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Attention Spillovers from News to Ads: Evidence from an Eye-Tracking Experiment

Andrey Simonov, Tommaso Valletti, and Andre Veiga

Abstract

The authors investigate the impact of online news content on the effectiveness of display advertising. In a randomized online experiment, participants read news articles randomly paired with brand advertisements. Leveraging nonintrusive eye-tracking technology, the authors measure individual attention to both articles and ads. The authors then measure ad recall, and participants choose between cash and brand-specific vouchers. Heightened attention to articles results in "spillover" attention to ads on the same page, which, in turn, increases both brand recall and purchase probability. The authors also consider the effect of news content type, differentiating between "hard" and "soft" news. They find that advertising next to hard news is at least as effective as advertising next to soft news. This provides evidence against the blunt implementation of "block lists" for sensitive news topics by advertisers. The authors discuss the implications of attention spillovers for firms contemplating investments in engaging news content within the digital advertising landscape.

Keywords

online advertising, online news, experiments, attention, e-commerce

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Spring 2020, the beginning of the COVID pandemic in the United States, was characterized by an unusual dynamic for digital advertising. While visits to online media sites and news consumption increased by almost 50% (Weitman 2020), digital advertising—a rapidly growing area of spending for companies over the last two decades (Statista 2023)—experienced a 25%–35% decline (eMarketer 2020). Part of this dip is explained by the overall uncertainty of companies due to the pandemic, but it was also largely driven by "block lists": advertising companies actively avoiding placing ads on pages with pandemic-related news content (Willen 2020). Such avoidance of "hard news" (i.e., news that is thought to be potentially sensitive and upsetting to some readers) is driven by the perception on the part of advertisers that placing ads with hard content could lead to negative associations with their brand, hurting the brand's image and dissuading readers from purchasing the advertised brand. In turn, this practice discourages news publishers from investing into "hard news" stories, leading to a potential underprovision of content that could have high societal benefits (e.g., IAB UK 2020; Sweney 2020).

We examine the effect of news content on the effectiveness of advertising via an online experiment that uses nonintrusive eye-tracking technology. By "ad effectiveness" we mean the incremental impact of an additional second of attention to ads on the probability of brand recall and purchase. In our study, participants were exposed to a random sequence of online articles from well-known news outlets. Individuals were also shown realistic ads for well-known brands. Importantly, the pairing of ads and articles was also randomized. Articles were selected to cover different news topics ("hard" and "soft" news). Eye tracking allows us to directly measure the attention paid by individuals to articles and to the ads placed next to them. After reading the articles, individuals were asked to recall the advertised brands and make purchase decisions (choose between a voucher for each advertised brand and cash). The purchase decision was incentivized: individuals received the outcome of one of their choices, selected at random. Since articles vary in how interesting they are for each user, random matching of articles to ads created experimental variation in the attention paid to each ad; we use this variation to

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determine the impact of ad attention on brand recall and purchases.

We consider an empirical model of attention where individual attention devoted to articles can "spill over" to ads, and vice versa. We allow these spillovers to be positive or negative. For instance, if a reader's eyes randomly move between articles and ads, more time spent on the article increases exposure to the ad (a positive spillover). Alternatively, if individuals are focused on an interesting article, more time might imply less attention devoted to the ad (a negative spillover). The attention consumers devote to ads ultimately can impact ad recall and purchase probabilities of the advertised brand.

Our estimates show that the attention readers devote to articles has a positive spillover effect on the attention to ads displayed on the page. Moreover, this incremental attention to ads increases ad recall and purchase probability (i.e., the probability of choosing a brand-specific voucher over a cash reward). Thus, more captivating news content—one that attracts more attention from readers—increases recall and purchase probabilities of brands whose ads are shown on the same page.

Based on our preferred specification (ordinary least squares [OLS], using the entire sample), one additional second of attention to a brand's ad results in a 3.4 percentage points higher probability of recall and .7 percentage points higher probability of choosing that brand's gift card over cash. The latter estimate is confirmed by an instrumental variable (IV) specification where we only use the incremental attention to ads generated by spillovers from the attention to news content.

We further show that at least some "hard news" content—articles about the COVID-19 pandemic or the Black Lives Matter (BLM) movement in the summer of 2020 that we use in the study—does not detectably impact ad effectiveness. We find that readers spend less time on articles covering hard news—and because of this, devote less attention to ads shown next to hard news articles. However, ad effectiveness (the effect of incremental attention to ads on recall and purchases) is 18%–43% higher (albeit not significantly different) when article content is "hard news" compared with "soft news," which is confirmed throughout all OLS and IV specifications. On balance, this higher ad effectiveness compensates for the lower amounts of attention that readers devote to ads next to hard news articles. In summary, we find no evidence that advertising next to hard news is less effective than advertising next to soft news.

Our results have important implications for both news producers and advertisers. Regarding news producers, we show that the key dimension to be optimized is how captivating news content is, whereas the content of articles is less important. Similarly, on the advertisers' side, we show that a key metric to keep in mind when allocating display advertising is the overall engagement of users with the web page, not necessarily the specific content on the page. As a result, our results suggest one should revisit the practice of blunt "block lists" of hard articles, providing an opportunity for optimizing ad allocation decisions for advertisers and marketing managers.

