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Does ad blocking have an effect on online shopping?

David Suárez *, Begoña García-Mariñoso

Department of Statistics and Knowledge Management, Comisión Nacional de los Mercados y la Competencia (CNMC), Barcelona, Spain

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ABSTRACT

The use of ad blocking software has risen sharply with online advertising and is recognized as challenging the survival of the ad supported web. However, the effects of ad blocking on consumer behavior have been studied scarcely. This paper uses propensity score matching techniques on a longitudinal survey of 4411 Internet users in Spain to show that ad blocking has a causal positive effect on their number of online purchases. This could be attributed to the positive effects of ad blocking, such as a safer and enhanced navigation. This striking result reinforces the controversial debate of whether current online ads are too bothersome for consumers.

1. Introduction

The impact of Internet on society is ubiquitous and advertising is not an exception. In comparison with offline advertisements, digital ads offer contextualized content and, hence, better consumer targeting. Concretely, the monitoring of consumers' click behavior in the web enables the knowledge of consumers' preferences and allows consumer segmentation and even personalized advertising. These opportunities have dramatically modified the spending on ads. Thus, in 2019, for the first time in the ads industry history, online advertising spending exceeded the traditional offline advertising expenditure in the US, reaching 129 billion dollars with a 19% inter-annual growth rate. During the same year, the US e-commerce market revenues increased by 14% reaching 586 billion dollars surpassing 10% of total US retail sales for the first time. Similarly, also in 2019, spending on digital advertising surpassed spending on television advertising in Spain reaching 2.3 billion euros,[1] with a yearly growth rate of 8.8%. That year, online spending peaked in Spain at 48.8 billion euros, exhibiting an annual growth of 25%.[2]

With the measures taken by governments around the world to fight against the 2020 COVID-19 pandemic (i.e., lockdowns, social distancing measures, etc.) the use of Internet is on a growth spurt which possibly may have lasting effects. This, coupled with an upward trend in e-commerce, will enhance online advertising and may have important effects on the interaction between companies and consumers challenging the survival of brick and mortar stores.

Unsurprisingly, the use of ad blocking software[3] has risen sharply as online advertising grew: it is estimated that one in four US

* Corresponding author.
E-mail addresses: david.suarez.lamas@gmail.com, david.suarez@cnmc.es (D. Suárez).

[1] See Infoadex report available at https://www.infoadex.es/home/wp-content/uploads/2020/02/NP-Estudio-InfoAdex-de-la-Inversi%C3%B3n-Publicitaria-en-Espa%C3%B1a-2020.pdf.

[2] See CNMC press release available at https://www.cnmc.es/en/node/381969. These statistics only consider online purchases that are paid for with credit or debit cards, and not other forms of payments.

[3] Ad blockers take the form of free to use browser extensions or mobile apps enforcing a set of community-defined rules for ads. The most popular ad blockers work by intercepting browser requests to lists of known ad servers.

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Internet users have installed some type of ad blocking tool in their devices.[4] Similar figures apply to Europe. For example, according to a Spanish survey of Internet users, in 2019, 35% used ad blockers.[5] These penetration rates are outstanding considering that the most widely used ad blocking tool, Adblock Plus, was created by Wladimir Palant just fourteen years ago (in 2006).

There are three main reasons to use ad blocking tools. First, and the most obvious one, to avoid (partially or totally) seeing ads while you navigate the web, particularly the most intrusive types such as auto playing audio/video ads, non-skippable video ads or pop-up ads. Second, to reduce the risk of malware and/or online tracking. Interestingly, a recent survey research in the US has revealed that the median consumer is willing to pay $5 per month to maintain his/her data privacy (Winegar & Sunstein, 2019). And third, to reduce bandwidth usage and increase screen space and speed of page uploading. Overall, ad blocking could improve consumers' web user experience. Yet, at the same time, it may also threaten the online ads ecosystem.

