Web Appendix

How Does the Adoption of Ad Blockers Affect News Consumption?

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WEB APPENDIX A:
INFORMATION ABOUT THE ADS ON OUR NEWS WEBSITE
AND COMPETING NEWS WEBSITES

Our news website runs display advertising according to the standard advertising formats provided by the Interactive Advertising Bureau (IAB 2017). More precisely, our website runs leaderboard ads (728 × 90 pixels) on top of the page and rectangle ads (300 × 250 to 336 × 280 pixels) in the middle of the page on both desktop and mobile devices. In addition, our website runs skyscraper ads (120 × 600 pixels) on the side of the page on desktops. On average, our website features five display ads on its homepage and three display ads on each article page. These levels of advertising are comparable to, and in some cases even lower than, the levels of advertising on other similar premium news websites such as *The New York Times*, the *Washington Post*, and *The Guardian*. We further note that our news website does not run large half-page ads (300 × 600 pixels) or sizeable mobile banner ads (320 × 100 pixels), whose removal by an ad blocker could lead to substantial changes in the display of the content. In addition, our website did not run native advertising during the observation period of our study.

Depending on the ads on competing news websites, ad blocker adoption might create substitution effects across news websites. Specifically, after adopting an ad blocker, a user might gravitate more to news websites that display more ads (which the user no longer needs to endure) and diminish her news consumption on websites with fewer ads. Our data do not enable us to fully examine this possibility, as we only observe consumption on our news website. However, we have carried out a preliminary analysis (elaborated below) that suggests that, if bias due to such substitution exists, the effects identified in our main analysis are likely to have been underestimated rather than overestimated.

To this end, we relied on comparisons between the number of ad slots per page on our website and on its competitors' websites, as elaborated in what follows. We identified competitors using several sources: Alexa's Audience Overlap tool (which lists websites sharing similar users), the Top 10 online news brands in our publisher's focal country, as listed by the Digital News Report (Newman et al. 2016), and the Top 10 global news brands (e.g., the *New York Times*). We went to the Internet Archive and used an ad blocker while browsing the historical websites of our focal publisher and its competitors, and we counted how many ads were blocked on each website. According to the number of blocked ad slots, we found that our website displayed 3–12 fewer ads per page than its competitors did. This result indicates that, if substitution effects were at play—such that ad blocker adopters consumed more news on sites displaying more ads—our estimates are likely to have understated the actual effect of ad blocker adoption on overall news consumption.

WEB APPENDIX B: CAUSAL ASSUMPTIONS AND HECKMAN SELECTION MODEL

Causal Assumptions, Challenges, and Solutions

To identify the causal effects of ad blocker adoption on our news consumption measures, we follow the Rubin Causal Model, the workhorse model in causal inference in the economics and marketing literature (Imbens and Wooldridge 2009; Rosenbaum and Rubin 1983). Imbens and Wooldridge (2009) summarize the causal assumptions under the Rubin Causal Model as follows:

Assumption 1. Unconfoundedness

$$w_i \perp (Y_i(0), Y_i(1)) | X_i.$$

The unconfoundedness assumption assumes that no observed or unobserved variables (X_i) correlate with the potential outcome ($Y_i(0)$ or $Y_i(1)$) and the treatment (w_i).

Assumption 2. Overlap

$$0 < pr(w_i = 1 | X_i = x) < 1, \text{for all x.}$$

The overlap assumption assumes that the support of the conditional distribution of X_i given $w_i = 0$ overlaps completely with that of the conditional distribution of X_i given $w_i = 1$.

We summarize these causal assumptions, the resulting identification challenges and our solutions in TABLE W1.

TABLE W1. CAUSAL ASSUMPTIONS, CHALLENGES, AND SOLUTIONS

Causal Assumption	Challenge	Solution	Specification
Unconfoundedness	Users differ in observed and time-invariant ways	Coarsened exact matching	Main Specification (TABLE 4)
	Users differ in unobserved and time-invariant ways	Individual-fixed effect	
	Seasonality	Week-fixed effect	
	Users differ in unobserved characteristics related to ad blocker adoption	Compare results for subsamples of ad blocker users (i.e., early vs. late adopters and abandoners vs. continuous users)	Robustness Check (TABLE 4)
	Unexplained part of adoption decision (error term) related to news consumption	Heckman selection model	Robustness Check (TABLE W2 & TABLE W3)
	Users differ in time-varying ways	Placebo test and adding time-varying controls	Robustness Check (TABLE W15 & TABLE W16)
Overlap	Unbalanced empirical distribution of covariates between treatment group and control group	Coarsened exact matching	TABLE 3

Heckman Selection Model

To formally test whether a user's ad blocker adoption involves a selection bias (e.g., a user anticipates reading more news and thus adopts an ad blocker), we use the Heckman selection model (Heckman 1979). In the marketing literature, the Heckman selection model has been used in the past to test and correct for selection bias in an individual's (a household's) decision to adopt a technology (Bronnenberg, Dubé, and Mela 2010; Narang and Shankar 2019).

In the first stage, we model the user's ad blocker adoption decision. Survey studies (Mathur et al. 2018; Newman et al. 2016; Pritchard 2021; Redondo and Aznar 2018; Singh and Potdar 2009; Sołtysik-Piorunkiewicz, Strzelecki, and Abramek 2019; Vratonjic et al. 2013) have identified three main reasons why users adopt ad blockers: the annoyance of ads, page loading speed, and privacy concerns. Therefore, we look for user characteristics that can serve as proxies for these three reasons to adopt an ad blocker.

First, we proxy for ad annoyance by the user's number of page views from mobile (rather than desktop) devices. We assume that ads are likely to be more annoying on mobile devices because mobile devices tend to have smaller screen sizes than desktops. Second, we capture page loading speed by the users' JavaScript versions. Specifically, we assume that users with older JavaScript versions load pages more slowly than users with newer JavaScript versions. Third, for the role of privacy concerns, we use a binary indicator that is one if a user has ever rejected a cookie (and zero otherwise). The underlying assumption is that users who have rejected at least one cookie have stronger privacy concerns than users who have never rejected a cookie.

In addition, we add a user's most frequently-used browser in the pre-treatment period as an explanatory variable into the model for the ad blocker adoption decision. The reason is that an external event happened during our observation period that triggered a large amount of consumer awareness of ad blockers, which was accompanied by a significant increase in ad blocker adoption. That event is the release of iOS 9 on the Apple iPhone in September 16, 2015, which is in week 15 of our observation period. With iOS 9, Apple offered, for the first time, a mobile operating system that allowed for a content blocking feature. That feature enabled mobile ad blocker software to be used on the iPhone, creating massive consumer awareness of ad blockers. Data from Google Search Trends support this massive increase in consumer awareness. Specifically, the Google Interest for the term "ad blocker" peaked at its largest volume ever (i.e., 100 - the highest popularity for this search term from 2004 till today) during September 2015, as shown in FIGURE W1 and FIGURE W2.

When we check the related queries for the keyword "ad blocker" during September 2015, we find that the search query with the largest increase is "best iOS 9 ad blocker", and the most popular search query is "chrome ad blocker", as shown in FIGURE W3 and FIGURE W4. The fact that the most popular search query was "chrome ad blocker" suggests that, during the iOS 9 event, users learned about ad blockers not only for Apple's browser but also for other browsers (here: Chrome). All these observations are in line with our expectation that the release of iOS 9 triggered a high ad blocker adoption rate during our observation period. Thus, we include a variable that captures a user's most frequently used browser in the pre-treatment period (for short: mode browser) as the exclusive variable for the ad blocker adoption decision. Our idea is that users who primarily used an Apple browser in the pre-treatment period were more likely than users of other browsers to adopt an ad blocker because of the external event in which Apple made an ad blocking feature available.