Apart from the substantive results, we provide a novel empirical strategy to measure advertising effectiveness using nonintrusive eye-tracking tools that have recently become more widely available. These tools enable us to run eye-tracking studies through a standard laptop or smartphone web camera, greatly reducing the costs of eye-tracking studies that are typically done in lab settings. This approach allows us to study how users engage with online content in a realistic way.

Related Literature

This article contributes to the vast literature that studies the effectiveness of online advertising. Relative to that literature, we make three key contributions.

Our first contribution is to show how more captivating news content creates attention spillovers toward ads and increases ad effectiveness. Two sets of papers are similar to ours. First, we build on the substream of the literature that has examined how the time spent on a web page with an ad affects users' memory and ad recall (e.g., Danaher and Mullarkey 2003; Goldstein, McAfee, and Suri 2011, 2015; Uhl, Nabout, and Miller 2020).[1] Compared with these studies, we use eye tracking to explicitly show the spillover from attention to web page content toward the ads presented. Separately measuring the respondents' eyesight "dwell" on article text and on ads allows us to rule out reverse causality as an alternative explanation (Becker and Murphy 1993; Tuchman, Nair, and Gardete 2018). We are also able to link the incremental attention users devote to ads to user willingness to pay for brands, going beyond the more upstream metric of ad recall.

Our work is also related to the eye-tracking literature that examines advertising effectiveness. However, to the best of our knowledge, there is no evidence of the effect of news content on advertising effectiveness. A substream of this literature leverages eye tracking to study the psychological mechanisms behind advertising effectiveness (e.g., Aribarg, Pieters, and Wedel 2010; Higgins, Leinenger, and Rayner 2014; Wedel and Pieters 2000; Wedel, Pieters, and Liechty 2008). Another substream studies how different features and designs of advertisements increase viewers' attention (e.g., Lee and Ahn 2012; MacKenzie 1986; Nixon 1924; Pieters and Wedel 2004; Pieters, Wedel, and Batra 2010; Pieters, Wedel, and Zhang 2007; Scott, Green, and Fairley 2016; Zhang and Yuan 2018). A third substream discusses how viewers' involvement and familiarity with the brand (effects typically grouped by the literature as "top-down") affect attention to advertising (e.g., Pieters and Wedel 2007; Rayner et al. 2001; Treistman and Gregg 1979).[2]

[1] Other related papers include literature that links online engagement and advertising effectiveness (see, e.g., Calder, Malthouse, and Schaedel 2009; Kilger and Romer 2007).

[2] Apart from these areas of inquiry related to advertising effectiveness, eye tracking has been used in the marketing literature to further our understanding of consideration set formation (e.g., Chandon et al. 2009), how consumers search and choose products (e.g., Janiszewski 1998; Lohse 1997; Meißner, Musalem, and Huber 2016; Russo and Leclerc 1994; Shi and Trusov 2021), and survey design (e.g., Redline and Lankford 2001). More broadly, eye tracking has been used in many fields, including marketing, psychology, and

Our contribution relative to this literature is that we employ eye-tracking data to examine how readers' attention to news content spills over to the advertising presented on the same page, allowing us to measure the causal effects of news content on attention to ads and thus assess the importance of investment in high-quality engaging content.[3] We present an empirical model of attention allocation to interpret this spillover effect and to disentangle this effect from consumers' ad avoidance. We also connect this incremental attention to ads to subsequent ad recall and willingness to pay for the advertised brands, thereby providing a needed link between the incremental visual attention and a downstream brand choice measure, called for by Wedel and Pieters (2007).[4] Our analysis is further related to Brasel and Gips (2008) and Teixeira, Wedel, and Pieters (2010), who use eye-tracking data to examine the determinants of attention to TV commercials.[5]

Our second contribution is to examine the effect of the news content on ad effectiveness. We find that more engaging news content increases the amount of attention the reader devotes to display advertising, adding to the results on the effect of targeting on ad effectiveness (e.g., Deng and Mela 2018; Goldfarb and Tucker 2011; Johnson, Shriver, and Du 2020; Rafieian and Yoganarasimhan 2021). Yet, beyond the effect of devoting more attention to the news page, news content does not have any detectable additional effect on ad effectiveness.[6] In other words, once one statistically controls for attention to the article, whether the article is "hard news" or not has no impact on purchase. This result cautions against the practice of blank blocking certain news content for the purposes of targeted advertising (e.g., Sweney 2020). Our results on the drivers of attention to online news contribute to the broader literature researching what makes people engage with news (e.g., Berger, Moe, and Schweidel 2019; Holmqvist et al. 2003; Kazai, Yusof, and Clarke 2016; Lagun and Lalmas 2016; Pitler and Nenkova 2008).

The third contribution of this article is to validate ad visibility—the amount of time that each ad is visible on the consumer's screen—as a reliable proxy of attention. For this, we first measure attention using scalable and nonintrusive eye-tracking technology and validate its precision on both desktop and mobile devices. We then show that our main analysis is robust to using attention metrics based on ad visibility metrics. While eye tracking is a more accurate measure of consumer attention, ad visibility is significantly more likely to be available to researchers and practitioners, expanding the potential application of our research.