Despite the popularity and the potential impact of ad blocking, research in this area is still scarce. Previous research has focused on why users adopt ad blocking, its impact on website traffic and quality, and on its effect on user engagement with the web. To our knowledge, there is almost no study addressing the impact of ad blockers on the propensity of e-commerce purchases. This study measures this impact by using data from a longitudinal survey.

The main contribution of this piece of research to the existing literature is the finding that the use of ad blockers has a positive impact on online shopping: on average the use of ad blockers raises the items purchased by roughly, 40%. This striking result reinforces the original message of Doc Searls in 2019[6]: "*advertising online has come to have massively negative value*" as we have found evidence that the exposure to online ads goes against e-commerce.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature on ad blockers. Section 3 presents the data. Section 4 introduces the econometric methodology. Section 5 shows the results. Finally, Section 6 concludes.

2. Literature review

The literature on ad blocking is quite recent and still scarce, and leads to inconclusive results with respect to its overall effects on consumers. First, Shiller, Waldfogel, and Ryan (2018) explore the impact of site-level ad blocker usage on website traffic and content, finding that each additional percentage point of a site's visitors blocking ads reduces the site's web traffic by 0.67% over 35 months and they also show that the impacted sites provide less content over time. Thus, they conclude that ad blocking poses a threat to the ad supported web.

Somewhat contrarily, Miroglio, Zeber, Kaye, and Weiss (2018) conducted an experiment showing that the group that installed an ad blocker increased both the active time spent in the browser (+28% over control) and the number of pages viewed (+15% over control).

On the other hand, Redondo and Aznar (2018) used survey data to show that "*(a) adoption of ad blockers is positively influenced by the level of knowledge of their advantageous features; (b) the decision to continue using ad blockers is negatively affected by attitude toward online advertising; and (c) this attitude is positively shaped by perceptions of online advertising's pleasure, credibility, and economic benefits, as well as negatively shaped by perceptions of online advertising's intrusiveness and clutter*". From these results they inferred that ad blockers' use will continue to spread rapidly and recommend reducing those ad characteristics that provoke negative reactions.

Frik, Haviland, and Acquisti (2020) conducted a lab experiment to focus on the effects of blocking ads on participants' online choice behavior and purchase experiences. They find that there is no effects on consumer choice, this is, they could not falsify the null hypothesis that the prices of products chosen by their subjects would be different or that the satisfaction with their purchases would differ. Thus, both groups were equally satisfied by their choices. Therefore, they concluded that ad blocking does not compromise the consumer economic welfare, although they did not study the effects of ad blocking on the propensity to purchase online.

In addition to the empirical research, some authors have considered the theoretical effects of ad blocking using mathematical models of consumer and firm behavior. Despotakis, Ravi, and Srinivasan (2020) by using a simple model with two competing platforms, show that the presence of ad blockers can actually benefit platforms. They show that under some conditions the optimal equilibrium strategy for the platforms is to allow the use of ad blockers instead of using an ad block wall or charging a fee for viewing ad free content. On the contrary, Gritckevich, Katona, and Sarvary (2020) study the strategic interaction between publishers and ad blockers to assess the effect of ad blocking on publishers' quality choices, consumer surplus and total welfare, showing an overall negative effect of ad blocking on these variables.

Finally, Gordon et al. (2020) review the inefficiencies in the digital advertising markets. They pinpoint ad blocking as one of the main four inefficiencies in these markets and point out that its effects on consumer behavior remain poorly understood encouraging for future research in this area.

3. Data

This study employs a rich dataset coming from a longitudinal survey. The source of the data is a survey conducted by the Spanish Markets and Competition Authority on the same sample of interviewees in the fourth quarter of 2017 and in the second quarter of 2018

[4] All figures for US are available in several reports by emarketer (www.emarketer.com).

[5] See AIMC Q Panel press release available at: https://www.aimc.es/a1mc-c0nt3nt/uploads/2019/10/2019_10_01_NP_AIMC_Q_Panel_Publicidad_Online_2019.pdf.