FIGURE W1. GOOGLE SEARCH FOR THE TERM "AD BLOCKER" (WORLDWIDE) FROM 2004 TO 2020

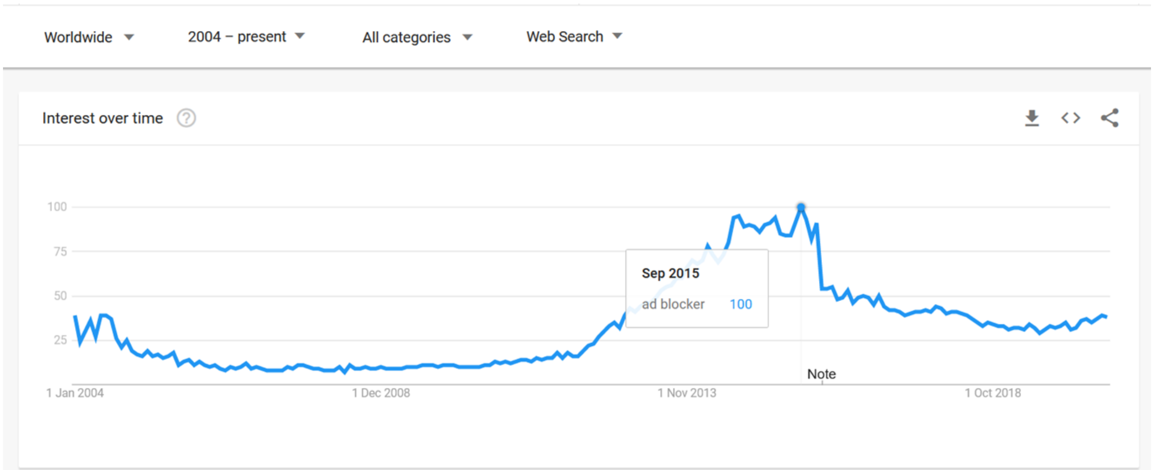


FIGURE W2. GOOGLE SEARCH FOR THE TERM "AD BLOCKER" (WORLDWIDE) IN SEPTEMBER, 2015

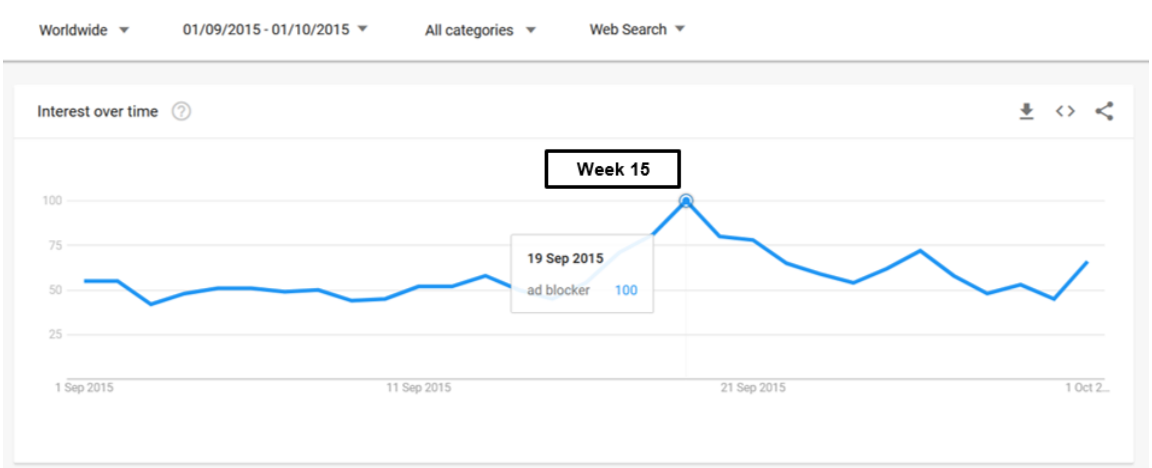


FIGURE W3. RELATED TOPICS AND RELATED QUERIES FOR "AD BLOCKER" WITH THE LARGEST INCREASES IN POPULARITY ACCORDING TO GOOGLE SEARCH TRENDS (WORLDWIDE) IN SEPTEMBER, 2015

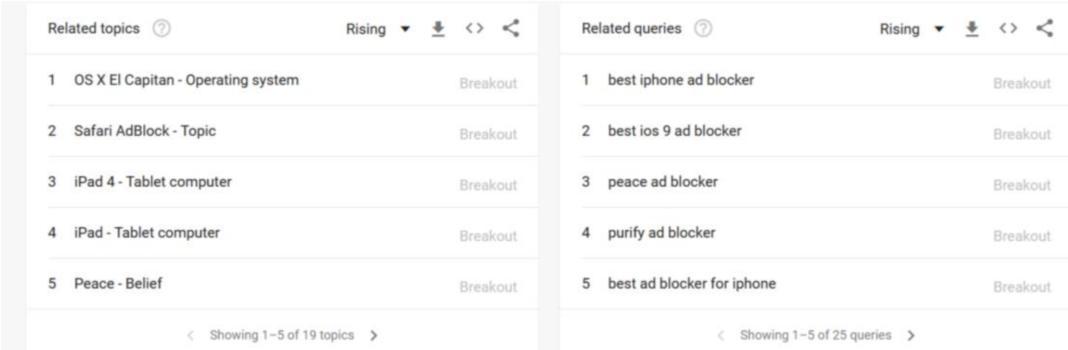
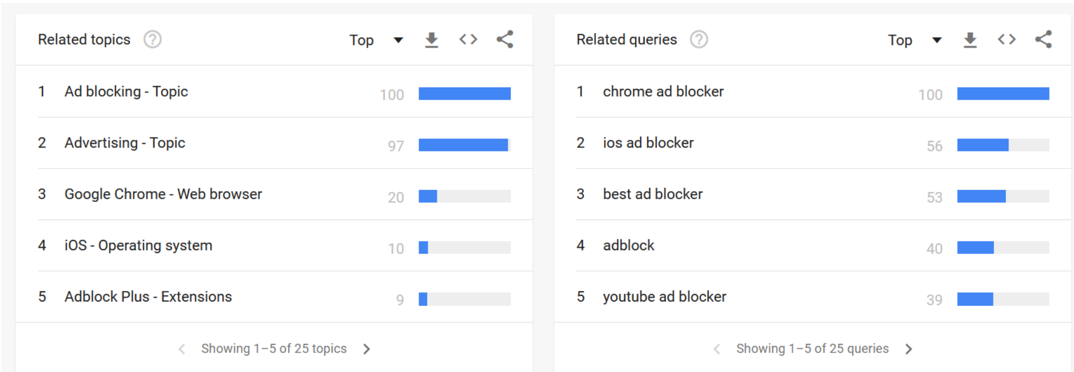


FIGURE W4. MOST POPULAR RELATED TOPICS AND RELATED QUERIES FOR "AD BLOCKER" ON GOOGLE SEARCH TRENDS (WORLDWIDE) IN SEPTEMBER, 2015



Thus, in the first stage, we estimate the following probit model:

$$\text{(W1)} \qquad \mathrm{Adoption}_i = \alpha + \beta_1 * \mathrm{CookieDeleted}_i + \beta_2 * \mathrm{MobileViews}_i + \beta_3 * \mathrm{JavaScript}_i + \beta_4 * \mathrm{ModeBrowser}_i + \delta_t + \varepsilon_i,$$

where $\mathrm{Adoption}_i$ is the ad blocker adoption decision of a user i; α is the intercept; $\mathrm{CookieDeleted}_i$ is coded as 1 if user i rejected at least one cookie in the pre-treatment period; $\mathrm{MobileViews}_i$ is a user i's average weekly number of page impressions generated on a mobile device in the pre-treatment period; $\mathrm{JavaScript}_i$ is the JavaScript version most frequently used by user i in the pre-treatment period, with a version below 1.5 as baseline; ModeBrowser_i is a dummy-coded categorical variable that describes whether a particular browser (which could be either Apple Safari, Google Chrome, Microsoft Internet Explorer, or "Others" (including Mozilla Firefox, Blackberry, or Opera)) is the most frequently used browser of user i in the pre-treatment period, with Microsoft Internet Explorer as a baseline because it is the default browser for Windows and most likely used by the least tech-savvy users; δ_t is a week-fixed effect; ε_i is the error term.

TABLE W2 reports the results of the first stage of the Heckman selection model. According to our expectation, users who are more likely to browse on mobile devices and primarily use Apple browsers (compared to users who primarily use Microsoft browsers) are more likely to adopt an ad blocker.

