Additionally, as a robustness check, Table A.2 of Appendix A also estimates the treatment effect of an ad-blocker using only the difference within the treatment group (i.e., before and after the treatment); the results corroborate the findings. Additional robustness checks and alternative identification strategies are discussed in Section 3.4.

3.1.1. Heterogeneity of Ad-blocker Effect: Heavy versus Light Online Advertisers. To assess the underlying mechanism of the above effect, I empirically examine whether ad-blockers have a differential impact for heavy versus light online advertisers. To do so, I have acquired advertising expenditure data from the ad intelligence company Kantar Media. The Kantar Media's Stradegy advertising spending data set provides access to advertising expenditures in dollar amounts for online advertising (e.g., display advertising, video advertising, etc.) for the brands

[7]In all tables, Model 1 controls for individual and weekly fixed effects; Model 2 also controls for the occurrence of time-paid-off holidays; Model 3 further controls for demographic groups fixed effects.

[8]Following the extant literature, I take the logarithm of the online purchase spending (e.g., ln(PurchaseAmount+1)) because its distribution is skewed. Figure A1 in Appendix A shows the kernel density estimate of the distribution of the purchase spending dependent variable.

Table 2 Effect of Ad-blockers on Online Purchase Spending

	Model 1	Model 2	Model 3
Treat × Post	-0.0144 **	-0.0144 **	-0.0146 **
	(0.0047)	(0.0047)	(0.0047)
Holidays		-0.0001	-0.0002
		(0.0033)	(0.0033)
Constant	0.2128 ***	0.2130 ***	0.1881 ***
	(0.0086)	(0.0101)	(0.0168)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,311,635.42	-7,311,635.41	-7,309,225.84
R-squared	0.156	0.156	0.156

Notes: Difference-in-differences panel data regression results. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

advertising in the United States; I have access to such data at the brand-week level during our observation period. Hence, I estimate the same model as before but separate consumer spending to heavy and light online advertisers. That is, the level of analysis and all the control variables remain the same, while the dependent variable has changed to capture the aforementioned purchasing behaviors accordingly. Tables 3 and 4 present the ad-blocker heterogeneous effect for heavy and light online advertisers, respectively. As shown in these tables, the coefficient of $Treat \times Post$ is negative and significant for the spending of consumers on brands that heavily advertise online, corresponding to an online purchase spending decrease of 1.38%; the effect is negative, albeit non significant and quite smaller, for light online advertisers. Thus, I find that *the ad-blocker effect is more prominent and significant for heavy online advertisers compared to light online advertisers*. In other words, blocking the online advertisements seems to have a disproportionately larger impact on the sales of heavy online advertisers compared to the sales of light online advertisers, further validating the main findings discussed above. These results remain robust under alternative model specifications, as shown in Tables A.3 and A.4 of Appendix A.

3.1.2. Heterogeneity of Ad-blocker Effect: Brand Experience. Next, to further investigate the underlying mechanism of the ad-blocker effect, I empirically examine whether ad-blockers have a differential impact on online consumer spending for brands consumers have experienced in

Table 3 Effect of Ad-blockers on Online Purchase Spending for Heavy Online Advertisers

	Model 1	Model 2	Model 3
Treat × Post	-0.0134 **	-0.0134 **	-0.0138 **
	(0.0046)	(0.0046)	(0.0046)
Holidays		-0.0022	-0.0023
		(0.0032)	(0.0032)
Constant	0.1926 ***	0.1961 ***	0.1816 ***
	(0.0081)	(0.0096)	(0.0164)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,232,317.19	-7,232,316.95	-7,229,919.10
R-squared	0.152	0.152	0.152

Notes: Difference-in-differences panel data regression results for heavy online advertisers (i.e., brands with advertising spending higher than the median). The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 Effect of Ad-blockers on Online Purchase Spending for Light Online Advertisers

	Model 1	Model 2	Model 3
Treat × Post	-0.0014	-0.0014	-0.0013
	(0.0010)	(0.0010)	(0.0010)
Holidays		0.0025 **	0.0025 **
		(0.0008)	(0.0008)
Constant	0.0517 ***	0.0478 ***	0.0343 ***
	(0.0043)	(0.0045)	(0.0054)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-782,633.35	-782,628.51	-783,109.60
R-squared	0.119	0.119	0.119

Notes: Difference-in-differences panel data regression results for light online advertisers (i.e., brands with advertising spending lower than the median). The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the past versus brands consumers have not experienced before, as captured by consumers' purchasing history. Table 5 reports the results of the estimate of the impact of the ad-blocker effect on online consumer purchase spending for brands consumers have not experienced in the past, while Table 6 reports the corresponding results for brands consumers have experienced before. For consistency, the level of analysis and all the control variables remain the same as before, while the dependent variable has changed to capture the aforementioned purchasing behaviors accordingly.

Table 5 Effect of Ad-blockers on Online Purchase Spending (Brands Consumers Have Not Experienced)

	Model 1	Model 2	Model 3
Treat × Post	-0.0522 ***	-0.0522 ***	-0.0508 ***
	(0.0034)	(0.0034)	(0.0034)
Holidays		0.0088 ***	0.0086 ***
		(0.0024)	(0.0024)
Constant	0.1040 ***	0.0904 ***	0.0267 ***
	(0.0052)	(0.0064)	(0.0113)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-5,862,458.46	-5,862,451.93	-5,860,458.10
R-squared	0.040	0.040	0.040

Notes: Difference-in-differences panel data regression results for consumer spending on brands consumers have not experienced in the past. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Interestingly, as shown in these tables, the coefficient of $Treat \times Post$ is negative and significant for online spending for brands consumers have not experienced in the past while it is positive and significant for online spending for brands they have experienced before. This finding demonstrates that while ad-blockers, on average, decrease consumers' online spending, they have asymmetric results for brands based on consumers' past experience with these brands. In particular, *ad-blockers significantly decrease spending for unfamiliar-to-the-consumer brands and partially shift spending towards familiar-to-the-consumer brands.* That is, consumers rely more heavily on their own past experiences with brands when making purchase decisions. These results remain robust under alternative model specifications, as shown in Tables A.5 and A.6 of Appendix A.