[6] See his blog post entitled: *Is ad blocking past 2 billion worldwide?* at https://blogs.harvard.edu/doc/2019/03/23/2billion/.

([dataset]CNMCData, 2019). The sample was designed to be representative of the population living in private households in Spain. The information was provided by 4411 Internet users ≥16 years old. At the baseline time point (fourth quarter of 2017) these individuals were asked if they regularly used ad blocking tools when navigating the web. Additionally, the survey collected information on their socio-demographic characteristics (age, gender, education level and employment status) and on how they used Internet (frequency of use of online services like: GPS navigation services, instant messaging, mobile gaming, social networks, e-mail and watching videos on the phone). Six months later (second quarter of 2018), the same individuals were asked how many online purchases they had made during the previous six months (these included goods and services purchases, irrespective of the form of payment). Thus, the outcome variable (number of online purchases) occurred later than the collection of the ad blocking information and the rest of variables (our X covariates).

Some recent research has uncovered what drives individuals' decisions to purchase online in Spain (Garín-Muñoz, López, Pérez-Amaral, Herguera, & Valarezo, 2019; Pérez-Amaral, Valarezo, López, Garín-Muñoz, & Herguera, 2020). Briefly, gender, age, income, education and the levels of Internet and computer skills were all significant in explaining the adoption of e-commerce by Internet users. Thus, our study collects properly all these drivers identified in the literature.[7]

Regarding the descriptive statistics of the sample, 20.3% of the individuals declared using ad blockers at the end of 2017. On average, the sampled individuals made 3.2 online purchases during the first six months of 2018 (standard deviation was 7.2, range: 0–120). The overall means for the rest of variables (all categorical) used in the study are shown in the first column of Table 1.

4. Empirical strategy

The methodology employed to estimate the effect of ad blockers' use on online shopping was propensity score matching (PSM). PSM has been used previously in the literature to study, for example, the causal impact of Internet use on job search (Beard, Ford, Saba, & Seals, 2012) or on economic growth in rural areas (Whitacre, Gallardo, & Strover, 2014). This technique allows to estimate the average causal difference in outcomes between a treated and a control group in nonrandomized studies (Rosenbaum & Rubin, 1983). In our study the "treatment" is the use of ad blockers and the "control" the non-use of them. Precisely, being i an individual indicator, Y_{i1} the number of e-commerce purchases by i using ad blockers and Y_{i0} the same number non-using them, and T which indicates the reference group (T = 1 when the individual uses ad blockers, T = 0 when she or he does not) the average treatment effect on the treated (ATT) of ad blockers' use on e-commerce is defined as:

$$\mathrm{ATT} = \mathrm{E}(Y_{i1} \mid T = 1) - \mathrm{E}(Y_{i0} \mid T = 1)$$

Notice that, regarding "treated individuals", in the sample one can only observe the number of purchases of individuals using ad blockers but cannot see the number of purchases that these individuals would have made if they had not used those. Therefore, the right term in the previous expression is non-observable: it is the expected value of the e-commerce purchases for the treatment group if, in fact, they had not used ad blockers. The goal of PSM is to consider a control group that "mimics" the treated group in order to estimate this non-observable term and, hence, the ATT.

To get an unbiased estimate of the ATT from PSM two key assumptions must hold: (i) the assumption of conditional independence and (ii) the assumption of common support. First, conditional independence means that given a set of observable covariates X, the potential outcomes are independent of the treatment assignment. This implies that there are no unobservable differences between treated and control individuals that could impact on the outcome. This is a critical point as it is a non-testable assumption. However, as we pointed out in the previous section the current literature has successfully identified the most relevant determinants of e-commerce use in Spain (Garín-Muñoz et al., 2019; Pérez-Amaral et al., 2020) and our dataset incorporates these variables.