On a related note, our observation period covers a time when ad blockers were first beginning to gain popularity. The adoption and dis-adoption rates are uneven due to the Apple events discussed above, and, more broadly, the fact that ad blockers were still in an early stage of diffusion. It is possible that the effects we identified might not fully generalize to ad blocker adopters in later stages of ad blocker diffusion.

TABLE W2. FIRST STAGE OF HECKMAN SELECTION MODEL

	Adoption
(Intercept)	3.798
	(48.178)
CookieDeleted	.396
	(.400)
MobileVisits	.012***
	(.001)
JavaScript1.5	-7.856
(Baseline: JavaScript below 1.5)	(68.134)
JavaScript1.6	-4.525
	(48.178)
JavaScript1.8	-4.045
	(48.178)
ModeBrowserApple	.831***
(Baseline: Microsoft)	(.022)
ModeBrowserGoogle	.258***
	(.028)
ModeBrowserOthers	.513***
	(.043)
Week 8	-.002
(Baseline: Week 7)	(.044)
Week 9	.001
	(.044)
Week 10	.051
	(.043)
Week 11	.038
	(.042)
Week 12	.031
	(.042)
Week 13	.046
	(.042)
Week 14	-.002
	(.042)
Week 15	-.064
	(.041)
Week 16	-.208***
	(.040)
N	21,068

Notes: The model is estimated on a sample not matched with the first stage variables but matched with all other variables in Table 3. Standard errors appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

In the second stage, we estimate the same model as in the main paper (Equation 1) but without individual-level fixed effects. Additionally, we include the inverse Mills ratio (from the first stage of the Heckman selection model, see TABLE W2), capturing the possibility that the first-stage error could affect the second-stage model. Notably, any variables omitted in the first stage would be captured in the error term, including whether users anticipate reading more news or spending more time online. A t-test on the inverse Mills ratio is thus a direct test on the selection bias of ad blocker adoption on news consumption while making only one joint normality assumption of the first- and second-stage error terms.

TABLE W3 reports the second-stage results of the Heckman selection model. As shown in TABLE W3, the 1-week and 5-week effects (β_1 and β_2 in Equation 1 in the main text) are still significant and qualitatively similar to our estimates from the main specification (shown in TABLE 4). More importantly, for article views, the parameter of the inverse Mills ratio is –.062 with a *p*-value of .118, and for breadth, the parameter is –.013 with a *p*-value of .644. Accordingly, we cannot reject the null hypothesis (i.e., the absence of a sample selection bias) at our conventional significance level ($p < .050$) for article views and breadth. Thus, we provide evidence for the absence of selection bias of the effect of ad blocker adoption on the quantity and breadth of news consumption. Overall, these results suggest that it is not a user's anticipated news consumption that influences her decision to adopt an ad blocker, especially considering that ad blockers perform the same function on all websites, whether or not it is a news website).

TABLE W3. SECOND-STAGE RESULTS OF HECKMAN SELECTION MODEL

	Article Views	Breadth
(Intercept)	1.612^{***}	1.281^{***}
	(.049)	(.034)
β_1	$.261^{***}$	$.173^{***}$
	(.044)	(.031)
β_2	$.221^{***}$	$.160^{***}$
	(.059)	(.041)
Week 8	.043	.015
	(.051)	(.036)
Week 9	.025	.012
	(.050)	(.035)
Week 10	.007	-.004
	(.048)	(.034)
Week 11	.011	.010
	(.048)	(.034)
Week 12	$.126^{**}$	$.088^{**}$
	(.049)	(.034)
Week 13	.003	-.005
	(.057)	(.040)
Week 14	.055	-.013
	(.061)	(.043)
Week 15	.024	-.045
	(.068)	(.047)
Week 16	-.052	.006
	(.073)	(.051)
invMillsRatio	-.062	-.013
	(.040)	(.028)
Sigma	.977	.683
Rho	-.063	-.019
N	21,068	21,068

Note: The model is estimated on a sample not matched with the first stage variables but matched with all other variables in Table 3. Standard errors appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

WEB APPENDIX C:
ROBUSTNESS CHECKS ON DIFFERENT NEWS CATEGORIES, CUT-OFF PERIODS, AND LONGER PRE-TREATMENT PERIODS

In this section, we examine the robustness of the effect on different news categories, different cut-off periods, and different pre-treatment periods.

First, we decompose the main effect (on the quantity of news consumption) across various news and non-news categories. These categories include "hard" news (political news, economic news, and opinion news, following Angelucci and Cagé (2019)), "soft" news (sports, culture & art, lifestyle news), and non-news pages (e.g., account settings and play pages that include games such as Sudoku or Mahjong).

As shown in TABLE W4, We find that the increase in article views attributable to ad blocker adoption is driven primarily by increases in the consumption of hard news. None of the soft news categories has significant effects over 5 weeks, though there are 1-week effects for Sports and for Art & Culture. In addition, our analysis reveals no effect of ad blocker adoption on views of non-news pages, except from homepage and archive. Importantly, none of the news category has a negative effect, indicating that no substitution happens across news categories.

From TABLE W6 to TABLE W8, we report the robustness of the effect with different cut-off periods. In TABLE W9, we report the robustness of the effect with longer pre-treatment period. For brevity, we report all results with news categories classified into hard news and soft news according to the definition above, instead of the original news category.

TABLE W4. TREATMENT EFFECT ON ARTICLE VIEWS IN EACH NEWS CATEGORY

	International Political	Regional Political	Local Political	Economy	Finance	Opinion	Sport	Art & Culture
β_1	.184***	.108***	.068**	.145***	.086***	.085***	.120***	.061***
	(.032)	(.028)	(.021)	(.027)	(.024)	(.022)	(.028)	(.018)
β_2	.092*	.055	.046	.088**	.065*	.056*	.034	.030
	(.040)	(.034)	(.027)	(.031)	(.028)	(.027)	(.030)	(.022)
N	9,370	9,370	9,370	9,370	9,370	9,370	9,370	9,370
R^2	.485	.454	.425	.437	.575	.346	.594	.348

	Lifestyle	Brief	News Ticker	Panorama	Transpor-tation	Science	Sunday News	Photo Stream
β_1	.015	.009	.016	.078***	.010	.025	.030*	.021
	(.011)	(.006)	(.016)	(.021)	(.007)	(.013)	(.015)	(.012)
β_2	.013	.013	-.007	.035	.019	-.004	.014	.005
	(.014)	(.009)	(.016)	(.026)	(.014)	(.013)	(.021)	(.014)
N	9,370	9,370	9,370	9,370	9,370	9,370	9,370	9,370
R^2	.314	.265	.471	.368	.348	.367	.266	.304

	Video	Digital	Special	Data
β_1	.013*	.041**	.004	.000
	(.006)	(.015)	(.004)	(.002)
β_2	.006	.015	.003	.001
	(.008)	(.018)	(.003)	(.003)
N	9,370	9,370	9,370	9,370
R^2	.136	.455	.160	.193

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample of ad blocker adopters and non-adopters : $Y_{it} = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W5. TREATMENT EFFECT ON PAGE VIEWS IN EACH NON-NEWS CATEGORY

	Homepage	Weather	Play Page	Account	Others	Search	Archive
β_1	.258***	.016	.002	.006	.015	.003	.008*
	(.035)	(.015)	(.005)	(.022)	(.011)	(.014)	(.004)
β_2	.137**	.012	.001	.000	.012	-.015	.006
	(.044)	(.018)	(.008)	(.030)	(.013)	(.018)	(.003)
N	9,370	9,370	9,370	9,370	9,370	9,370	9,370
R^2	.665	.709	.759	.332	.207	.283	.191

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample of ad blocker adopters and non-adopters: $Y_{it} = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W6. ROBUSTNESS CHECK USING 1 WEEK AS CUT-OFF PERIOD

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	.262***	.157***	.224***	.035***	.239***	.178***
	(.008)	(.005)	(.006)	(.004)	(.008)	(.007)
β_2	.132***	.070***	.130***	.010*	.140***	.142***
	(.010)	(.007)	(.007)	(.004)	(.010)	(.008)
N	203,852	203,852	203,852	203,852	203,852	203,852
R^2	.689	.677	.747	.602	.686	.656