3.2. Effect of Ad-blockers on Search Behavior

To gain a richer understanding on the effects, I also empirically investigate whether in an ad-blocking environment consumers increasingly utilize alternative information channels, such as search engines or website visits, or whether they use such alternative information channels less frequently because of the potential negative downstream effects of ad-blockers across the purchase funnel (Todri et al. 2020, Hoban and Bucklin 2015). Table 7 reports the results of the estimate of the ad-blocker effect on search engine visits. I use a Poisson fixed effects model as the dependent

Table 6 Effect of Ad-blockers on Online Purchase Spending (Brands Consumers Have Experienced)

	Model 1	Model 2	Model 3
Treat × Post	0.0355 ***	0.0355 ***	0.0339 ***
	(0.0036)	(0.0036)	(0.0036)
Holidays		-0.0078 **	-0.0077 **
		(0.0025)	(0.0025)
Constant	0.1224 ***	0.1346 ***	0.1651 ***
	(0.0072)	(0.0083)	(0.0135)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-6,079,753.48	-6,079,748.71	-6,077,729.77
R-squared	0.198	0.198	0.198

Notes: Difference-in-differences panel data regression results for consumer spending on brands consumers have experienced in the past. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

variable is a count number.[9] Interestingly, the coefficient of $Treat \times Post$ is negative and significant, indicating that ad-blockers significantly reduce the search activities of consumers as captured by the search sessions consumers initiate on search engines. In particular, the analysis reveals that *ad-blockers reduce search engine sessions by* 5.6%. Additionally, since consumers more frequently collect additional information via website visits as they progress through the purchase funnel (Moe 2003), I also examine the impact of ad-blockers on e-commerce website visits. Table 8 reports the results of the estimate of the ad-blocker effect on website visits. The coefficient of $Treat \times Post$ is again negative and significant, indicating that *ad-blockers significantly reduce the information acquisition activities of consumers*. Specifically, I find that *ad-blockers reduce shopping website visits by* 5.5%. These findings remain robust when I also control for consumer's overall amount of internet usage, as shown in Tables B.1 and B.2 of Appendix B. It should also be noted that any potential anti-adblocker strategies cannot possibly drive the aforementioned findings since, due to their core business models, e-commerce retailers and search engine providers are not likely to block ad-blocker adopters (Nithyanand et al. 2016).

[9]The Poisson fixed effects model is more commonly used for fixed effects count models since it is consistent under much weaker distributional assumptions (Cameron and Trivedi 2005). Nonetheless, I confirm the robustness of the results to alternative fixed effects models.

Table 7 Effect of Ad-blockers on Search Behavior (Search Engine Visits)

	Model 1	Model 2	Model 3
Treat × Post	-0.0591 ***	-0.0591 ***	-0.0581 ***
	(0.0135)	(0.0135)	(0.0136)
Holidays		0.0069 *	0.0067 *
		(0.0028)	(0.0028)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log pseudo-likelihood	-18,469,060.00	-18,469,037.00	-18,461,548.00
Wald χ^2	28,138.49	28,658.31	28,675.74

Notes: Poisson fixed effects specification. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 Effect of Ad-blockers on Search Behavior (E-commerce Web Visits)

	Model 1	Model 2	Model 3
Treat × Post	-0.0571 ***	-0.0572 ***	-0.0565 ***
	(0.0163)	(0.0163)	(0.0163)
Holidays		0.0219 ***	0.0219 ***
		(0.0047)	(0.0047)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log pseudo-likelihood	-11,449,978.00	-11,449,885.00	-11,446,329.00
Wald χ^2	14,540.46	14,659.39	14,735.28

Notes: Poisson fixed effects specification. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9 Parallel Trends

	Model 1	Model 2	Model 3
Trend	0.0003 ***	0.0004 ***	0.0004 ***
	(0.0000)	(0.0000)	(0.0000)
Trend × Treatment	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)
Holidays		-0.0142 ***	-0.0142 ***
		(0.0013)	(0.0013)
Constant	0.3831 ***	0.3831 ***	0.3362 ***
	(0.0011)	(0.0011)	(0.0130)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,570,262.71	-7,570,206.54	-7,567,888.20
R-squared	0.146	0.146	0.146

Notes: Regression results for the pre-treatment period allowing treated and control groups to have different time trends. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.3. Examining the Validity of the Main Identification Strategy

The employed DID panel data estimator exhibits great strengths for estimating the average treatment effect as it allows for self-selection on unobserved time-invariant factors. The consistency of the employed DID panel data estimator though relies on the implicit assumption that the pre-treatment trends are common across treated and untreated individuals, typically known as parallel trends. Hence, I follow the widely adopted approach of Angrist and Krueger (1999) and Bronnenberg et al. (2020) that exploits the long time series in the panel data to formally test for the parallel trends assumption during the pre-treatment period. As shown in Table 9, the deviation from the common trend for the treatment group is very small (-0.0001) and not statistically significant, *further confirming the validity of the DID identification strategy.* I reach the same conclusion for all the dependent variables of the study as shown in Tables C.1 and C.2 of Appendix C. In other words, the conducted tests support the assumption of parallel trends and, due to the statistical power of the study, it is also unlikely that if such pre-trends existed they would remain undetected. This evidence, in conjunction with the individual-specific fixed effects, should ensure the consistency of the average treatment effect estimates. This conclusion is also supported by the normalized differences tests discussed in Section 2.1. Besides, I also confirm that the parallel trends is likely to hold based on the leads and lags model estimates (Autor 2003), as shown in Figure 1. In particular, I estimate the interaction effect of treatment with monthly time indicators before and after the treatment; the base level is five months before the treatment or before. As shown in Figure 1, the effects in the pre-treatment period are not statistically significant from zero, further indicating that the common trends assumption is likely to hold. In the following section, I also check the robustness of the average treatment effect estimates using *alternative identification strategies* that further relax the parallel trends assumption, such as instrumental variables and matching DID.

3.4. Instrumental Variables, Matching Difference-in-Differences, and Other Robustness Checks

3.4.1. Instrumental Variables: Despite the above evidence in favor of the parallel trends assumption, I now examine the robustness of the findings when relaxing the aforementioned identifying assumption. In case the adoption of an ad-blocker is correlated with a time-varying unobserved