More broadly, our work is related to other papers that have shown connections between user exposure to ads and later purchase choices. Several papers link exposure to users becoming aware of the ad (e.g., Danaher and Mullarkey 2003; Elsen, Pieters, and Wedel 2016; Wilson, Baack, and Till 2015). Other articles explore the link between exposure, awareness, and purchase (e.g., Hoyer and Brown 1990; Khurram, Qadeer, and Sheeraz 2018; Macdonald and Sharp 2000; Martins et al. 2019). Another stream of literature examines the effectiveness of online advertising on product sales using natural experiments (e.g., Jeziorski and Moorthy 2018; Narayanan and Kalyanam 2015; Rutz, Bucklin, and Sonnier 2012; Simonov and Hill 2021) and field experiments (e.g., Gordon, Moakler, and Zettelmeyer 2023; Hoban and Bucklin 2015; Johnson, Lewis, and Nubbemeyer 2017a, 2017b; Lewis and Reiley 2014; Sahni 2015; Simonov, Nosko, and Rao 2018).

Experimental Setting

In late July and early August 2020, we recruited 1,013 individuals, stratified evenly across two countries (the United Kingdom and the United States) and two device types (desktop and smartphone). Respondents matched the U.K./U.S. online population in terms of age, gender, income, and location. They were recruited via a specialist supplier of research panels, Panelbase.[7]

The experiment proceeded as follows. First, we confirmed participants' consent. At the start of the experiment, participants were told only that they were a part of "an academic study about media consumption," but were not given additional details. At this stage, participants were asked to report their age, education, income, gender, and postal code.

Each participant was then invited to read articles from two online newspapers. In each country, we chose outlets with a wide online readership: *The Guardian* and *The Daily Mail* for U.K. participants, and *The New York Times* and *USA Today* in the United States.

We presented each individual with nine articles. All articles had been published in the short time window prior to the experiment taking place, to maximize the probability that the articles were relevant and interesting. Within each newspaper, articles were split between soft and hard news. To select the latter, we followed the advice of industry experts and focused on articles about the COVID-19 pandemic and the BLM protests of the summer of 2020, two topics frequently blocked by

economics, to study individual choices (e.g., Armel, Beaumel, and Rangel 2008; Brasel and Gips 2008; Brocas et al. 2014; Camerer et al. 1993; Ghaffari and Fiedler 2018; Knoepfle, Wang, and Camerer 2009; Pärnamets et al. 2015; Reutskaja et al. 2011). See Wedel and Pieters (2007) and Wedel (2015) for reviews.

[3] One mechanism behind the spillover of attention can be a visual distraction (e.g., Navalpakkam, Rao, and Slaney 2011). Such distraction has a negative effect on news content consumption (Yan, Miller, and Skiera 2022).

[4] See the discussion on page 144 of Wedel and Pieters (2007). Treistman and Gregg (1979) is the most similar paper that compares the designs of two commercials and links higher attention to more sales. Zhang, Wedel, and Pieters (2009) show that ad features (e.g., size, color, and location of the ad) influence product sales by affecting consumer attention (measured through gaze duration), and Van der Lans, Pieters, and Wedel (2021) show that online advertising can speed up product search by visually suppressing competing products.

[5] Other recent studies of attention to TV ads include McGranaghan, Liaukonyte, and Wilbur (2022) and Liu, Shum, and Ueteke (2021).

[6] This suggests a limited interplay of information diagnosticity and accessibility between news content and ads (e.g., Lynch, Marmorstein, and Weigold 1988).

[7] See https://www.panelbase.net/.

advertisers.[8] The text of the articles shown on desktop and mobile was the same. However, in our analysis, we consider these to be different articles, since the format of the text is quite different across devices.

Eight out of nine articles were accompanied by ads from well-known and widely available brands; one of the articles was randomly shown with blank spaces in the location where ads would be otherwise shown. In each country, we chose eight prominent brands (see Web Appendix A). All ads accompanying a given article were for the same brand, inserted at fixed points along the article's page. We included one horizontal "billboard" ad before the text of the article and two smaller "side" ads on the side of the article text (desktop) or between paragraphs of the text (mobile). Our goal was to approximate, as much as possible, the typical reading experience online.

Each participant was exposed to all nine articles and all eight brands. Each article and brand was shown only once. We randomized the order in which articles were presented to individuals and the pairing between articles and brands. Individuals were allowed to read the articles at their preferred pace.

For each individual, we obtained two measures of the attention devoted to each article and ad. First, the amount of time the article and the ad were visible on screen, which does not require eye tracking. Second, we recorded, via eye tracking, the time that each individual's sight dwelled on each article and ad, referred to as dwell time.

After reading all articles, individuals were asked if they could remember the brands whose ads they had seen. Individuals were presented with a list containing the eight brands shown and eight "decoy" brands, in a random order. The decoy brands were chosen to be well known in each country and of the same industries as the shown brands. All brands (shown and decoy) were presented to the participant simultaneously, and participants selected which of the 16 brands they remembered seeing.[9]

After the recall task, participants were asked to make purchase decisions. For each of the brands whose ads were shown, individuals were offered to choose between (1) an e-voucher worth £10 (in the United Kingdom) or $10 (in the United States) specific to one of the brands shown, or (2) a randomized amount of cash (£3–£7 in the United Kingdom and $3–$7 in the United States). Individuals were informed that one of their e-voucher versus cash choices—selected later on at random—would be sent to them. As a result, purchase decisions were incentivized.