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the unmatched sample: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W7. ROBUSTNESS CHECK USING 3 WEEKS AS CUT-OFF PERIOD

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	.240***	.136***	.205***	.031***	.203***	.191***
	(.011)	(.007)	(.008)	(.005)	(.012)	(.010)
β_2	.083***	.040***	.073***	.011	.089***	.113***
	(.014)	(.009)	(.010)	(.006)	(.014)	(.011)
N	167,668	167,668	167,668	167,668	167,668	167,668
R^2	.678	.672	.734	.604	.677	.641

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the unmatched sample: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W8. ROBUSTNESS CHECK USING 4 WEEKS AS CUT-OFF PERIOD

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	.268***	.152***	.215***	.040***	.255***	.190***
	(.019)	(.013)	(.013)	(.009)	(.019)	(.017)
β_2	.093**	.047*	.050*	.033*	.122***	.097***
	(.029)	(.020)	(.020)	(.014)	(.031)	(.027)
N	142,074	142,074	142,074	142,074	142,074	142,074
R^2	.672	.670	.720	.609	.673	.629

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the unmatched sample: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W9. ROBUSTNESS CHECK USING WEEK 1 TO WEEK 11 AS PRE-TREATMENT PERIOD

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	.330***	.207***	.243***	.069***	.299***	.169***
	(.037)	(.023)	(.024)	(.017)	(.038)	(.029)
β_2	.199***	.127***	.169***	.028	.196***	.064
	(.047)	(.030)	(.033)	(.020)	(.048)	(.033)
N	14,273	14,273	14,273	14,273	14,273	14,273
R^2	.434	.432	.549	.382	.479	.494

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on a matched sample from week 1 to week 16 (full observation period): $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$.
R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

WEB APPENDIX D: ROBUSTNESS CHECKS ON MATCHING METHOD

In this section, we provide background information of coarsened exact matching (CEM) and check for the robustness of the results with another matching method.

CEM is a nonparametric method of controlling for observed confounders, more commonly called "covariates" in the matching literature (herein, the terms "confounder" and "covariate" are used interchangeably). CEM involves matching on a vector of covariates (instead of on a scalar representing a distance metric summarizing all covariates, as in other matching methods) and using the covariates' original dimensions. CEM keeps categorical covariates at their actual values. Continuous covariates, in turn, are "coarsened" into bins. In our context, for example, the number of page views per week, which may range between 1 and 50, can be coarsened into the bins 1 to 5, 6 to 10, etc. Then, CEM conducts exact matching with all covariates, with the continuous covariates coarsened.

Specifically, each observation is assigned to a unique stratum containing all (treated and control) observations with identical values of all covariates. For example, a male who is 30-35 years old, who views 11-15 pages a week, is placed in a stratum containing other males who are 30-35 years old and who view 11-15 pages a week. Thus, each stratum matches a set of treated units to a set of control units with the same values for the covariates. Strata containing zero treated units or zero control units are then "pruned" out of the dataset. In the remaining strata, weights are used to adjust for unequal numbers of matched treated and control units. These weights are incorporated into subsequent analyses.

In this way, CEM balances the covariates on their original dimensions and eliminates differences in the covariates between the treatment and control groups in all moments, quantiles, and functional forms (Iacus, King, and Porro 2012). In contrast, other matching methods that focus on the univariate balance of the means of covariates (e.g., through estimating and matching on a propensity score obtained from a logit regression on covariates) might not remove, and in fact, can even increase, bias due to imbalances of other moments or functional forms (King and Nielsen 2019).

We can then combine CEM with other causal inference methods, which normally require a model. In these cases, applying CEM (as opposed to reliance on a full, non-matched sample or a sample matched by another model-dependent matching method) can help decrease model dependence and statistical bias (Iacus, King, and Porro 2012). However, when the number of covariates is large, it can be challenging to find exactly matched pairs, even with coarsened variables. In this case, matching on a univariate score (such as propensity score) is more efficient. In addition, a univariate score also helps in terms of visualization, as illustrated in FIGURE 3.

We report our results using CEM in TABLE 4. Herein, we report the robustness of the result with other matching and non-matching methods.

First, we check the robustness of our results by running our model (Equation 1 in the main manuscript) using the unmatched sample. The results are reported in TABLE W10 and remain similar to our main results.

Second, we run Equation W2 to check for robustness to missing observations due to matching on demographics (i.e., age, gender, income). The demographics data came from the news publisher's customer relationship management (CRM) dataset. A demographic value could be missing because a user deliberately did not report that value or because of a coding error. To evaluate the effects of missing demographic values, we add an interaction between each treatment effect variable in our model and a dummy variable Missing_i, whose value is 1 if user i is missing any demographic variables (Equation W2 below). We report the results in TABLE W11. The coefficients (β_3 and β_4) of the interaction terms are statistically insignificant, which indicates that missing demographic values occur at random (and, therefore, do not induce bias in the estimation). In addition, our main effect remains similar.

(W2)
$$\mathrm{Y_{it}} = \alpha_i + \delta_t + \beta_1 * \mathrm{I_{it1}}(\text{within 1 week of Treatment}_{\mathrm{it}}) + \beta_2 * \mathrm{I_{it2}}(\text{remaining weeks since Treatment}_{\mathrm{it}}) + \beta_3 * \mathrm{I_{it1}}(\text{within 1 week of Treatment}_{\mathrm{it}}) * \text{Missing}_{\mathrm{i}} + \beta_4 * \mathrm{I_{it2}}(\text{remaining weeks since Treatment}_{\mathrm{it}}) * \text{Missing}_{\mathrm{i}} + \varepsilon_{\mathrm{it}}.$$

Third, we check for the robustness of controlling for observed variables (rather than using them in the matching; see TABLE 3 or TABLE W12 for the list of these variables). In addition, we add an interaction between the week-fixed effect and the browser mode in the pre-treatment period because we know that the Apple iOS 9 event triggered ad blocker adoption and, thus, users with different browsers might experience different time trends. We run Equation W3 with these additional variables: matching variables ($\text{MatchingVariables}_{\mathrm{i}\tau}$ in W3) and interactions between week-fixed effect and mode browser($\delta_t * \text{ModeBrowser}_{\mathrm{i}}$ in W3) and report the results in TABLE W12. Our main effects again remain similar.

$$\text{(W3)} \qquad Y_{it} = \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it})$$
$$+\beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it})$$
$$+ \sum_{\tau=1}^{\tau=n} \gamma_\tau * \text{MatchingVariables}_{i\tau} + \delta_t + \eta_{it} * (\delta_t * \text{ModeBrowser}_i) + \varepsilon_{it}$$

Fourth, we check for the robustness of the results to the CEM procedure. To this end, we create a matched sample using an alternative matching method, propensity score matching. We rerun the model specified in the main text (Equation 1) on this sample. The results (reported in TABLE W13) continue to remain similar.