Additionally, conditional independence means that the ATT can be estimated conditioning the outcome on the X covariates. Theoretically, the conditioning could be done by seeking and exact matching for each treated individual, this is, by finding a control individual with the same X's profile than the treated one. However, this approach is unpractical because of the curse of dimensionality. To deal with this problem, Rosenbaum and Rubin (1983) suggest to use the propensity score, i.e. to match individuals by considering the probability for each individual to participate in a treatment given his observed covariates X. They showed that if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on propensity score, and, therefore, the ATT can be estimated by matching the treated individuals with the untreated in the sample by using propensity scores.

Second, the assumption of common support or overlap condition implies that individuals should have a propensity score which is not equal to 0 or 1, thus ruling out the perfect predictability of the outcome. This warrants that individuals with the same X covariates have a positive chance of being both treated or control individuals. Usually, this assumption is validated by checking that the distributions of the propensity scores in treated and control groups overlap.

In order to estimate the propensity scores the most usual alternative is fitting a logit model. So, we fitted a logit model where the outcome considered was the use of ad blockers and the independent variables the set of X covariates described in Section 3.

The next step in the PSM methodology is to match each treated individual with a control one with the most similar propensity score. There are several alternatives to perform these matches. To make our results more robust we implemented two of these methods:

[7] We use as a proxy for income, the individual employment status and education level. One should note that ad blockers are free to use by consumers.

Table 1
Covariate balance across treated (ad blockers' users) and control (non ad blockers' users) groups before and after matching.