In addition to the voucher/cash reward, participants were paid a fixed participation fee. Participants were anonymous to the research team, with all payments delivered via the recruiting firm. The study protocol received ethical approval prior to the start of the experiment (see Web Appendix A.4).

We do not use a standard between-subjects experimental design. This is because our main goal is not to measure the extensive margin (i.e., the effect of the presence of ads relative to their absence). Instead, we aim to study the intensive margin: how incremental attention to articles results in incremental attention spillovers to ads. In our experiment, exogenous variation in attention to ads was induced by the random pairing of articles and ads. Some articles are more interesting than others, leading participants to devote more attention to those articles, which then influences the attention devoted to the ads placed next to them. It is this exogenous variation in attention to ads that we use to discuss the causal effect of attention on recall and purchase. This method for identifying the causal effect of attention to ads closely tracks our research question—the possible complementarity of the news content and ads—and is, to our knowledge, a novel way to measure ad effectiveness.[10]

For the purposes of this study, an online experiment provided several advantages. It allows for a large data collection effort, across multiple countries and devices, at a relatively low cost. It also allows us to show recently published articles to a large number of individuals, which would have been challenging in a lab environment. Our setting is also closer to the conditions under which individuals normally engage with online content.

The eye-tracking technology used was supplied by Lumen Research, a specialist advertising research agency.[11] The technology employs software that uses the camera of a desktop or mobile phone to measure where on the screen the participant's retina focused. No additional hardware is needed. See Web Appendix A for more details on the eye-tracking technology, its calibration, and validation.

The heat map provided in Figure 1, Panel A, is an example of how these metrics are constructed. The figure shows an article, as well as the ads (a "billboard" ad and two "side" ads) for one brand. The map highlights the regions on the screen that were actively dwelled upon by the participant. In Figure 1, Panel B, we present examples of heat maps for ads of two different brands.

Data

Variables

Table 1 presents summary statistics for our sample, which is at the individual × article level. About half of the observations occur on

[8] We provide article titles and links to the articles we used in Web Appendix A. We validate our categorization of articles as "hard" or "soft" news using an independent survey on Amazon Mechanical Turk, described in Web Appendix B.

[9] Immediately before collecting this "aided" recall measure, we also collected a measure of "unaided" recall, where we asked participants to write the names of the brands they recalled seeing. These two measures of recall are highly correlated (65%), and all results are robust to using either measure. For brevity, we only report results using the aided recall measure. The robustness of our results to an unaided recall measure suggests that additional attention to ads leads to short-term memory activation; unaided recall requires participants to remember the advertised brands.

[10] Goldstein, McAfee, and Suri (2011) also randomize pairings of articles and ads in their first study, but they force ads to always be visible on the page and do not measure attention to ads via eye tracking.

[11] See https://lumen-research.com/.