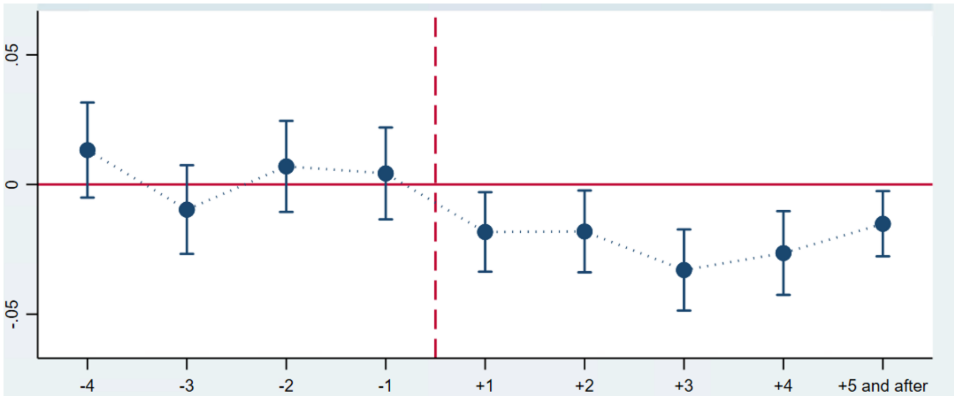

Figure 1 **Leads and lags model estimates. The base level is more than five months before the treatment (i.e., -5 and before).**

variable or other endogeneity issues exist, the DID estimate of the ad-blocker effect could be biased. To address this concern, I first employ the instrumental variables technique with two-stage least squares for panel-data models. I use as an instrumental variable the percentage of other panelists who have adopted ad-blockers and reside in the same zip code with the focal user. In particular, the panelists in the data reside in 17,404 different zipcodes across the United States and in each zipcode reside on average 6 panelists with a standard deviation of 12 panelists; there is also a small fraction of panelists that changes zip code location during the observation window of the dataset. Hence, I utilize the variation in local ad-blocker adoption patterns over the geographic areas and over time in the dataset for the instrumental variable analyses. A valid instrumental variable needs to be correlated with the adoption of an ad-blocker by the focal user but not directly impact the online spending decision of the focal user. The employed instrumental variable indeed satisfies the relevance criterion because the higher the percentage of panelists who reside in the same zip code that adopts ad-blockers, the more likely the focal user will be to also adopt an ad-blocker due to the information dissemination processes that can take place in the users' local networks. I also confirm the relevance criterion empirically in the data and indeed find that an increasing percentage of ad-blocker adopters in the same zip code has a positive and statistically significant impact on the adoption of an ad-blocker from the focal user, as shown in Table D.1 of Appendix D. Additionally, the instrumental variable satisfies the exclusion restriction because the percentage of panelists who reside in the same zip code with the focal user and have adopted ad-blockers should not directly affect the online spending decision of the focal user, conditional on the control variables. I also conduct a variety of instrumental variable tests to further confirm the validity of the instrument and I find that the instrumental variable passes the weak identification and overidentification tests, as shown in Table D.2. Lastly, when I conduct the endogeneity test, as also shown in Table D.2, it is encouraging that we fail to reject the null hypothesis that we may treat the adoption of an ad-blocker on Equation 1 as exogenous while accounting for self-selection on unobserved time-invariant confounds. Nonetheless, even when I allow for potential unobserved time-varying confounds, I find that *the results remain robust when employing the instrumental variables technique for panel-data as an alternative identification strategy*, as shown in Table D.3.

Additionally, I further extend the aforementioned instrumental variable analyses by capturing the ad-blocker information dissemination process that can also take place in the users' non-local networks. In particular, in addition to the percentage of other panelists who reside in the same zip code that adopts ad-blockers, I use as a second instrument the weighted average of ad-blocker adopters in counties that are socially connected with the county of the focal user. I construct this additional second instrument by using publicly available data from Facebook on the Social Connectedness Index (Bailey et al. 2018), as discussed in appendix D. I confirm the relevance criterion for this extended set of instruments, as shown in Table D.5, and find that *the results remain robust under this alternative set of instruments*, as shown in Table D.6; as before, I confirm the validity of the extended set of instruments with a variety of tests, as shown in Table D.7.

3.4.2. Propensity Score Matching: To further address any potential concerns regarding identification, I also examine the robustness of the results to the alternative identification strategy of combining the DID treatment-effects estimation with a matching method (Heckman et al. 1997). Specifically, the matching DID estimator allows for selection into treatment as a function of consumers' past browsing and purchasing behaviors and further controls for any potential differences between treated and non-treated individuals. As shown in Table E.1 of Appendix E, *the results remain robust when employing the matching DID estimator*; the matching was performed based on the one-to-one nearest neighbor matching algorithm using the generalized Mahalanobis distance.[10] I assess the quality of the matching method by evaluating the balance of the covariates. As shown in Table E.2, the matching method indeed produced great covariate balance (Austin 2011).

3.4.3. Additional Robustness Checks: I conduct several additional robustness checks. For instance, it is possible that after consumers install ad-blockers, advertising still affects their purchasing decisions due to potential ad carryover effects. Hence, I examine the effect of ad-blockers when allowing for such carryover effects. For instance, as shown in Table F.1 of Appendix F, the results remain robust when allowing for a period of two months of advertising carryover effects; the results remain robust to alternative carryover time periods as well. Additionally, I allow for a pre-treatment period of at least six months for all individuals to ensure that I have sufficient data to understand their purchase spending before the treatment, if any. As shown in Table F.2, after excluding from the analysis any individuals who have a pre-treatment period of less than six months, the results remain again robust. Similarly, the results remain robust to removing outliers of purchase spending, as shown in Table F.3; I use an interquartile range of 1.5 to detect outliers while the results are also robust to alternative ranges.

Moreover, I conduct several robustness checks that further alleviate concerns for potential confounders. For instance, users might be installing ad-blockers to speed up their internet connections while the connection might also affect their purchase spending. To alleviate such concerns, I examine the robustness of the findings when controlling for the speed of the connection of the consumer (i.e., broadband internet connection or not). As shown in Table G.1 of Appendix G, the results remain robust. Another potential concern of a time-varying unobserved confounder is the new stories related to advertising; ad-related news stories could affect the likelihood of consumers adopting an

[10]The treatment and control groups are matched based on the frequency of past purchases, time they spend online, time they spend on websites that contain ads, web visits, visits to websites that contain ads, visits to shopping websites, and all the demographic variables available in the data; the results remain robust to including various alternative variables; I collect data on whether a website contains ads based on the use of web technologies (i.e., ad networks) from W3Techs.

ad-blocker as well as the purchasing behavior of consumers. To alleviate such concerns, I examine the robustness of the findings when controlling for the number of news stories across online and offline media outlets related to "advertisements", "privacy", and "personalization" as well as relevant blog posts, based on data collected from the leading news data provider Nexis Uni. As shown in Table G.2, the results remain robust. In addition, another potential concern might be that adults of the household share devices with the children of the household, who might install an ad-blocker and buy less. To alleviate such concerns, I conduct subsample analyses and examine the treatment effect for households that do not have children; as shown in Table G.3, the results remain robust. Similarly, I confine the dataset on panelists whose income levels are above the U.S. household median income since such households are less likely to share electronic devices (Yardi and Bruckman 2012); as shown in Table G.4, the results remain robust.