Sample	Unmatched				Matched Nearest Neighbor			Matched Kernel Matching		
Variable	Overall	Treated	Control	Bias	Treated	Control	Bias	Treated	Control	Bias
Frequency of GPS use: Every day	0.031	0.053	0.026	13.9	0.053	0.060	−4.0	0.053	0.053	−0.2
Frequency of GPS use: Almost every day	0.070	0.111	0.060	18.3	0.111	0.099	4.0	0.111	0.106	1.8
Frequency of GPS use: Every week	0.122	0.191	0.104	24.6	0.191	0.179	3.5	0.191	0.185	1.8
Frequency of GPS use: Less than every week	0.467	0.466	0.467	−0.3	0.466	0.454	2.5	0.466	0.469	−0.6
Frequency of GPS use: Never	0.310	0.180	0.343	−37.8	0.180	0.208	−6.5	0.180	0.188	−1.8
Frequency of instant messaging: Every day	0.797	0.849	0.784	17.0	0.849	0.855	−1.4	0.849	0.844	1.2
Frequency of instant messaging: Almost every day	0.141	0.115	0.148	−9.6	0.115	0.111	1.3	0.115	0.119	−1.2
Frequency of instant messaging: Every week	0.030	0.016	0.034	−11.6	0.016	0.012	2.2	0.016	0.015	0.5
Frequency of instant messaging: Less than every week	0.016	0.010	0.017	−6.1	0.010	0.008	1.9	0.010	0.010	−0.3
Frequency of instant messaging: Never	0.017	0.010	0.018	−6.9	0.010	0.015	−3.8	0.010	0.011	−0.7
Frequency of mobile gaming: Every day	0.119	0.131	0.115	4.6	0.131	0.123	2.4	0.131	0.127	1.2
Frequency of mobile gaming: Almost every day	0.112	0.141	0.104	11.2	0.141	0.149	−2.4	0.141	0.138	0.7
Frequency of mobile gaming: Every week	0.074	0.098	0.068	11.1	0.098	0.096	0.8	0.098	0.096	0.8
Frequency of mobile gaming: Less than every week	0.161	0.177	0.156	5.4	0.177	0.151	6.9	0.177	0.181	−1.1
Frequency of mobile gaming: Never	0.535	0.454	0.556	−20.6	0.454	0.482	−5.6	0.454	0.458	−0.9
Frequency of e-mail use on phone: Every day	0.288	0.401	0.259	30.5	0.401	0.431	−6.5	0.401	0.391	2.1
Frequency of e-mail use on phone: Almost every day	0.248	0.267	0.243	5.5	0.267	0.270	−0.8	0.267	0.269	−0.3
Frequency of e-mail use on phone: Every week	0.131	0.121	0.133	−3.8	0.121	0.092	8.7	0.121	0.122	−0.5
Frequency of e-mail use on phone: Less than every week	0.178	0.125	0.191	−18.2	0.125	0.115	2.8	0.125	0.130	−1.4
Frequency of e-mail use on phone: Never	0.155	0.086	0.173	−26.0	0.086	0.092	−1.7	0.086	0.088	−0.5
Frequency of social networks use: Every day	0.333	0.387	0.319	14.2	0.387	0.356	6.3	0.387	0.387	−0.2
Frequency of social networks use: Almost every day	0.202	0.199	0.203	−1.1	0.199	0.203	−1.1	0.199	0.196	0.7
Frequency of social networks use: Every week	0.074	0.097	0.068	10.7	0.097	0.112	−5.3	0.097	0.095	0.7
Frequency of social networks use: Less than every week	0.104	0.096	0.106	−3.1	0.096	0.087	3.0	0.096	0.096	0.1
Frequency of social networks use: Never	0.287	0.221	0.304	−19.0	0.221	0.241	−4.6	0.221	0.225	−0.9
Frequency of watching videos on phone: Every day	0.127	0.149	0.122	7.8	0.149	0.134	4.2	0.149	0.145	0.9
Frequency of watching videos on phone: Almost every day	0.247	0.295	0.234	13.8	0.295	0.315	−4.6	0.295	0.298	−0.7
Frequency of watching videos on phone: Every week	0.183	0.235	0.170	16.1	0.235	0.237	−0.6	0.235	0.226	2.1
Frequency of watching videos on phone: Less than every week	0.264	0.212	0.278	−15.2	0.212	0.202	2.3	0.212	0.218	−1.2
Frequency of watching videos on phone: Never	0.178	0.110	0.196	−24.2	0.110	0.112	−0.6	0.110	0.113	−1.0
Gender: Male	0.420	0.513	0.397	23.5	0.513	0.512	0.2	0.513	0.508	1.1
Age: 16 to 24	0.110	0.170	0.095	22.2	0.170	0.166	1.0	0.170	0.164	1.6
Age: 25 to 34	0.087	0.147	0.072	24.4	0.147	0.130	5.8	0.147	0.136	3.9
Age: 35 to 49	0.304	0.328	0.298	6.6	0.328	0.340	−2.4	0.328	0.338	−2.0
Age: 50 to 64	0.366	0.301	0.383	−17.4	0.301	0.318	−3.8	0.301	0.308	−1.6
Age: 65 or over	0.132	0.054	0.152	−32.9	0.054	0.046	2.6	0.054	0.054	−0.2
Employment: Full time	0.436	0.464	0.429	6.9	0.464	0.479	−3.1	0.464	0.467	−0.7
Employment: Part time	0.081	0.069	0.084	−5.4	0.069	0.084	−5.5	0.069	0.069	0.2
Employment: Retired	0.126	0.066	0.141	−24.9	0.066	0.067	−0.4	0.066	0.068	−0.7
Employment: Unemployed	0.154	0.159	0.152	1.7	0.159	0.145	3.7	0.159	0.162	−1.0
Employment: Student	0.128	0.208	0.108	27.8	0.208	0.187	5.9	0.208	0.199	2.4
Employment: Non-employed	0.075	0.035	0.086	−21.7	0.035	0.038	−1.4	0.035	0.035	−0.1
Education: Primary	0.383	0.289	0.406	−24.8	0.289	0.284	1.2	0.289	0.290	−0.2
Education: Secondary	0.325	0.361	0.316	9.4	0.361	0.390	−6.1	0.361	0.360	0.3
Education: University 3-years degree	0.140	0.154	0.137	5.0	0.154	0.128	7.3	0.154	0.155	−0.3
Education: University 5-years degree	0.152	0.196	0.141	14.7	0.196	0.198	−0.6	0.196	0.194	0.3

Mean values for overall, treated and control groups. Bias is the standardized bias as a percentage.

nearest-neighbor (NN) matching and kernel matching (KM).