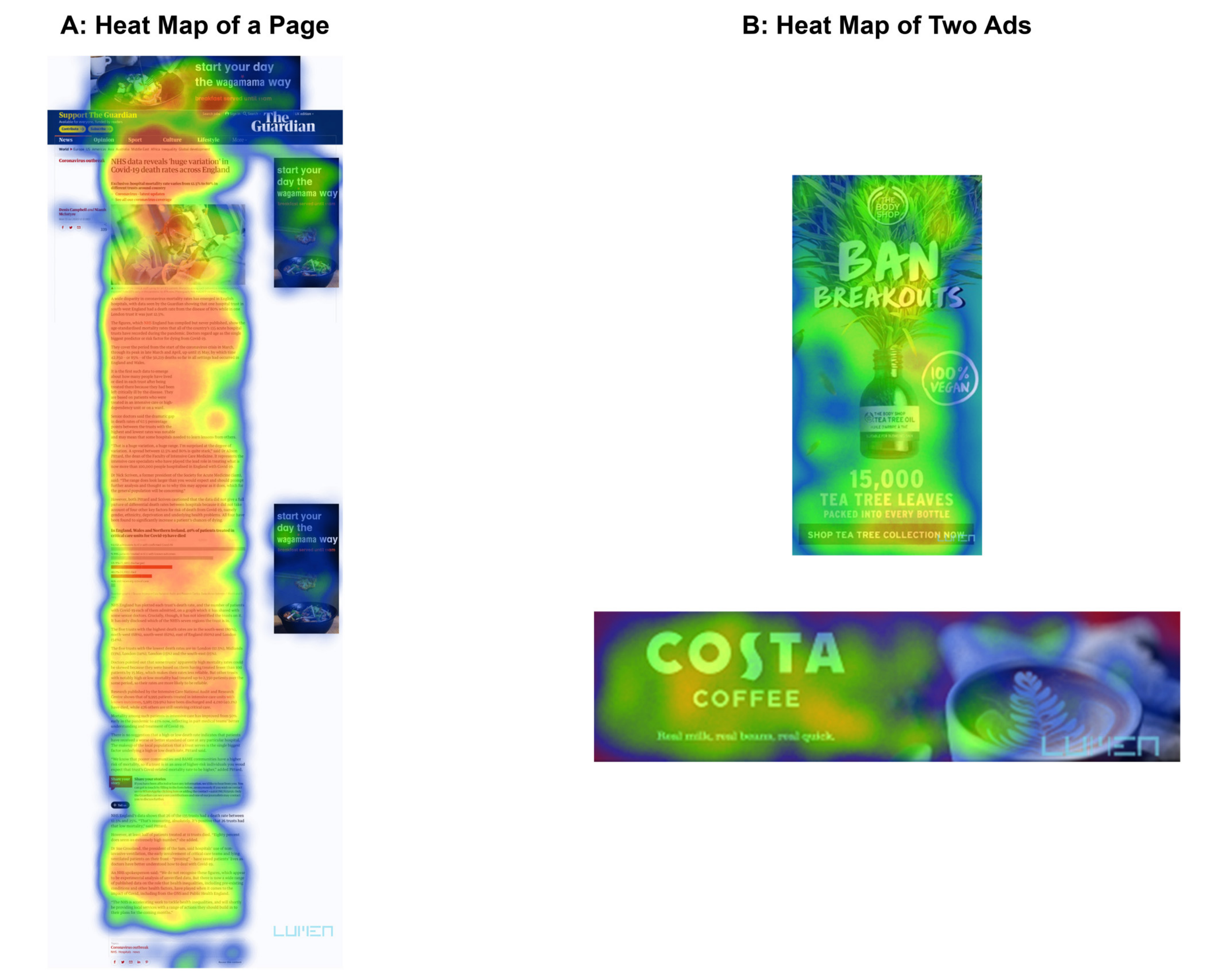

Figure 1. Example of Heat Maps.
Notes: In the heat maps, the dark inner (red) parts signify more attention, and the lighter inner parts and heat map boundaries signify less attention.

desktops (56%), correspond to female participants (55%), are from the United States (48%), and have "hard" news articles (55%).

Visibility measures. The variable Article Visible reports the number of seconds any part of the article was visible on screen (sample mean is about 2 minutes and 23 seconds), while Ad Visible reports the total number of seconds that any ad on the page was visible on the screen. To measure Ad Visible, we used Media Rating Council standards: an ad is considered visible if at least 50% of the pixels of the ad are displayed on the screen for 1 continuous second or more. The sample mean is approximately 19 seconds per article. These measures do not use eye tracking.

Eye-tracking measures. The variable Article Dwell is the total time an article was actively being read, recorded via eye tracking. The sample mean is about 1 minute and 15 seconds per article. Similarly, Ad Dwell reports the total time that all ads associated with an article were actively viewed (i.e., the sum of the dwell time of the three ads shown on each page). The sample mean is just short of 3 seconds. Intuitively, Article Dwell and Ad Dwell should be lower than Article Visible and Ad Visible, respectively, since articles and ads can be present on the screen but not actively viewed by the user.

Purchase. Participants in the United States (United Kingdom) were offered choices between vouchers worth \$10 (£10) for each of the advertised brands and random amounts of cash. The amount of cash offered to individuals is captured by the variable Price, since this is the opportunity cost of choosing the voucher. For about 35% of observations, individuals chose the voucher (measured by the dummy variable Buy), while the rest opted for cash.

Recall. About 48% of observations had individuals recall the associated brand (measured by the dummy variable Recall). In contrast to brand purchase choices, recall was not

Table 1. Summary Statistics.

Statistic	N	Mean	SD	Min	Max
Desktop	6,431	.563	.496	0	1
Female	6,431	.556	.497	0	1
U.S.	6,431	.483	.500	0	1
Hard News	6,431	.550	.498	0	1
Article Visible (s)	6,431	143.301	169.341	20.130	1,894.635
Ad Visible (s)	5,707	19.027	17.371	.000	291.905
Price (USD/GBP)	5,707	5.017	1.436	3.000	7.000
Recall	5,707	.484	.500	.000	1.000
Buy	5,707	.347	.476	.000	1.000
Article Dwell (s)	4,426	74.813	97.918	.112	966.945
Ad Dwell (s)	3,925	2.755	3.161	.000	40.214

Notes: s = seconds. Each observation is at the individual × article level.

incentivized, but this measure is commonly used in the marketing literature (e.g., Danaher and Mullarkey 2003; Elsen, Pieters, and Wedel 2016).

Individual demographics. We recorded the following individual-level demographics: gender, age, education, income, country and device type. We also asked individuals about their self-report political leaning (liberal, conservative, or moderate) but only at the end of the experiment, so as not to prime their responses to the articles.[12] The sample characteristics are similar when data is split by device type (mobile vs. desktop) and country (United Kingdom vs. United States). In Tables W12 and W13 in Web Appendix C, we replicate Table 1 for mobile and desktop devices separately and find demographic composition, news types, prices, purchasing, and brand recall summaries to be consistent. The only notable difference is that ads are more visible on desktop computers (average of 23.4 seconds) than on mobile phones (13.4 seconds). Ad Dwell is around 2.7 seconds on average on both device types. Consumers also spend more time reading articles on desktops (average 83 seconds) than on mobile phones (65 seconds).