Lastly, I have conducted several additional analyses to further examine any potential heterogeneity effects and the corresponding robustness of the results. For instance, to investigate whether the results might be greatly influenced by any possible anti-adblocker strategies, I examine –in addition to the IV analyses that alleviate such concerns– the ad-blocker effect for users who are heavy "news and media" website visitors, since such users are more likely to be affected by any possible anti-adblockers strategies (Nithyanand et al. 2016) and turn off their ad-blockers. As shown in Table G.5, the heterogeneity analysis illustrates that the effect of ad-blockers does not vary significantly for heavy "news and media" users, alleviating concerns that the results are greatly influenced by anti-adblocker strategies. Similarly, I find that the results do not vary significantly for heavy versus light online users, in general, while the ad-blocker effect also does not vary significantly for strong versus weak brands (Lovett et al. 2014).

3.4.4. Falsification Test: I also conduct a falsification test with a placebo treatment variable randomly indicating which user is treated and when they are treated. As shown in Table H.1 of

Appendix H, the effect of the placebo treatment is not statistically significant, further alleviating concerns that the main effect is driven by potential confounds.[11]

4. Conclusion and Implications

This research is the first to examine the effect of ad-blockers for consumers and brands, focusing on online consumer purchase and search behavior. The estimates suggest that online consumer spending decreases by 1.45% due to the consumers' adoption of ad-blockers, which approximately corresponds to a total decrease of $14.2 billion a year. This finding is of significant importance as it reveals that *ad-blockers can have adverse effects for other parties of the digital advertising ecosystem as well.* That is, contrary to the popular belief that publishers alone bear the ruinous implications of ad-blockers, this research shows that ad-blockers can also have negative implications for advertisers. This finding also refutes the belief that consumers who install ad-blockers are the ones that would not be affected by advertising either way (eMarketer 2019a). In showing that ad-blockers reduce consumers' online purchase spending, this paper draws important implications for academics as well, providing evidence against the phenomenon of "ad blindness" and recent works showing that digital ads are ineffective in driving consumers' purchases. To mitigate the adverse effects of ad-blockers, marketers might try to engage with alternative formats of digital marketing activities, such as influencer marketing, native advertising, and sponsored recommendations. Besides, as the penetration of ad-blockers continues, it becomes increasingly crucial for marketers to strengthen their social media strategies and engineer content dissemination in these platforms. Similarly, marketers might alleviate the negative consequences of ad-blockers by adopting new direct firm-to-consumer communication and sales channels enabled by technological advancements (Adamopoulos et al. 2020), such as voice-controlled apps or purchasing capabilities embedded in social media platforms (Adamopoulos et al. 2018, Schneier 2019). Importantly, the findings highlight the need

[11]This falsification check also tests the existence of common trends between treatment and control groups in the pre-treatment period and provides additional empirical evidence against any differential trends, further corroborating the results of section 3.3.

for the digital advertising stakeholders to take industry-wide initiatives to collectively form policies for self-regulating what constitutes acceptable advertising practices on the web and tackle the prominence of ad-blockers. Such coordination might be especially critical since publishers and advertisers who engage in questionable advertising practices, triggering the adoption of ad-blockers, currently impose negative externalities on the rest of the digital advertising ecosystem.

Second, examining the underlying mechanism of the ad-blocker effects, this research reveals that *ad-blockers significantly decrease online spending for heavy online advertisers and brands consumers have not experienced in the past*, partially shifting spending towards brands consumers have experienced before. That is, when ads are blocked, consumers rely more heavily on their own past experiences with the brands to make purchase decisions. Put simply, from the brands' perspective, not all impact is created equal as brands with smaller existing user base are likely to be hurt more than others, making the markets potentially more concentrated. From a managerial point of view, this finding also has important implications for the business-expanding strategies of firms as it demonstrates that it might become more challenging to acquire new customers online who do not already have any experience with the brand as ad-blockers continue becoming more mainstream. Hence, as ad-blockers increase in popularity, brands might focus on consumer retention, rather than acquisition, strategies. Importantly, it is also timely and prudent for advertisers to predict which consumers are likely to install an ad-blocker and try to attract them before the imminent ad-blocker adoption. Additionally, firms should bolster their business-expanding strategies by strategically choosing their location for offline presence taking into account the positive impact it can have on online purchase decisions (Wang and Goldfarb 2017) and by providing the opportunity to new customers to experience their products without the need to first purchase them (e.g., showrooms, samples).

Third, this research demonstrates that ad-blockers have additional unintended consequences as they significantly reduce the tendency of consumers to engage in search activities across various information channels, as captured by the search sessions consumers initiate on search engines and the visits they make to shopping websites. This finding is of significant importance as it reveals that *the ad-blockers have downstream effects as they impact the information consumers would discover on their own* after being exposed to the digital ads. This result is also particularly important in the light of research indicating that marketers prefer consumers to engage in additional search activities, due to the often restricted bandwidth of marketing communications (Mayzlin and Shin 2011). Additionally, this finding draws important insights as it demonstrates that advertising and search are complementary information channels in providing information to consumers while they have often been presumed to act as substitutes (Fong 2017). From a managerial point of view, marketers may need to increase the influence of organic channels as they cope with the adverse effects of ad-blockers. For instance, managers may utilize search engine optimization techniques to enhance the visibility of the websites in search results. Importantly, brands might enhance the consumers' website experience and regularly update the content to entice website visits. Similarly, managers could invest in content marketing by creating high-quality articles and videos that can engage consumers.

Beyond the aforementioned managerial and theoretical implications, this research may also seed new research directions on the underexplored phenomenon of ad-blockers. For instance, future research is needed –beyond the retail sector– to understand better the economic value of the internet without digital advertising. Future research may also seek to examine the impact of ad-blockers on explicit consumer satisfaction. Although the analyses demonstrate that consumers are likely to save money when they install ad-blockers, it remains unclear whether they are more or less satisfied with their purchases in an ad-blocker environment. Similarly, it would be interesting if future research seeks to understand additional implications of ad-blockers on online user behavior beyond their consumption patterns. Future work could also further examine relevant strategies of publishers investigating, for instance, the impact of anti-adblocker strategies. Lastly, this work highlights the need for industry-wide initiatives to inhibit the fast growth of ad-blockers and, thus, future work could propose and evaluate the relative effectiveness of such strategies.