Matching by the NN pairs each treated individual with individuals with closer propensity scores within the control group. On the contrary to the NN algorithm, KM estimation makes use of all the available controls for each treated individual but gives higher weights to the control cases that are closer to the propensity score of the treated individual to match.

Different variants of NN matching are available. First, one must consider the use of a single or multiple neighbors for each treated individual. Second, one should consider whether to use a caliper or not. A caliper is a threshold on the maximum distance between the treated and the control individual's propensity scores. And a third matter of choice is to allow (or not) the replacement of matches, that is to use more than once an individual in the control group during the matching. In our NN analysis we allowed for replacement and considered a single neighbor with the use of a caliper.[8] This combination is encouraged to reduce the bias of the ATT estimator, though it could decrease its efficiency (Caliendo & Kopeinig, 2008).

Finally, once the matching process has been completed one must assess its quality. If the matching has been successful the distributions of the X covariates in the treated and the control groups should be as close as possible to ensure conditional independence. One of the most recommended indicators to assess these distances is the standardized bias.[9] Analogously, this indicator/variable can be used to compare the treated and the original control group before the matching. If matching has been conducted properly the standardized bias should decrease dramatically after the matching for each covariate. In addition, to consider the match satisfactory the figures for the standardized bias after the matching should remain in absolute terms below 10% (Cannas & Arpino, 2019) or 5% (Caliendo & Kopeinig, 2008) for most of the X covariates.

4.1. Additional analyses

In order to assess the robustness of the PSM results we considered two alternative techniques: stratification on propensity scores and coarsened exact matching.

Stratification (or subclassification) on propensity scores is another method that relies on propensity scores (as PSM). Once the propensity scores are calculated the original sample is divided into strata by using the propensity score values, and then the treatment differences are estimated within each strata as if the propensity scores were constant and, thus, the data can be assimilated to a randomized trial. Finally, the results obtained within each strata are combined to get the ATT. Previous studies have suggested the use five of strata, based on quintiles of the propensity scores, because it seems that five groups is enough to remove over 90% of the bias coming from confounding variables (Imbens & Wooldridge, 2009). Nonetheless, to further check the robustness of our results we employed first, five strata and then, ten strata.

Coarsened exact matching (CEM) is an alternative matching technique to PSM. While PSM tries to mimic a completely randomized trial from an observational study, the goal of CEM is to mimic a blocked randomized trial (Iacus, King, & Porro, 2012). Although it is not a widespread methodology, recently it has been used to quantify, for example, the relationship between broadband speed and economic growth (Ford, 2018). Its implementation is simple. First, one has to "coarsen" the covariates, that is, one has to select cutoffs for each covariate to make those categorical. Second, an exact matching is conducted considering the coincidences of the new coarsened covariates values among individuals. This is, for each combination of the coarsened covariates values (also called a bin), individuals are matched only if their bins coincide, and individuals that belong to a bin where there are only treated or untreated individuals are not considered in the analysis. So, finally, the ATT is estimated from the subsample of bins with treated and untreated individuals.

The most up-to-date research comparing the results of CEM and PSM techniques shows that CEM usually achieves the best covariate balance. However, it also often leads to higher bias and lower precision of the ATT due to the extreme losses in sample size especially when datasets have many covariates (Ripollone, Huybrechts, Rothman, Ferguson, & Franklin, 2020). These authors recommend the use of CEM only if there are less than ten confounders to control for. Given that in our study we have ten covariates, the use of CEM seems precluded.