TABLE W10. ROBUSTNESS CHECK ON UNMATCHED SAMPLE

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	.260***	.159***	.231***	.032***	.229***	.185***
	(.009)	(.006)	(.007)	(.004)	(.010)	(.008)
β_2	.110***	.067***	.122***	.002	.120***	.122***
	(.012)	(.007)	(.008)	(.005)	(.012)	(.009)
N	252,428	252,428	252,428	252,428	252,428	252,428
R^2	.631	.624	.685	.541	.633	.606

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the unmatched sample: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W11. ROBUSTNESS CHECK ON MISSING OBSERVATIONS IN DEMOGRAPHICS

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	.245***	.151***	.212***	.036***	.216***	.198***
	(.015)	(.010)	(.010)	(.007)	(.015)	(.013)
β_2	.088***	.052***	.096***	.007	.119***	.115***
	(.017)	(.012)	(.013)	(.008)	(.018)	(.015)
β_3	.010	-.008	.006	-.001	.023	-.031
	(.022)	(.014)	(.015)	(.010)	(.022)	(.019)
β_4	.026	.001	.027	-.002	.012	.007
	(.025)	(.016)	(.018)	(.010)	(.026)	(.021)
N	118,696	118,696	118,696	118,696	118,696	118,696
R^2	.679	.668	.745	.562	.676	.636

Notes: Each column refers to a separate regression of the following model on the unmatched sample:
$\log(Y_{it}+1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \beta_3 * I_{it1}(\text{within 1 week of Treatment}_{it}) * \text{Missing}_i + \beta_4 * I_{it2}(\text{remaining weeks since Treatment}_{it}\text{for treated } * \text{Missing}_i) + \varepsilon_{it}$.
β_1 represents the 5-week effect, and β_2 represents the interaction effect of the 5-week effect and any missing observations (e.g., due to users not revealing full information in our CRM data). Insignificant β_3 and $\beta_4$indicate matching does not induce bias in the estimation. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses.
$^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W12. ROBUSTNESS CHECK ON CONTROLLING FOR OBSERVED VARIABLES (INSTEAD OF USING MATCHING METHOD)

Independent Variables \ Dependent Variables	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
(Intercept)	-.277	-.148	.481**	.091	-.224	-.552*
	(.226)	(.161)	(.159)	(.129)	(.231)	(.215)
I_{it1}	.302***	.196***	.290***	.042***	.227***	.206***
	(.013)	(.009)	(.009)	(.007)	(.013)	(.012)
I_{it2}	.175***	.127***	.239***	-.004	.157***	.140***
	(.014)	(.010)	(.010)	(.008)	(.014)	(.013)
Gender	-.007	.009	.016**	-.016***	-.021**	-.004
	(.007)	(.005)	(.005)	(.004)	(.007)	(.007)
Income2	.015	-.018	-.007	.006	-.012	.034*
	(.017)	(.012)	(.012)	(.010)	(.017)	(.016)
Income3	.040*	.006	.011	.007	.014	.027
	(.016)	(.011)	(.011)	(.009)	(.016)	(.015)
Income4	.006	-.010	.002	-.009	.003	-.005
	(.017)	(.012)	(.012)	(.010)	(.018)	(.016)
Income5	.018	-.003	.010	-.002	-.008	.013
	(.016)	(.011)	(.011)	(.009)	(.016)	(.015)
Income6	.028	.000	.004	.004	.010	-.007
	(.015)	(.011)	(.011)	(.009)	(.016)	(.015)
Age25-29	.051	.045	.024	.018	.070	.030
	(.041)	(.029)	(.029)	(.023)	(.042)	(.039)

Independent Variables \ Dependent Variables	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
Age30-34	.009	-.004	.013	-.012	.021	-.038
	(.038)	(.027)	(.027)	(.022)	(.039)	(.036)
Age35-39	.015	.030	.020	-.019	.045	-.103**
	(.035)	(.025)	(.025)	(.020)	(.036)	(.033)
Age40-44	.008	.014	.030	-.034	-.000	-.010
	(.034)	(.024)	(.024)	(.019)	(.035)	(.032)
Age45-49	-.014	.016	.028	-.031	-.017	.001
	(.033)	(.024)	(.023)	(.019)	(.034)	(.032)
Age50-54	-.033	-.006	.006	-.033	-.027	-.010
	(.033)	(.024)	(.023)	(.019)	(.034)	(.032)
Age55-59	-.014	.008	.013	-.022	-.014	.034
	(.033)	(.024)	(.024)	(.019)	(.034)	(.032)
Age60-64	-.039	-.012	.003	-.035	-.017	.020
	(.034)	(.024)	(.024)	(.019)	(.034)	(.032)
Age65-69	-.025	-.012	-.008	-.020	.002	.033
	(.034)	(.024)	(.024)	(.019)	(.034)	(.032)
Age70-74	-.028	-.010	-.009	-.023	.020	.001
	(.034)	(.024)	(.024)	(.019)	(.034)	(.032)
Age75-79	.003	.006	.020	-.021	.029	.038
	(.034)	(.024)	(.024)	(.020)	(.035)	(.033)
Age80-84	.034	.031	.048	-.023	.079*	.026
	(.035)	(.025)	(.025)	(.020)	(.036)	(.033)
Pre-ArticleViews	.006***	-.005***	-.008***	.008***	.004***	.004***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Pre-Breadth	.254***	.218***	.053***	.121***	.245***	.113***
	(.002)	(.001)	(.001)	(.001)	(.002)	(.002)
Pre-Visits	.001*	-.002***	.069***	-.036***	.000	.005***
	(.001)	(.000)	(.000)	(.000)	(.001)	(.001)
Firstweek1	.172***	.133***	.090***	.083***	.085***	.045*
	(.020)	(.014)	(.014)	(.011)	(.020)	(.019)
Firstweek2	.122***	.095***	.018	.097***	.058**	-.018
	(.021)	(.015)	(.015)	(.012)	(.021)	(.020)
Firstweek3	.072***	.065***	-.011	.088***	.018	-.041*
	(.021)	(.015)	(.015)	(.012)	(.022)	(.020)
Firstweek4	.055*	.041**	-.029	.076***	.018	-.027
	(.022)	(.015)	(.015)	(.012)	(.022)	(.020)
Firstweek5	.041	.024	-.022	.062***	.004	-.020
	(.022)	(.015)	(.015)	(.012)	(.022)	(.021)
Firstweek6	.079***	.059***	-.027	.097***	.052*	-.009
	(.022)	(.016)	(.016)	(.013)	(.023)	(.021)
Firstweek7	.028	.012	-.023	.057***	.015	-.012
	(.022)	(.016)	(.016)	(.013)	(.023)	(.021)
Firstweek8	.038	.033*	-.011	.056***	.009	-.016
	(.023)	(.017)	(.016)	(.013)	(.024)	(.022)
Firstweek9	.031	.014	-.051**	.067***	-.016	-.004
	(.027)	(.019)	(.019)	(.015)	(.027)	(.025)
Firstweek10	.053*	.033	-.024	.052***	.040	-.009

Independent Variables \ Dependent Variables	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
	(.026)	(.019)	(.018)	(.015)	(.027)	(.025)
Lastweek11	.060*	.034	-.003	.041*	.033	.017
	(.028)	(.020)	(.020)	(.016)	(.029)	(.027)
Lastweek12	.058*	.043*	-.009	.058***	.018	.012
	(.027)	(.020)	(.019)	(.016)	(.028)	(.026)
Lastweek13	.090***	.074***	.007	.077***	.031	.017
	(.026)	(.018)	(.018)	(.015)	(.026)	(.024)
Lastweek14	.123***	.100***	.015	.105***	.040	.029
	(.024)	(.017)	(.017)	(.014)	(.025)	(.023)
Lastweek15	.172***	.150***	.085***	.114***	.055*	.031
	(.023)	(.016)	(.016)	(.013)	(.023)	(.022)
Lastweek16	.330***	.260***	.288***	.119***	.182***	.066**
	(.022)	(.016)	(.015)	(.012)	(.022)	(.021)
Pre-Mobile Page Views	.011***	.005***	.007***	.002***	.011***	.009***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Week8	.195	.106	-.061	.216	.112	-.117
	(.342)	(.243)	(.241)	(.195)	(.349)	(.325)
Week9	.051	.199	-.096	.181	.091	-.021
	(.342)	(.243)	(.240)	(.195)	(.349)	(.325)
Week10	.445	.377	.129	.283	.133	.342
	(.302)	(.214)	(.212)	(.172)	(.308)	(.286)
Week11	.429	.368	.091	.251	.324	.314
	(.308)	(.218)	(.216)	(.175)	(.314)	(.292)
Week12	.435	.469*	.292	.164	.267	.277
	(.322)	(.229)	(.226)	(.183)	(.328)	(.305)
Week13	.838*	.513*	.181	.487**	.735*	.334
	(.331)	(.235)	(.233)	(.188)	(.338)	(.314)
Week14	.576	.322	.243	.203	.466	.479
	(.314)	(.223)	(.221)	(.179)	(.321)	(.298)
Week15	.399	.230	-.093	.397*	.378	.233
	(.322)	(.229)	(.226)	(.183)	(.329)	(.305)
Week16	.329	.023	-.078	.280	.525	.180
	(.322)	(.229)	(.226)	(.183)	(.329)	(.305)
ModeBrowserApple	.429	.331*	.238	.179	.263	.537*
	(.223)	(.158)	(.157)	(.127)	(.227)	(.211)
ModeBrowserGoogle	.338	.263	.243	.110	.236	.418*
	(.224)	(.159)	(.157)	(.127)	(.228)	(.212)
ModeBrowserMicrosoft	.493*	.335*	.315*	.183	.329	.487*
	(.223)	(.158)	(.157)	(.127)	(.227)	(.211)
ModeBrowserMozilla	.439*	.318*	.324*	.124	.300	.526*
	(.224)	(.159)	(.157)	(.127)	(.228)	(.212)
Week8*ModeBrowserApple	-.149	-.069	.066	-.194	-.038	.118
	(.343)	(.244)	(.241)	(.195)	(.350)	(.325)
Week9*ModeBrowserApple	-.045	-.203	.057	-.156	-.066	.012
	(.343)	(.244)	(.241)	(.195)	(.350)	(.325)
Week10*ModeBrowserApple	-.428	-.360	-.166	-.256	-.152	-.297
	(.303)	(.215)	(.213)	(.172)	(.309)	(.287)