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Appendix A: Difference Regressions Within Treatment Groups, Additional Purchase Spending Robustness Checks, and Tests

Table A.1 Normalized Differences Tests

	Normalized Differences Test	Difference from +/-0.25 Threshold
Purchase Spending	0.0018	-99.3%
Visits	-0.1758	-29.7%
Domains	-0.1046	-58.1%
Pageviews	-0.1067	-57.3%
Duration	-0.1662	-33.5%
Products Purchased	0.0006	-99.8%
Age	0.1387	-44.5%
Education	-0.0374	-85.0%
Income	-0.0835	-66.6%
Household Size	-0.0600	-76.0%
Speed Connection	-0.0316	-87.4%
Search Engine Visits	-0.1172	-53.1%
Visits E-commerce Sites	-0.0458	-81.7%

Notes: Normalized differences across the two groups (Imbens and Rubin 2015). The normalized difference is defined as the difference in means between the treatment and control groups, divided by the square root of half the sum of the treatment and control group variances.

Table A.2 Effect of Ad-blockers on Purchase Spending (Treatment Group)

	Model 1	Model 2	Model 3
Treat × Post	-0.0194 ***	-0.0194 ***	-0.0168 ***
	(0.0054)	(0.0054)	(0.0055)
Holidays		0.0039	0.0037
		(0.0115)	(0.0115)
Constant	0.1866 ***	0.1806 ***	0.2483 ***
	(0.0224)	(0.0289)	(0.0473)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-761,355.42	-761,355.36	-760,802.39
R-squared	0.154	0.154	0.154

Notes: Panel data regression results for treatment group only. For consistency, I use the same fixed effects and control variables as in the main difference-in-differences panel data regression. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

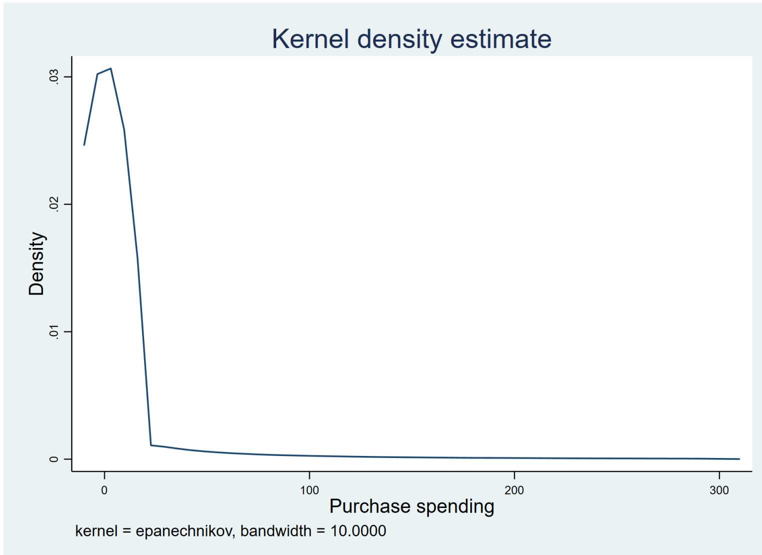

Figure A1 Kernel density estimate of purchase spending.
Notes: The distribution of purchase spending is positively skewed (right-skewed) and leptokurtic. To enhance the visualization of the graph, the top 1% percentile of the data is not depicted (Miller 2017).

Table A.3 Effect of Ad-blockers on Purchase Spending (Heavy Online Advertisers vs Light Online Advertisers - Alternative Specification 1)

	Model 1	Model 2	Model 3
Treat × Post	-0.0109 **	-0.0109 **	-0.0113 **
	(0.0039)	(0.0039)	(0.0039)
Holidays		-0.0029	-0.0029
		(0.0027)	(0.0027)
Constant	0.8194 ***	0.8239 ***	0.8186 ***
	(0.0066)	(0.0079)	(0.0137)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-6,481,991.27	-6,481,990.74	-6,479,869.34
R-squared	0.146	0.146	0.146

Notes: Difference-in-differences panel data regression results for the ratio of purchase spending for heavy online advertisers to spending for light online advertisers. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4 Effect of Ad-blockers on Purchase Spending (Heavy Online Advertisers vs Light Online Advertisers - Alternative Specification 2)

	Model 1	Model 2	Model 3
Treat × Post	-0.0133 **	-0.0133 **	-0.0136 **
	(0.0046)	(0.0046)	(0.0046)
Holidays		-0.0023	-0.0023
		(0.0032)	(0.0032)
Constant	0.1781 ***	0.1816 ***	0.1667 ***
	(0.0080)	(0.0095)	(0.0163)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,196,368.06	-7,196,367.82	-7,193,972.42
R-squared	0.152	0.152	0.152

Notes: Difference-in-differences panel data regression results for the difference in purchase spending between heavy online advertisers and light online advertisers. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.5 Effect of Ad-blockers on Purchase Spending (Brands Consumers Have Experienced in The Past vs Brands Consumers Have not Experienced in the Past - Alternative Specification 1)

	Model 1	Model 2	Model 3
Treat × Post	-0.0479 ***	-0.0479 ***	-0.0465 ***
	(0.0028)	(0.0028)	(0.0028)
Holidays		0.0074 ***	0.0073 ***
		(0.0020)	(0.0020)
Constant	0.7487 ***	0.7372 ***	0.6879 ***
	(0.0040)	(0.0051)	(0.0092)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-4,988,067.32	-4,988,060.41	-4,986,318.26
R-squared	0.032	0.032	0.032

Notes: Difference-in-differences panel data regression results for the ratio of purchase spending for brands user i has not experienced in the past to spending for brands user i has experienced in the past. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.6 Effect of Ad-blockers on Purchase Spending (Brands Consumers Have Experienced in The Past vs Brands Consumers Have not Experienced in the Past - Alternative Specification 2)

	Model 1	Model 2	Model 3
Treat × Post	-0.0508 ***	-0.0508 ***	-0.0494 ***
	(0.0035)	(0.0035)	(0.0035)
Holidays		0.0077 ***	0.0075 ***
		(0.0024)	(0.0024)
Constant	0.0909 ***	0.0790 ***	0.0156
	(0.0051)	(0.0064)	(0.0116)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-5,499,471.42	-5,499,466.67	-5,497,557.04
R-squared	0.044	0.044	0.044

Notes: Difference-in-differences panel data regression results for the difference in spending between brands user i has not experienced in the past and brands the user i has experienced in the past. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix B: Search Behavior Robustness Checks

Table B.1 Effect of Ad-blockers on Search Behavior (Search Engine Visits)