Nonetheless, Ripollone et al. (2020) suggest that, in these cases, to make the most of the balancing properties of CEM, stratification by using CEM could be applied to the subset of most important covariates within the larger group to ensure a better control over these covariates before applying a propensity score-based technique to balance the remaining confounders. Blackwell, Iacus, King, and Porro (2009) suggest a similar approach to enhance the PSM results. Thus, in our study we explored this approach and classified the confounding variables in two groups: variables related to the use of Internet apps (GPS, instant messaging, gaming, e-mail, social networks and videos) and to socio-demographic variables (gender, age, employment and education). Since both groups of variables are significant drivers of online shopping we applied the method twice. First, we pruned the original sample by using CEM on the use of Internet apps' variables and then, used PSM to estimate the ATT in the obtained subsample by considering the socio-demographic variables. Second, we repeated the same analysis but switching the roles of the two covariates' groups. In both cases we implemented PSM by using the NN algorithm[10].

5. Results

Table 1 shows the mean values of the X covariates for treated and control groups, and their respective standardized bias, in three different scenarios. First, in the unmatched (raw) data. Here, we can observe some important differences between treated and control groups. For example, in the treated group 18% of the individuals declared that they never use GPS apps, whilst on the contrary, in the control group this percentage raises to 34.3% being the standardized bias −37.8%. Similarly, the percentage of individuals of 65 or over years old was only 5.4% in the treated group versus 15.2% in the control group (with a standardized bias of −32.9%). These

[8] We started with a caliper width of 0.1, moving to 0.05, and finally to 0.029 which is the 0.2 of the standard deviation of the propensity score, caliper recommended by Stuart & Rubin, 2007. All the ATT estimations remained the same.

[9] For each covariate X it is defined as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups.

[10] We also used the KM approach getting similar results.

Table 2
Estimated average treatment effects of ad blockers on online shopping (number of purchases in six months).

	N	Treated	Controls	Difference (ATT)	95% LCI	95% UCI	p-value
Unmatched	4411	5.084	2.735	2.348	–	–	–
PSM - NN	1648	5.084	3.325	1.759	0.994	2.523	<0.001
PSM - KM	4411	5.084	3.733	1.351	0.658	2.044	<0.001
Stratification on PS quintiles	4411	5.084	3.686	1.398	0.724	2.072	<0.001
Stratification on PS deciles	4411	5.084	3.774	1.310	0.626	1.994	<0.001
PSM – NN after CEM pruning (1)	1160	4.979	3.773	1.206	0.165	2.246	0.023
PSM – NN after CEM pruning (2)	1622	5.082	3.476	1.605	0.830	2.380	<0.001

ATT: average treatment effect on the treated. PSM: propensity score matching. NN: nearest neighbor. KM: kernel matching. PS: propensity scores. CEM: coarsened exact matching. LCI: lower confidence interval. UCI: upper confidence interval. (1) CEM pruning by using use of Internet apps covariates. (2) CEM pruning by using socio-demographic covariates.

striking differences are not surprising as the treatment, the use of ad blockers, was not assigned randomly to each individual in the sample due to the observational design of this study. On the contrary, it was a free choice for every individual.

Second, we have the same comparison for the NN matched sample. Notice than the treatment group is exactly the same as for the unmatched scenario but the control group is substantially different as a consequence of the matching. Here, the treatment and the control groups are alike (similar covariate values) and the standardized bias for the X covariates are all below 10%. Third, we consider the same comparison but for the KM matched sample. In this case, the corresponding standardized bias were even smaller, below 5% for all the X covariates.

Moreover, by plotting the distribution of the estimated propensity scores before the matching in the treatment and control groups we observed that the overlap of the propensity scores across treatment and control groups was satisfactory.[11]

Therefore, assuming that there were no unmeasured confounders, the overlap and the conditional independence assumptions reasonably hold and we can estimate unbiasedly the ATT.

Table 2 shows the estimated ATTs. Note that the ATT obtained from the PSM - NN matching is 1.759 and statistically significant ($p < 0.001$). This is, the use of ad blockers increases, on average, online purchases in 1.759 items, which is economically relevant. Consistently, the estimated ATT with the PSM - KM matching was similar (1.351) and, also, statistically significant.[12] Table 2 also includes the results of our additional analyses based on subclassification on propensity scores and CEM combined with posterior PSM balancing. The ATTs obtained are also statistically significant and in line with the previous ones, ranging from 1.206 to 1.605.