Article characteristics. The main article characteristic we consider is whether the article constitutes "hard news." As described previously, for this purpose we selected articles focusing on the COVID-19 pandemic and the BLM protests during the summer of 2020. For some robustness checks, we also use the article's word count.

Final sample. Our final dataset comprises 6,431 observations at the individual × article level. This is less than the originally targeted 9 observations per person, for two reasons. First, due to connectivity issues, no data were recorded for around 30% of individual–article pairs. These missing observations are slightly more prominent on mobile phones (43%) than on desktop computers (13.5%), and in later steps of the study. We confirm this does not introduce bias in our analysis by showing that there is no selection bias in terms of which brands' and articles' observations experienced connectivity issues (see Web Appendix D). Second, for a subset of participants, eye-tracking quality was poor. High-quality eye tracking relies on minimal head movement for continuous tracking of the individual's retina. We only include in our analysis individuals with high-quality eye-tracking data. This explains why we have fewer observations (around 70%) with eye tracking than visibility data. In our main sample, observations with low-quality eye-tracking data are identified using metrics typically used by the eye-tracking technology provider. Web Appendices A.3, D, and E provide additional information about the final sample, show that there is no selection bias in terms of brands' and articles' observations, and offer robustness checks using alternative metrics of eye-tracking data quality.

Descriptive Statistics

Distributions of attention measures. Figure 2 compares our measures of attention (Ad Dwell, Article Dwell) and visibility (Ad Visible, Article Visible).[13] In the top section of the figure, we present ratios of Article Dwell to Article Visible for each country and device type. On average, Article Dwell is around 50% of Article Visible, indicating that an average reader looks at the article 50% of their time when the page is loaded.[14]

The lower part of Figure 2 presents ratios of Ad Dwell to Ad Visible. The average ratio is much lower compared with the analogous ratio for articles (around 18% instead of 50%). This is consistent with the finding in existing literature that TV ads can be visible for around 55% of viewers—meaning that viewers stay in the room for commercials—but only 7.7% of viewers actually devote visual attention to TV commercials (McGranaghan, Liaukonyte, and Wilbur 2022). The ratio of Ad Dwell to Ad Visible is slightly higher for mobile devices (21%) than desktops (15%). This reflects different prominence of display ads on desktop and mobile devices, and, in particular, the difference in prominence of "side" ads: on desktops, side ads are on the right side of the page, visible but easy not to devote attention to, whereas on mobile phones they occupy blocks between the text in the center of the screen.

Attention decreases throughout the experiment on both mobile and desktop devices. Web Appendix Figure W6 illustrates Article Dwell and Ad Dwell for the nine experimental steps (e.g., the third article shown corresponds to step 3). On average, Article Dwell is 117 seconds on desktops in the first step, decreasing to 64 seconds in the last step (99 to 42

[12] For brevity, we omit most of the demographic variables from Table 1 and present them in Web Appendix Figure W11.

[13] Web Appendix Figures W3 and W4 present marginal distributions of attention (Article Dwell, Ad Dwell) and visibility measures (Article Visible, Ad Visible) for all observations and averaged per consumer.

[14] The average is slightly lower for mobile devices (45%) as compared with desktops (62%). This is largely explained by the desktop page design of *USA Today*, which shows only a small fraction of the article at first and therefore undercounts Article Visible. If we exclude *USA Today* articles, the average ratio of dwell-to-visible measures is 48% for mobile devices and 54% for desktops. The desktop page design of *USA Today* also explains almost all of the (rare) cases where the ratio of Article Dwell to Article Visible is greater than 1.