Independent Variables \ Dependent Variables	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
Week11*ModeBrowserApple	-.451	-.372	-.128	-.246	-.374	-.297
	(.308)	(.219)	(.217)	(.175)	(.315)	(.292)
Week12*ModeBrowserApple	-.396	-.434	-.291	-.150	-.252	-.243
	(.323)	(.229)	(.227)	(.184)	(.329)	(.306)
Week13*ModeBrowserApple	-.883**	-.549*	-.220	-.503**	-.782*	-.268
	(.332)	(.236)	(.233)	(.189)	(.339)	(.315)
Week14*ModeBrowserApple	-.572	-.353	-.283	-.192	-.491	-.364
	(.315)	(.224)	(.221)	(.179)	(.321)	(.299)
Week15*ModeBrowserApple	-.402	-.260	.067	-.399*	-.360	-.157
	(.323)	(.229)	(.227)	(.184)	(.329)	(.306)
Week16*ModeBrowserApple	-.420	-.039	-.090	-.261	-.485	-.134
	(.323)	(.229)	(.227)	(.184)	(.329)	(.306)
Week8*ModeBrowserGoogle	-.169	-.088	.078	-.214	-.103	.149
	(.344)	(.244)	(.242)	(.196)	(.351)	(.326)
Week9*ModeBrowserGoogle	.079	-.094	.083	-.082	.035	.069
	(.344)	(.244)	(.242)	(.196)	(.351)	(.326)
Week10*ModeBrowserGoogle	-.259	-.223	-.116	-.163	.010	-.222
	(.303)	(.215)	(.213)	(.173)	(.310)	(.288)
Week11*ModeBrowserGoogle	-.313	-.263	-.098	-.168	-.260	-.216
	(.309)	(.219)	(.217)	(.176)	(.315)	(.293)
Week12*ModeBrowserGoogle	-.300	-.342	-.298	-.071	-.159	-.188
	(.323)	(.230)	(.227)	(.184)	(.330)	(.307)
Week13*ModeBrowserGoogle	-.696*	-.409	-.171	-.398*	-.612	-.182
	(.333)	(.236)	(.234)	(.189)	(.339)	(.316)
Week14*ModeBrowserGoogle	-.408	-.240	-.270	-.083	-.337	-.287
	(.316)	(.224)	(.222)	(.180)	(.322)	(.299)
Week15*ModeBrowserGoogle	-.269	-.173	.089	-.315	-.240	-.096
	(.323)	(.230)	(.227)	(.184)	(.330)	(.307)
Week16*ModeBrowserGoogle	-.240	.076	-.038	-.162	-.338	.007
	(.323)	(.230)	(.227)	(.184)	(.330)	(.307)
Week8*ModeBrowserMicrosoft	-.148	-.079	.064	-.194	-.080	.112
	(.343)	(.244)	(.241)	(.195)	(.350)	(.325)
Week9*ModeBrowserMicrosoft	-.108	-.175	.042	-.191	-.071	.053
	(.343)	(.244)	(.241)	(.195)	(.350)	(.325)
Week10*ModeBrowserMicrosoft	-.460	-.335	-.175	-.284	-.110	-.240
	(.303)	(.215)	(.213)	(.172)	(.309)	(.287)
Week11*ModeBrowserMicrosoft	-.462	-.332	-.137	-.260	-.319	-.237
	(.308)	(.219)	(.217)	(.175)	(.315)	(.292)
Week12*ModeBrowserMicrosoft	-.450	-.418	-.316	-.169	-.244	-.218
	(.323)	(.229)	(.227)	(.184)	(.329)	(.306)
Week13*ModeBrowserMicrosoft	-.899**	-.491*	-.245	-.500**	-.696*	-.254
	(.332)	(.236)	(.233)	(.189)	(.339)	(.315)
Week14*ModeBrowserMicrosoft	-.610	-.309	-.302	-.203	-.441	-.327
	(.315)	(.224)	(.221)	(.179)	(.321)	(.299)
Week15*ModeBrowserMicrosoft	-.435	-.237	.056	-.417*	-.320	-.122
	(.323)	(.229)	(.227)	(.184)	(.329)	(.306)
Week16*ModeBrowserMicrosoft	-.439	-.011	-.101	-.276	-.456	-.060

Dependent Variables / Independent Variables	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
	(.323)	(.229)	(.227)	(.184)	(.329)	(.306)
Week8*ModeBrowserMozilla	-.183	-.110	.033	-.190	-.085	.101
	(.344)	(.244)	(.242)	(.196)	(.351)	(.326)
Week9*BrowsertypeMozilla	-.076	-.192	-.023	-.108	-.065	.003
	(.344)	(.244)	(.242)	(.196)	(.351)	(.326)
Week10:BrowsertypeMozilla	-.437	-.347	-.224	-.217	-.131	-.322
	(.304)	(.216)	(.213)	(.173)	(.310)	(.288)
Week11*ModeBrowserMozilla	-.442	-.349	-.192	-.194	-.351	-.299
	(.309)	(.220)	(.217)	(.176)	(.315)	(.293)
Week12*ModeBrowserMozilla	-.429	-.413	-.390	-.089	-.216	-.266
	(.324)	(.230)	(.227)	(.184)	(.330)	(.307)
Week13*ModeBrowserMozilla	$-.983^{**}$	$-.576^{*}$	-.370	$-.477^{*}$	$-.803^{*}$	-.375
	(.333)	(.236)	(.234)	(.189)	(.340)	(.316)
Week14*ModeBrowserMozilla	-.602	-.329	-.428	-.114	-.468	-.420
	(.316)	(.224)	(.222)	(.180)	(.322)	(.300)
Week15*ModeBrowserMozilla	-.458	-.290	-.057	-.343	-.406	-.214
	(.324)	(.230)	(.227)	(.184)	(.330)	(.307)
Week16*ModeBrowserMozilla	-.456	-.067	-.218	-.203	-.505	-.153
	(.324)	(.230)	(.227)	(.184)	(.330)	(.307)
R^2	.554	.547	.624	.290	.492	.270
N	68,393	68,393	68,393	68,393	68,393	68,393

Notes: Each column refers to a separate regression of Equation W3 on the unmatched sample. Each cell refers to the respective coefficient of the independent variables in the first column on the unmatched sample. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W13. ROBUSTNESS CHECK USING PROPENSITY SCORE MATCHING INSTEAD OF COARSEND EXACT MATCHING

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	$.255^{***}$	$.166^{***}$	$.201^{***}$	$.049^{***}$	$.240^{***}$	$.145^{***}$
	(.020)	(.013)	(.014)	(.009)	(.021)	(.018)
β_2	$.129^{***}$	$.082^{***}$	$.104^{***}$	$.027^{*}$	$.162^{***}$	$.082^{***}$
	(.027)	(.017)	(.020)	(.011)	(.028)	(.024)
N	30,766	30,766	30,766	30,766	30,766	30,766
R^2	.623	.590	.698	.556	.636	.621