	Model 1	Model 2	Model 3
Treat × Post	-0.0581 ***	-0.0522 **	-0.0324 *
	(0.0136)	(0.0159)	(0.0155)
Holidays	0.0067 *	-0.0007	0.0029
	(0.0028)	(0.0088)	(0.0030)
Websites		0.0035	
		(0.0037)	
Visits			0.0026 ***
			(0.0008)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE	✓	✓	✓
Log pseudo-likelihood	-18,461,548	-18,220,120	-17,730,820
Wald χ^2	28,675.74	30,141.26	29,984.12

Notes: Poisson fixed effects specification controlling for consumer's overall internet usage. Model 2 controls for the number of distinct websites each user visits and Model 3 controls for the number of visits each user makes. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.2 Effect of Ad-blockers on Search Behavior (E-commerce Web Visits)

	Model 1	Model 2	Model 3
Treat × Post	-0.0565 ***	-0.0573 ***	-0.0486 **
	(0.0163)	(0.0157)	(0.0159)
Holidays	0.0219 ***	0.0174 ***	0.0193 ***
	(0.0047)	(0.0049)	(0.0044)
Websites		0.0021 **	
		(0.0010)	
Visits			0.0013 **
			(0.0004)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE	✓	✓	✓
Log pseudo-likelihood	-11,446,329	-11,267,436	-11,194,179
Wald χ^2	14,735.28	16,354.60	16,596.41

Notes: Poisson fixed effects specification controlling for consumer's overall internet usage. Model 2 controls for the number of distinct websites each user visits and Model 3 controls for the number of visits each user makes. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C: Additional Parallel Trends Tests

Table C.1 Parallel Trends - Search Engine Visits

	Model 1	Model 2	Model 3
Trend	-0.0047 ***	-0.0042 ***	-0.0042 ***
	(0.0001)	(0.0001)	(0.0001)
Trend × Treatment	-0.0001	-0.0004	-0.0004
	(0.0004)	(0.0004)	(0.0004)
Holidays		-0.1014 ***	-0.1014 ***
		(0.0014)	(0.0014)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log pseudo-likelihood	-18,836,389	-18,808,486	-18,801,571
Wald χ^2	3414.53	7474.75	7503.55

Notes: Poisson fixed effects regression results for the pre-treatment period allowing treated and control groups to have different time trends. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.2 Parallel Trends - E-commerce Website Visits

	Model 1	Model 2	Model 3
Trend	-0.0009 ***	-0.0007 ***	-0.0007 ***
	(0.0002)	(0.0002)	(0.0002)
Trend × Treatment	0.0013	0.0012	0.0011
	(0.0008)	(0.0008)	(0.0008)
Holidays		-0.0442 ***	-0.0442 ***
		(0.0024)	(0.0024)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log pseudo-likelihood	-11,637,635	-11,635,524	-11,632,427
Wald χ^2	34.69	346.40	356.23

Notes: Poisson fixed effects regression results for the pre-treatment period allowing treated and control groups to have different time trends. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D: Alternative Identification Strategy (1): Instrumental Variables Panel Data Model

Table D.1 Instrumental Variables 2SLS for Panel Data - First Stage Regression

	Model 1	Model 2	Model 3
Local Adopters Pct	1.3578 ***	1.3578 ***	1.3535 ***
	(0.0046)	(0.0046)	(0.0046)
Holidays		0.0010 **	0.0010 **
		(0.0003)	(0.0003)
Constant	0.0305 ***	0.0290 ***	0.0049 *
	(0.0009)	(0.0010)	(0.0019)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	3,628,229.60	3,628,234.45	3,629,193.83
R-squared	0.806	0.806	0.806

Notes: Results from the first stage regression of 2SLS for panel data. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.2 Instrumental Variables Tests

		Model 1	Model 2	Model 3
Weak identification test (Cragg-Donald Wald F statistic)	:	6.5e+05	6.5e+05	6.4e+05
Stock-Yogo weak ID test critical values: 10% maximal IV size	:	16.38	16.38	16.38
15% maximal IV size	:	8.96	8.96	8.96
20% maximal IV size	:	6.66	6.66	6.66
25% maximal IV size	:	5.53	5.53	5.53
Hansen-Sargan statistic (overidentification test)	:	0.000	0.000	0.000
		(equation exactly identified)		
Endogeneity test of endogenous regressor:	:	0.7640	0.7640	0.8980
Chi-sq(1) P-val	:	0.3821	0.3820	0.3432

Notes: The instrument passes the weak identification and overidentification tests. Also, based on the endogeneity test, it is encouraging that we fail to reject the null hypothesis that we may treat the adoption of an ad-blocker on Equation 1 as exogenous.

Table D.3 Effect of Ad-blockers on Purchase Spending (Instrumental Variables 2SLS for Panel Data - Second Stage Regression)

	Model 1	Model 2	Model 3
Treat × Post	-0.0311 *	-0.0311 *	-0.0329 *
	(0.0133)	(0.0133)	(0.0134)
Holidays		-0.0002	-0.0002
		(0.0033)	(0.0033)
Constant	0.2139 ***	0.2141 ***	0.1889 ***
	(0.0086)	(0.0101)	(0.0168)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,311,637.30	-7,311,637.30	-7,309,227.60
R-squared	0.156	0.156	0.156

Notes: 2SLS for panel data regression results. The instrumental variable is the percentage of panelists who have adopted ad-blockers and reside in the same zip code with the focal user. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.1. The Extended Set of Instrumental Variables: The Social Connectedness Index

I construct the additional second instrument by using publicly available data from Facebook on the Social Connectedness Index (2018 dataset; Bailey et al. (2018)). The Social Connectedness Index measures the likelihood and strength of connectedness between two geographic areas (i.e., counties) as represented by Facebook friendship ties. These connections can reveal important insights about social connectedness and flow of information between uses who reside in various geographic areas (Bailey et al. 2018).

I explain in detail how this instrument is constructed below. Suppose that we have focal user i residing in county j. Using the Social Connectedness Index, we know with which counties a user i residing in county j might be socially connected with (i.e., county-county pairs as captured by the Facebook Social Connectedness Index dataset) as well as the strength of such a potential social connection (i.e., Social Connectedness Index (SCI) weight in the aforementioned dataset). For instance, as shown in the following illustrative table, such a user might be likely to have social connections in counties k_1,k_2, and k_3, with connectedness indices of w_{jk_1}, w_{jk_2}, and w_{jk_3}, respectively.