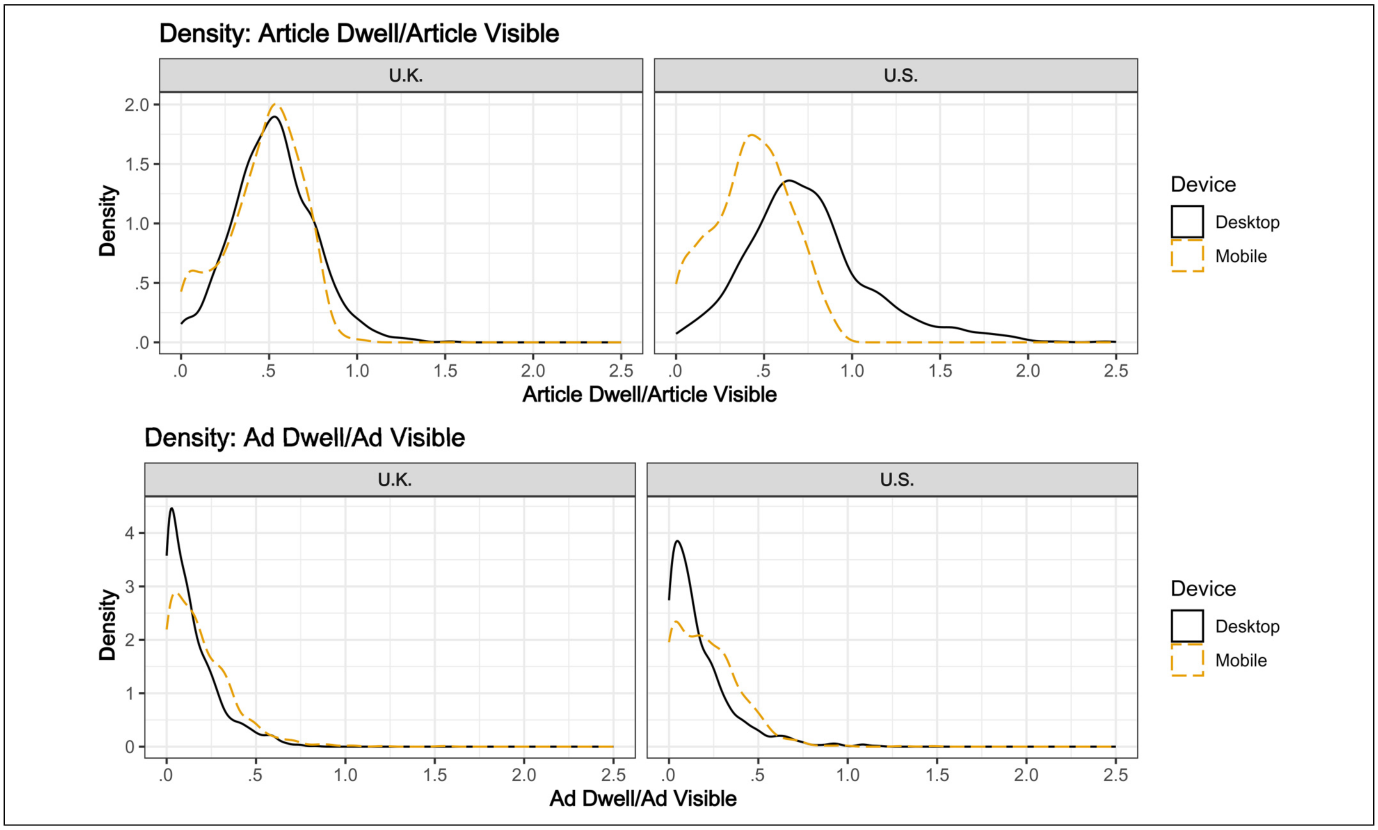

Figure 2. Dwell to Visible Ratios, by Country and Device.
Notes: The plots show the ratio between time spent dwelling and time visible, for both articles and ads, computed across all observations in the data.

seconds on mobile devices, respectively). Ad Dwell is approximately 4 seconds in the first step on both device types, decreasing to 2.2 seconds in the last step.

There is a robust positive correlation between attention devoted to articles and their associated ads. Figure 3 displays a scatter plot of Ad Dwell and Article Dwell. Across countries and device types, we observe a positive correlation of .36.[15] The correlation is more pronounced for mobile devices (.65) compared with desktops (.16). Web Appendix Figure W7 shows that this positive correlation persists within each article. Even after controlling for country, device, step order, and demographic fixed effects (hereinafter "FEs"), the positive correlation between Article Dwell and Ad Dwell remains robust.[16] In Web Appendix E, we show that this positive correlation is robust to a battery of checks accounting for potential measurement error in attention.

Purchase and recall measures. Our key outcome measures are the recall of the shown brand and participants' choices in an incentivized "purchase" scenario. We ensure the meaningfulness of these purchase choices by examining demand curves derived from randomly assigned cash amounts (Web Appendix Figure W9). Here, we describe the average share of U.S. and U.K. consumers opting for the brand voucher over cash. On average, 52% of U.S. consumers and 40% of U.K. consumers choose the brand voucher over \$3/£3. This preference diminishes as the cash amount increases, with only 34% of U.S. consumers and 20% of U.K. consumers selecting the brand voucher over \$7/£7. In Web Appendix Figure W10, we separately estimate demand curves for each brand, confirming that this pattern is not influenced by outlier brands.

In Figure 4, we examine how recall and purchase correlate with attention devoted to ads, Ad Dwell. The percentage of individuals who chose the voucher and recalled seeing the brand increases with the amount of attention devoted to the ad.

Web Appendix C contains several additional data descriptives, including marginal densities of our attention metrics, attention by types of ads (side vs. top), how attention changes with step order, demand curves for the different brands, and distributions of other individual characteristics (gender, education, age, income, and political leaning).

Determinants of Attention Allocation

A Stylized Model of Attention Allocation

We first present a simple model to microfound how individuals allocate their attention to articles and ads. We then discuss the empirical specification that follows from the model.

[15] This correlation is nearly identical (.35) if we drop observations with Ad Dwell of 0 (5.5% of the sample).

[16] Web Appendix Figure W8 presents a version of Figure 3 using only residualized variation in attention measures.