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on a matched sample of ad blocker adopters and non-adopters using propensity score matching:
$\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$.
R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses.
$^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

WEB APPENDIX E: EXAMINATION OF THE ASSOCIATIONS BETWEEN USER DEMOGRAPHICS AND AD BLOCKER ADOPTION

TABLE W14. LOGISTIC REGRESSION OF AD BLOCKER ADOPTION ON USER DEMOGRAPHICS

	Ad Blocker Adoption
(Intercept)	-1.564^{***}
	(.119)
Gender (Male)	$.287^{***}$
	(.058)
Income Index 2	$-.460^{***}$
	(.127)
Income Index 3	$-.251^{*}$
	(.115)
Income Index 4	$-.370^{**}$
	(.130)
Income Index 5	$-.380^{**}$
	(.116)
Income Index 6	$-.285^{*}$
	(.113)
Age 18 – 30	.108
	(.127)
Age 31 – 40	$.254^{**}$
	(.090)
Age 41 – 50	$.207^{*}$
	(.082)
Age 51 – 60	.126
	(.084)
Age 61 – 70	-.097
	(.087)
AIC	13,159.080
BIC	13,249.781
Log Likelihood	-6,567.540
Deviance	13,135.080
N	14,164

Notes: This table reports the coefficient of the following logit model on the unmatched sample: $\text{Adoption}_i = \alpha + \beta_1 * \text{Gender}_i + \beta_2 * \text{Income}_i + \beta_3 * \text{Age}_i + \varepsilon_i$; The income index increases with more income. exp (β) is the odds ratio between ad blocker adopters and non-adopters. The reference group for Gender is female, for income is income index 1 (the lowest income category), for age is 71-80. The coefficient of Gender (male) indicates that the odds of being an ad blocker adopter in the male group is exp (.287) = 1.332 times that of being an ad blocker in the female group. The coefficient of Income Index 2 indicates that the odds of being an ad blocker adopter in the Income Index 2 group is exp (-.460) = .631 times that of being an ad blocker in the Income Index 1 group. The coefficient of Age 31-40 indicates that the odds of being an ad blocker adopter in the 31-40 age group is exp (.254) = 1.290 times that of being an ad blocker in the 71-80 age group. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

WEB APPENDIX F:
PLACEBO TREATMENT TEST AND TIME-VARYING CONFOUNDS

Placebo Treatment Test for Parallel Pre-Treatment Trend

The identification assumption under difference-in-differences (DiD) is that in the absence of treatment (in our case, ad blocker adoption), there would have been no difference between the treatment and control groups in terms of change in news consumption. This assumption also means that we should have comparable changes in news consumption between the two groups before the treatment. The condition fulfilling this assumption is that we have parallel pre-treatment trends. To formally test this condition, we perform a "placebo" treatment test by estimating the week-wise treatment effects before and after the treatment (Angrist and Pischke 2008). Specifically, for each user i, we replace the variables I_{it1} and I_{it2} in Equation 1 in the main manuscript with two sets of week-wise dummy variables: $I_{it-\tau}$, which is equal to 1 if week t is τ weeks before the treatment (and zero otherwise); and $I_{it+\tau}$, which is equal to 1 if week t is τ weeks after the treatment (and zero otherwise):

$$Y_{it} = \alpha_i + \delta_t + \sum_{\tau=2}^{\tau=5} \beta_{-\tau} * I_{it-\tau}(\tau \text{ weeks before Treatment}_{it}) + \sum_{\tau=0}^{\tau=4} \beta_{\tau} * I_{it+\tau}(\tau \text{ weeks since Treatment}_{it}) + \varepsilon_{it}, \quad \text{(W4)}$$

where Y_{it} is the news consumption for user i in week t; α_i is a user-level fixed effect; δ_t is the week-fixed effect; ε_{it} is the standard error clustered at the user-level. We choose the last week before treatment (I_{it-1}) as the omitted default category. If the trends of the treatment and control group are parallel, then the parameters $\beta_{-\tau}$ will be statistically indistinguishable from zero. As reported in TABLE W15, all the main news consumption measures we use pass this test because the parameters $\beta_{-\tau}$ in the pre-treatment period have non-significant point estimates.

TABLE W15. PLACEBO TREATMENT TEST ON NEWS CONSUMPTION VARIABLES

	Article Views	Breadth	Visits	Article Views per Visit	International Political News	Regional Political News	Local Political News	Economy News
β_{-2}	-.054	-.065	-.023	-.029	.007	-.029	-.012	-.003
	(.042)	(.031)	(.028)	(.022)	(.030)	(.030)	(.027)	(.027)
β_{-3}	-.010	-.037	.037	-.023	.054	-.007	.006	-.016
	(.047)	(.035)	(.030)	(.023)	(.034)	(.031)	(.028)	(.031)
β_{-4}	-.014	-.039	.018	-.013	-.018	-.004	.005	-.010
	(.049)	(.036)	(.032)	(.024)	(.032)	(.032)	(.027)	(.033)
β_{-5}	-.048	-.054	-.039	.004	-.015	-.060	-.016	-.038
	(.047)	(.035)	(.035)	(.024)	(.032)	(.033)	(.027)	(.030)
R^2	.505	.492	.628	.452	.487	.455	.426	.438
N	9,370	9,370	9,370	9,370	9,370	9,370	9,370	9,370
	Finance News	Opinion News	Sport News	Art & Culture News	Lifestyle News	Weather Forecast	Play Page	Account
β_{-2}	-.016	-.001	-.013	-.009	.001	.020	-.004	.011
	(.029)	(.027)	(.029)	(.018)	(.015)	(.017)	(.004)	(.027)
β_{-3}	-.013	-.007	.064	-.017	.019	.007	-.000	.022
	(.030)	(.029)	(.030)	(.021)	(.018)	(.022)	(.004)	(.028)
β_{-4}	-.030	-.002	.019	.001	-.023	-.023	-.001	.035
	(.029)	(.030)	(.029)	(.021)	(.017)	(.021)	(.004)	(.032)
β_{-5}	-.064	-.004	.002	.005	-.028	-.002	-.002	-.021
	(.029)	(.030)	(.030)	(.022)	(.014)	(.020)	(.005)	(.027)
R^2	.575	.347	.595	.348	.315	.709	.759	.332
N	9,370	9,370	9,370	9,370	9,370	9,370	9,370	9,370
	Home Page Views per Visit	Title Length per Article	Title Length per Visit	Time per Visit	Direct Visits	Social Media Visits	Search Engine Visits	Newsletter Visits
β_{-2}	-.018	-.028	-.079	-.121	-.029	-.002	.016	.000
	(.017)	(.018)	(.044)	(.110)	(.030)	(.008)	(.021)	(.000)
β_{-3}	-.004	-.028	-.074	-.044	.042	.010	.008	.001
	(.017)	(.019)	(.045)	(.114)	(.031)	(.009)	(.023)	(.001)
β_{-4}	.029	-.048	-.062	.107	.026	.003	-.013	.001
	(.019)	(.021)	(.048)	(.116)	(.034)	(.009)	(.023)	(.000)
β_{-5}	.012	-.023	-.028	-.023	-.022	.004	-.040	.000
	(.019)	(.018)	(.046)	(.119)	(.036)	(.007)	(.021)	(.000)
R^2	.514	.306	.437	.360	.662	.568	.551	.167
N	9,370	8,037	9,370	9,370	9,370	9,370	9,370	9,370

Notes: Each column refers to a separate regression with the following model: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \sum_{\tau=2}^{\tau=5} \beta_{-\tau} * I_{it-\tau}(\tau \text{ weeks before Treatment}_{it}) + \sum_{\tau=0}^{\tau=4} \beta_\tau * I_{it+\tau}(\tau \text{ weeks since Treatment}_{it}) + \varepsilon_{it}$ on the matched sample of ad blocker adopters and non-adopters. $\beta_{-\tau}$ are the placebo treatment effects and are reported with β_{-1} omitted as the default category. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^*p < .01$.