Thus, using the Social Connectedness dataset, the second instrument is estimated as:

Table D.4 The Social Connectedness Index (County-County Pairs)

County	County	Social Connectedness Index
j	k_1	w_{jk_1}
j	k_2	w_{jk_2}
j	k_3	w_{jk_3}

$$\frac{w_{jk_1}\text{AdoptersCounty}_{k_1} + w_{jk_2}\text{AdoptersCounty}_{k_2} + w_{jk_3}\text{AdoptersCounty}_{k_3}}{\sum_l w_{jk_l}}$$

The following tables, present the first stage and second stage results for the updated instrumental variable estimator, in Table D.5 and Table D.6 respectively. Additionally, as before, I conduct a variety of instrumental variable tests and find that the instrumental variables pass the weak identification, overidentification, and endogeneity tests, as shown in Table D.7.

Table D.5 Instrumental Variables 2SLS for Panel Data - First Stage Regression (Social Connectedness Index)

	Model 1	Model 2	Model 3
Local Adopters Pct	1.4550 ***	1.4549 ***	1.4511 ***
	(0.0050)	(0.0050)	(0.0050)
SCI Adopters	0.0001 ***	0.0001 ***	0.0001 ***
	(0.0000)	(0.0000)	(0.0000)
Holidays		0.0023 **	0.0023 **
		(0.0003)	(0.0003)
Constant	0.0280 ***	0.0245 ***	-0.0018
	(0.0009)	(0.0010)	(0.0019)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	3,593,551.40	3,593,578.25	3,594,539.07
R-squared	0.808	0.808	0.808

Notes: Results from the first stage regression of 2SLS for panel data. The instrumental variables are the percentage of panelists who have adopted ad-blockers and reside in the same zip code with the focal user as well as the weighted average of ad-blocker adopters in counties that are socially connected with the county of the focal user, as determined by the Social Connectedness Index dataset. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6 Effect of Ad-blockers on Purchase Spending (Instrumental Variables 2SLS for Panel Data - Second Stage Regression - Social Connectedness Index)

	Model 1	Model 2	Model 3
Treat × Post	-0.0465 ***	-0.0465 ***	-0.0467 ***
	(0.0135)	(0.0135)	(0.0135)
Holidays		-0.0011	-0.0011
		(0.0034)	(0.0034)
Constant	0.2154 ***	0.2171 ***	0.1934 ***
	(0.0087)	(0.0102)	(0.0170)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,186,976.02	-7,186,975.96	-7,184,597.17
R-squared	0.156	0.156	0.156

Notes: 2SLS for panel data regression results. The instrumental variables are the percentage of panelists who have adopted ad-blockers and reside in the same zip code with the focal user as well as the weighted average of ad-blocker adopters in counties that are socially connected with the county of the focal user, as determined by the Social Connectedness Index (SCI) dataset. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.7 Instrumental Variables Tests

		Model 1	Model 2	Model 3
Weak identification test (Cragg-Donald Wald F statistic)	:	3.3e+05	3.3e+05	3.3e+05
Stock-Yogo weak ID test critical values: 10% maximal IV size	:	16.38	16.38	16.38
15% maximal IV size	:	8.96	8.96	8.96
20% maximal IV size	:	6.66	6.66	6.66
25% maximal IV size	:	5.53	5.53	5.53
Hansen-Sargan statistic (overidentification test)	:	2.7130	2.8880	2.8300
Chi-sq(1) P-val	:	0.0996	0.0893	0.0925
Endogeneity test of endogenous regressor:	:	2.9500	2.9720	2.9370
Chi-sq(1) P-val	:	0.0859	0.0847	0.0865

Notes: The instruments pass the weak identification and overidentification tests. Also, based on the endogeneity test, it is encouraging that we fail to reject the null hypothesis that we may treat the adoption of an ad-blocker on Equation 1 as exogenous.

Appendix E: Alternative Identification Strategy (2): Matching Difference-in-Differences

Table E.1 Effect of Ad-blockers on Purchase Spending (Matching DID)

	Model 1	Model 2	Model 3
Treat × Post	-0.0168 ***	-0.0168 ***	-0.0164 ***
	(0.0050)	(0.0050)	(0.0050)
Holidays		-0.0006	-0.0006
		(0.0079)	(0.0079)
Constant	0.1999 ***	0.2008 ***	0.2013 ***
	(0.0177)	(0.0217)	(0.0370)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-1,437,766.99	-1,437,766.99	-1,437,050.38
R-squared	0.152	0.152	0.152

Notes: One-to-one nearest neighbor matching algorithm is used for the matching reducing the sample to 892,177 observations. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E.2 Covariate Balance

	Matched
Purchases	0.0257
Time_Spent_Online	0.0390
Time_Spent_Websites_with_Ads	0.0292
Website_Visits	0.0248
Website_with_Ads_Visits	0.0311
Shopping_Websites_Visits	0.0349
College education	-0.0001
Income category	0.0000
Age group	0.0017
Household size	0.0005

Notes: Covariate balance of variables used for matching based on the matched data; one-to-one nearest neighbor matching algorithm was employed for matching individuals. These estimates are based on the individuals used in the matching procedure and the values of the matching variables correspond to the averages per user in the pre-treatment period.

Appendix F: Additional Robustness Checks

Table F.1 Effect of Ad-blockers on Purchase Spending (Carryover Effects)

	Model 1	Model 2	Model 3
Treat × Post	-0.0159 **	-0.0159 **	-0.0159 **
	(0.0052)	(0.0052)	(0.0052)
Holidays		-0.0004	-0.0005
		(0.0034)	(0.0034)
Constant	0.2108 ***	0.2150 ***	0.1866 ***
	(0.0087)	(0.0103)	(0.0178)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-6,090,974.21	-6,090,974.20	-6,089,104.36
R-squared	0.166	0.166	0.166

Notes: This specification allows for carryover effects of advertising for a period of two months.The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.2 Effect of Ad-blockers on Purchase Spending (Length Pre-Treatment Period)

	Model 1	Model 2	Model 3
Treat × Post	-0.0162 **	-0.0162 **	-0.0166 **
	(0.0053)	(0.0053)	(0.0053)
Holidays		0.0003	0.0003
		(0.0034)	(0.0034)
Constant	0.2164 ***	0.2159 ***	0.1923 ***
	(0.0088)	(0.0103)	(0.0171)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-6,945,129.22	-6,945,129.22	-6,943,185.49
R-squared	0.156	0.156	0.156

Notes: This specification allows for a pre-treatment period of at least six months for each individual before treatment, if any. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F.3 **Effect of Ad-blockers on Purchase Spending (No Outliers)**