In conclusion, the results show that the use of ad blockers has a positive and statistically significant effect on online purchasing. This is, somehow, a counterintuitive result. The primary goal of advertising is to persuade people that the services or products offered are so good that they should contract or buy them. Thus, one may think that the less ads you are exposed to, the less are the chances that they convince you to consume, and, at the end, less purchases you should make.

However, the results do not support this reasoning, and rather imply that an increased ad exposure reduces the number of purchases of individuals. What may be behind the result is the primary effect of the ad blockers' use, and this is nothing other than making the experience of web navigation safer and more comfortable. Thus, a smaller exposure to digital ads boosts online shopping.

Note, however, that the results may have some limitations. To get unbiased estimates, the methodology employed assumes that all the potential variables that could affect the outcome are included in the analysis. Although we included all of the relevant drivers of online shopping identified in the most up-to-date research (Garín-Muñoz et al., 2019; Pérez-Amaral et al., 2020) we cannot completely discard some limited degree of unmeasured confounding. Additionally, we cannot entirely discard some reverse causality or simultaneity, that is, that online shopping could cause the use of ad blockers. However, in our data the online shopping activity takes place well after the individual's decision to use ad blockers, which should mitigate reverse causality.

6. Conclusions and policy implications

Digital advertising revenues sustain many of the webpages and services offered over the Internet as in many occasions those are provided for free to Internet surfers. Social media services, electronic communication services such as email, instant messaging or calls over the public Internet, online media and many other services over the Internet are funded by sourcing revenues from third parties and one of their main sources of revenues is advertising placement. The growth in the use of ad blockers severely compromises the survival of those "free to the consumer" web services. Shiller et al. (2018) show us that each additional percentage point of a site's visitors blocking ads reduces the site's web traffic by 0.67% over 35 months. They also show that the impacted sites provide less content over time, hence, provide some evidence than ad blocking poses a threat to the ad supported web.

However, this research finds evidence that ad blocking has a positive effect on e-commerce online shopping. The explanation hinges on the positive effects of ad blocking on the web-browsing experience, as it prevents undesirable interruptions due to advertising, increases confidence in a safe web navigation (as digital ads may include bugs and malware and ad blockers prevent customization based on browsing history) and releases bandwidth and screen space for other uses that consumers may prefer. It may even

[11] The background logit model results and the propensity score balance's plot can be obtained from the authors.
[12] In the raw (unmatched) sample the users of ad blockers bought on average 2.348 more items than the non-users.

be that by reducing their exposure to large amounts of ads, these consumers are less distracted, more aware and choice-confident.

Given the role of digital advertising in sustaining the web, stakeholders, including advertisers, companies and regulators, should pay attention to our controversial result, as it is indicative of a trade-off between the maintaining of the ad supported web and the enhancing of the browsing experience (so that there is more online shopping). As pointed out by Redondo and Aznar (2018) a possible way to improve browsing experience would be to regulate the types of ads in the web avoiding the most annoying and intrusive ones. In this way, most consumers would not resort to the use of ad blockers to prevent nuisance advertising. Interestingly, it seems that stakeholders are moving towards these approaches. Thus, recently a group of leading associations and companies involved in online media (including the two major players in the online ad market, Facebook and Google) has created the "Coalition for Better Ads" to improve consumers' experience with online advertising. This coalition promotes "Better Ads Standards" identifying the type of ads that are more troublesome and, hence, most likely to drive consumers to use ad blockers.[13] Additionally, Google announced in May 2020 its plan to *"limit the resources a display ad can use before the user interacts with the ad"* (i.e., blocking it) within its owned browser Chrome.[14]

Disclaimer

The opinions and analysis that appear in this paper are responsibility of the authors only and do not necessarily represent those of the CNMC.

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[13] See https://www.betterads.org.
[14] See https://blog.chromium.org/2020/05/resource-heavy-ads-in-chrome.html.