Robustness Check on Adding Time-Varying Controls

The placebo treatment test (reported in TABLE W15) statistically validates the identification condition (parallel pre-treatment trend) of DiD. Recall that DiD removes all time-invariant confounders. DiD will also eliminate any bias from time-varying confounders if the parallel pre-treatment trend holds. The reason is that a common pre-treatment trend implies that time-varying confounders, if any, impact both groups (i.e., treatment and control group) in the same way in the pre-treatment period and thus will be eliminated by DiD.

Concerns may remain that a time-varying confounder kicks in at the same time when the treatment occurs and, thus, will bias our result. An example of such a scenario is as follows: A user reads news on a browser with no ad-blocking feature. Then, the user installs an additional more user-friendly browser with an ad-blocking feature and, at the same time, starts reading the news with multiple browsers. So, this installation of a browser changes her ad blocker usage, and the more user-friendly browser also impacts her news reading behavior.

To further establish the robustness of our main result, we rerun our main estimation by adding the following time-varying control variables: browser switching (i.e., the number of different browsers that a user uses during a particular week), ordering (i.e., the number of orders that a user places on the website during a particular week, such as purchasing access to the news archive), and commenting (i.e., the number of comments that a user leaves during a particular week).

Specifically, we estimate the following model

(W5) $$Y_{it} = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it})$$
$$+\beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \beta_3 * \text{Browsers}_{it} + \beta_4 * \text{Orders}_{it}$$
$$+ \beta_5 * \text{Comments}_{it} + \varepsilon_{it}$$

The results, reported in TABLE W16, show that our main treatment effects (β_1 and β_2) remain highly robust, because they are similar to the treatment effects reported in Table 4. For brevity, the table classifies the various news categories into the following: hard news (political, economic and opinion news) and soft news (sports, culture & art, lifestyle news).

TABLE W16: ROBUSTNESS CHECK OF MAIN MODEL AFTER ALSO CONTROLLING FOR BROWSER SWITCHING, ORDERING, & COMMENTING

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	$.255^{***}$	$.170^{***}$	$.169^{***}$	$.065^{***}$	$.244^{***}$	$.133^{***}$
	(.037)	(.026)	(.024)	(.017)	(.038)	(.031)
β_2	$.119^{*}$	$.071^{*}$	$.086^{**}$	.026	$.143^{**}$	.028
	(.047)	(.035)	(.032)	(.021)	(.048)	(.035)
β_3 (Browsers_{it})	$.373^{***}$	$.250^{***}$	$.342^{***}$	$.024^{*}$	$.335^{***}$	$.161^{***}$
	(.023)	(.018)	(.016)	(.010)	(.023)	(.019)
β_4 (Orders_{it})	-.291	$-.352^{*}$	-.040	-.218	-.208	-.115
	(.286)	(.150)	(.151)	(.130)	(.239)	(.143)
β_5(Comments_{it})	-.035	-.012	.032	$-.049^{**}$	-.003	.028
	(.032)	(.024)	(.017)	(.016)	(.034)	(.030)
N	9,370	9,370	9,370	9,370	9,370	9,370
R^2	.529	.514	.663	.453	.558	.548

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample of ad blocker adopters and non-adopters:
$\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \beta_3 * \text{Browsers}_{it} + \beta_4 * \text{Orders}_{it} + \beta_5 * \text{Comments}_{it} + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

WEB APPENDIX G:
ROBUSTNESS CHECK ON LOGARITHMIC TRANSFORMED DEPENDENT VARIABLE

TABLE W17. ROBUSTNESS CHECK ON USING ORIGINAL VALUE (INSTEAD OF LOG) AS DEPENDENT VARIABLE

	Ad Blocker Adoption		Ad Blocker Early Adoption		Ad Blocker Abandonment	
	Article Views	Breadth	Article Views	Breadth	Article Views	Breadth
β_1	2.309***	.873***	3.126**	1.039**	-1.350	-.530
	(.356)	(.111)	(1.192)	(.340)	(1.215)	(.377)
β_2	1.419***	.425**	.441	.214	.281	.168
	(.412)	(.143)	(1.473)	(.383)	(1.998)	(.490)
N	9,370	9,370	1,423	1,423	1,009	1,009
R^2	.503	.497	.477	.442	.554	.570

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample: $Y_{it} = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W18. ROBUSTNESS CHECK ON USING LOG (Y + .1) AS DEPENDENT VARIABLE

	Ad Blocker Adoption		Ad Blocker Early Adoption		Ad Blocker Abandonment	
	Article Views	Breadth	Article Views	Breadth	Article Views	Breadth
β_1	.434***	.315***	.450*	.312*	-.420*	-.250
	(.063)	(.051)	(.197)	(.149)	(.187)	(.151)
β_2	.232**	.161*	-.041	-.002	.134	.127
	(.083)	(.069)	(.198)	(.152)	(.218)	(.172)
N	9,370	9,370	1,423	1,423	1,009	1,009
R^2	.465	.455	.425	.384	.524	.507

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample: $\log(Y_{it} + .1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

WEB APPENDIX H: ROBUSTNESS CHECKS ON EFFECT DECOMPOSITION USING OTHER QUASI-EXPERIMENTAL DESIGNS

TABLE W19. ROBUSTNESS CHECK ON EFFECT DECOMPOSITION USING AD BLOCKER EARLY ADOPTERS AS TREATMENT GROUP AND AD BLOCKER LATE ADOPTERS AS CONTROL GROUP

	Article Views	Breadth	Visits	Article Views per Visit	Hard News	Soft News
β_1	.322*	.207*	.072	.211**	.272*	.092
	(.127)	(.082)	(.059)	(.079)	(.126)	(.098)
β_2	-.010	.019	-.037	.093	.060	-.037
	(.133)	(.086)	(.058)	(.092)	(.130)	(.110)
N	1,423	1,423	1,423	1,423	1,423	1,423
R^2	.462	.423	.588	.478	.550	.557

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample of early and late adopters. R^2 computation includes the explanatory power of the fixed effects:
$\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$
Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W20. ROBUSTNESS CHECK ON EFFECT DECOMPOSITION USING AD BLOCKER ABANDONERS AS TREATMENT GROUP AND CONTINUOUS AD BLOCKER USERS AS CONTROL GROUP

	Article Views	Breadth	Visits	Article Views per	Hard News Visit	Soft News
β_1	-.204***	-.127***	-.161***	-.038***	-.195***	-.063***
	(.016)	(.010)	(.011)	(.007)	(.016)	(.013)
β_2	-.115***	-.076***	-.109***	-.017	-.107***	.019
	(.023)	(.014)	(.016)	(.009)	(.023)	(.020)
N	48,833	48,833	48,833	48,833	48,833	48,833
R^2	.748	.702	.790	.654	.743	.725

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the unmatched sample of abandoners and continuous ad blocker users.: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. R^2 computation includes the explanatory power of the fixed effects. Standard errors clustered at the user-level appear in parentheses. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

WEB APPENDIX I:
ROBUSTNESS CHECK ON ZERO VISIT WEEKS

TABLE W21. ROBUSTNESS ON ARTICLE VIEWS AND BREADTH WITH ZERO VISIT WEEKS

	Article Views	Breadth
β_1	.510***	.372***
	(.037)	(.028)
β_2	.254***	.178***
	(.048)	(.036)
N	13,220	13,220
R^2	.531	.527

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample of ad blocker adopters and non-adopters with user zero visit weeks included: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. "User zero visit weeks" refer to weeks in which a user did not visit the news website. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

TABLE W22. ROBUSTNESS ON ARTICLE VIEWS AND BREADTH WITH TOBIT MODEL

	Article Views	Breadth
β_1	.362***	.221***
	(.037)	(.024)
β_2	.205***	.118***
	(.044)	(.029)
Log Likelihood	-7689.2	-5240.8
N	9,370	9,370

Notes: β_1 represents the 1-week effect and β_2 represents the 5-week effect. Each column refers to a separate regression of the following model on the matched sample without user zero visit week using a truncated regression model: $\log(Y_{it} + 1) = \alpha_i + \delta_t + \beta_1 * I_{it1}(\text{within 1 week of Treatment}_{it}) + \beta_2 * I_{it2}(\text{remaining weeks since Treatment}_{it}) + \varepsilon_{it}$. User zero visit weeks refer to weeks where a user did not visit the news website. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

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