	Model 1	Model 2	Model 3
Treat × Post	-0.0136 **	-0.0136 **	-0.0138 **
	(0.0046)	(0.0046)	(0.0046)
Holidays		0.0006	0.0006
		(0.0033)	(0.0033)
Constant	0.2123 ***	0.2114 ***	0.1867 ***
	(0.0086)	(0.0101)	(0.0167)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,266,250.81	-7,266,250.79	-7,263,864.79
R-squared	0.155	0.155	0.155

Notes: Difference-in-differences panel data regression results when excluding outliers of purchase spending amounts. I use the interquartile range rule with a constant of 1.5 to detect and remove outliers. Results are robust to alternative interquartile ranges. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix G: Ruling Out Additional Alternative Explanations

Table G.1 Effect of Ad-blockers on Purchase Spending (Controlling for Speed Connection)

	Model 1	Model 2	Model 3
Treat × Post	-0.0144 **	-0.0146 **	-0.0147 **
	(0.0047)	(0.0047)	(0.0047)
Holidays		-0.0001	-0.0002
		(0.0033)	(0.0033)
Conn. Speed	-0.0294	-0.0294	-0.0292
	(0.0194)	(0.0194)	(0.0194)
Constant	0.2420 ***	0.2422 ***	0.2171 ***
	(0.0211)	(0.0218)	(0.0255)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,311,634.49	-7,311,634.49	-7,309,224.93
R-squared	0.156	0.156	0.156

Notes: Difference-in-differences panel data regression results when controlling for the connection speed of the consumer (i.e., broadband internet connection or not). The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.2 Effect of Ad-blockers on Purchase Spending (Controlling for News Stores related to Advertising)

	Model 1	Model 2	Model 3	Model 4
Treat × Post	-0.0150 **	-0.0163 **	-0.0144 **	-0.0130 **
	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Holidays	0.0004	-0.0001	0.0005	0.0024
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
News Stories “Ads”	-0.0093 *	-0.0134 **	-0.0113 *	0.0023
	(0.0044)	(0.0047)	(0.0051)	(0.0053)
Blog Posts “Ads”		0.0063 *	0.0097 ***	0.0318 ***
		(0.0027)	(0.0029)	(0.0031)
News Stories “Privacy”			-0.0064 **	-0.0123 ***
			(0.0022)	(0.0037)
News Stories “Personalization”			-0.0048	0.0192 ***
			(0.0036)	(0.0037)
Blog Posts “Privacy”				-0.0834 ***
				(0.0048)
Blog Posts “Personalization”				0.0114 ***
				(0.0024)
Constant	0.2524 ***	0.2283 ***	0.2568 ***	0.6897 ***
	(0.0344)	(0.0356)	(0.0393)	(0.0486)
Individual FE	✓	✓	✓	✓
Week FE	✓	✓	✓	✓
Demographics FE	✓	✓	✓	✓
Log-likelihood	-7,309,223.48	-7,309,220.86	-7,309,213.13	-7,309,039.11
R-squared	0.156	0.156	0.156	0.156

Notes: Difference-in-differences panel data regression results when controlling for news stories related to “ads” (and “advertisements”), “privacy, and “personalization” in offline and online news and media outlets. I use the leading subscription-based news dataset of Nexis Uni (a LexisNexis product) for information on the number of such news stories. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.3 Effect of Ad-blockers on Purchase Spending (Subsample Analysis - No Children)

	Model 1	Model 2	Model 3
Treat × Post	-0.0164 *	-0.0164 *	-0.0161 *
	(0.0080)	(0.0080)	(0.0080)
Holidays		0.0061	0.0061
		(0.0053)	(0.0053)
Constant	0.2296 ***	0.2220 ***	0.2452 ***
	(0.0146)	(0.0169)	(0.0274)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-3,107,979.9	-3,107,979.2	-3,107,969.8
R-squared	0.162	0.162	0.162

Notes: Difference-in-differences panel data regression results when confining the sample to households that do not have children. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.4 Effect of Ad-blockers on Purchase Spending (Subsample Analysis - Income Above Median)

	Model 1	Model 2	Model 3
Treat × Post	-0.0161 *	-0.0161 *	-0.0164 *
	(0.0067)	(0.0067)	(0.0067)
Holidays		-0.0016	-0.0015
		(0.0049)	(0.0049)
Constant	0.2568 ***	0.2592 ***	0.1960 ***
	(0.0131)	(0.0151)	(0.0271)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-3,827,287.25	-3,827,287.19	-3,826,485.84
R-squared	0.163	0.163	0.164

Notes: Difference-in-differences panel data regression results when confining the sample to households with income above the U.S. median income. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G.5 Effect of Ad-blockers on Purchase Spending (Heterogeneity Analysis for Heavy "News and Media" Users)

	Model 1	Model 2	Model 3
Treat × Post	-0.0146 **	-0.0176 **	-0.0144 **
	(0.0047)	(0.0048)	(0.0048)
Holidays	-0.0002	-0.0002	-0.0002
	(0.0033)	(0.0033)	(0.0033)
Treat × Post		0.0348	-0.0032
× Heavy N&M Users		(0.0205)	(0.0215)
Constant	0.1881 ***	0.1869 ***	0.1882 ***
	(0.0168)	(0.0168)	(0.0168)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE	✓	✓	✓
Log-likelihood	-7,309,225.84	-7,309,223.70	-7,309,225.83
R-squared	0.156	0.156	0.156

Notes: Difference-in-differences panel data regression heterogeneity results for heavy "news and media" users. Heavy "news and media" users are captured based on the number of distinct "news and media" domains each user visits (Model 2) as well as the total "news and media" visits each user makes (Model 3). The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix H: Falsification Test

Table H.1 Effect of Ad-blockers on Purchase Spending (Placebo Treatment)

	Model 1	Model 2	Model 3
Placebo Treatment	-0.0032	-0.0032	-0.0037
	(0.0066)	(0.0066)	(0.0066)
Holidays		-0.0142 ***	-0.0142 ***
		(0.0029)	(0.0029)
Constant	0.2483 ***	0.2672 ***	0.2197 ***
	(0.0043)	(0.0059)	(0.0142)
Individual FE	✓	✓	✓
Week FE	✓	✓	✓
Demographics FE			✓
Log-likelihood	-7,562,176.13	-7,562,164.82	-7,559,843.66
R-squared	0.149	0.149	0.149

Notes: Falsification test with a placebo treatment that randomly indicates who is treated and when. The demographics fixed effects include fixed effects for income groups, level of education groups, age groups, and household size. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$