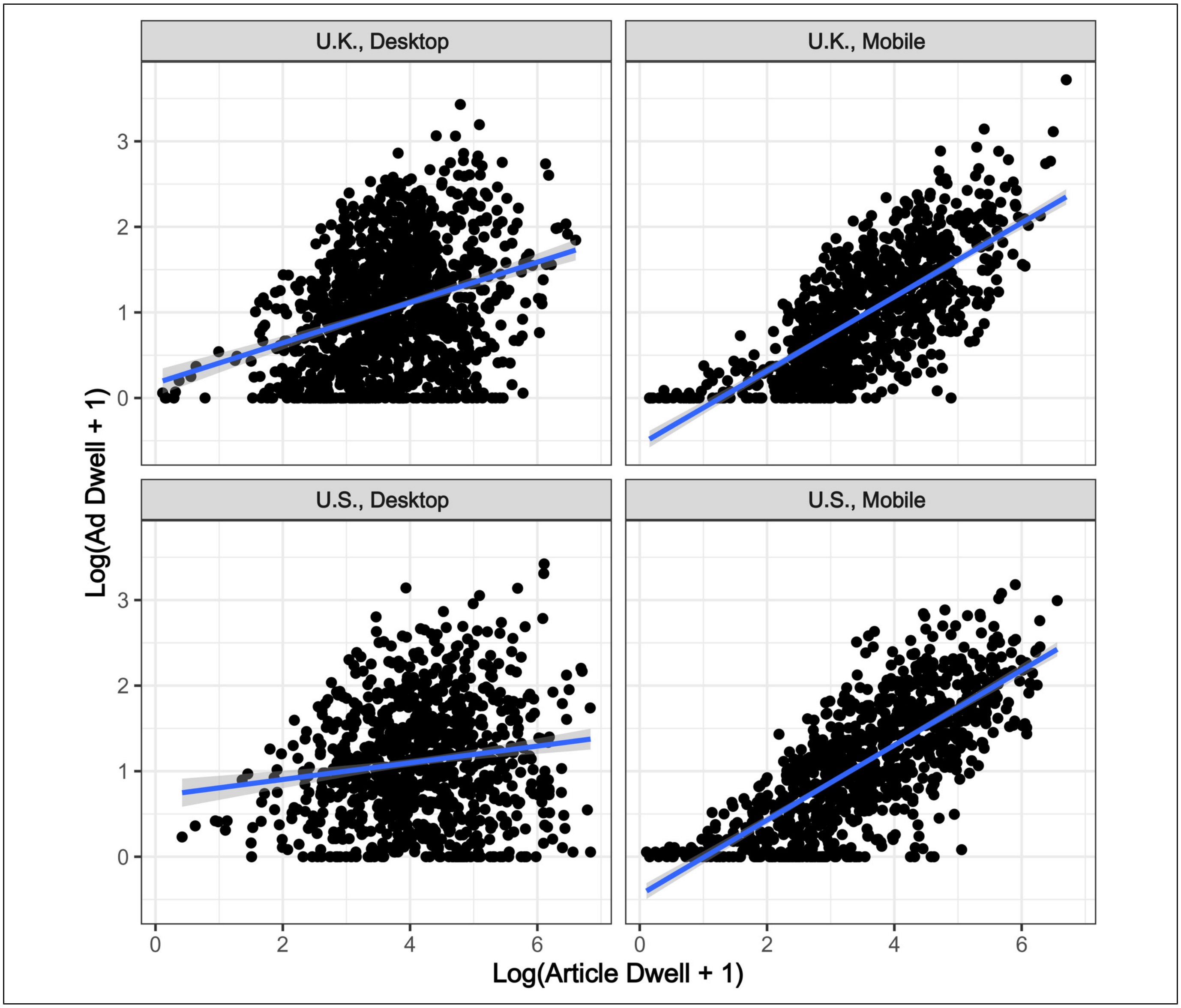

Figure 3. Positive Correlation in Article and Ad Dwell.
Notes: Correlation between attention to article and ad, split by country (United Kingdom and United States) and device type (desktop, mobile). Ad and article dwell times are transformed into the logarithmic scale to improve visualization. The blue line corresponds to the best linear prediction of the variable on the vertical axis by the variable on the horizontal axis. The gray area corresponds to 95% confidence intervals.

Consider a reader deciding how much attention to devote to an article (x_{art}) and display ads of a given brand shown next to this article (x_{ad}). The reader chooses x_{art}, x_{ad} to maximize utility from examining the web page,

$$U(x_{art}, x_{ad}) = \alpha x_{art} - \frac{x_{art}^2}{2} + \mathbb{1}\left(-\beta x_{art} + \delta x_{ad} + \gamma x_{art} x_{ad} - \frac{x_{ad}^2}{2}\right). \quad (1)$$

Here, α captures the reader's interest in the article. The indicator 1 describes whether the ad of the brand was shown next to the article for that reader. The coefficient β is the reader's disutility from devoting attention to the article when an ad is shown next to it (or utility if $-\beta > 0$). The coefficient δ is the reader's preference for devoting attention to the ad. Finally, γ determines whether the reader prefers to spend more attention on the ad if they spend more attention on the article, and vice versa (i.e., it measures the complementarity or substitutability between the article and ad). We capture the reader's costs of devoting increasing attention to the article and ad by including negative quadratic terms $x_{art}^2/2$ and $x_{art}^2/2$, which ensure an interior solution while keeping the setting simple.[17]

[17] The model can be easily extended to allow for an overall time constraint such that $x_{art} + x_{ad} \leq \bar{x}$, and for differential costs of attention for ads and articles. However, such extensions do not provide additional insights.

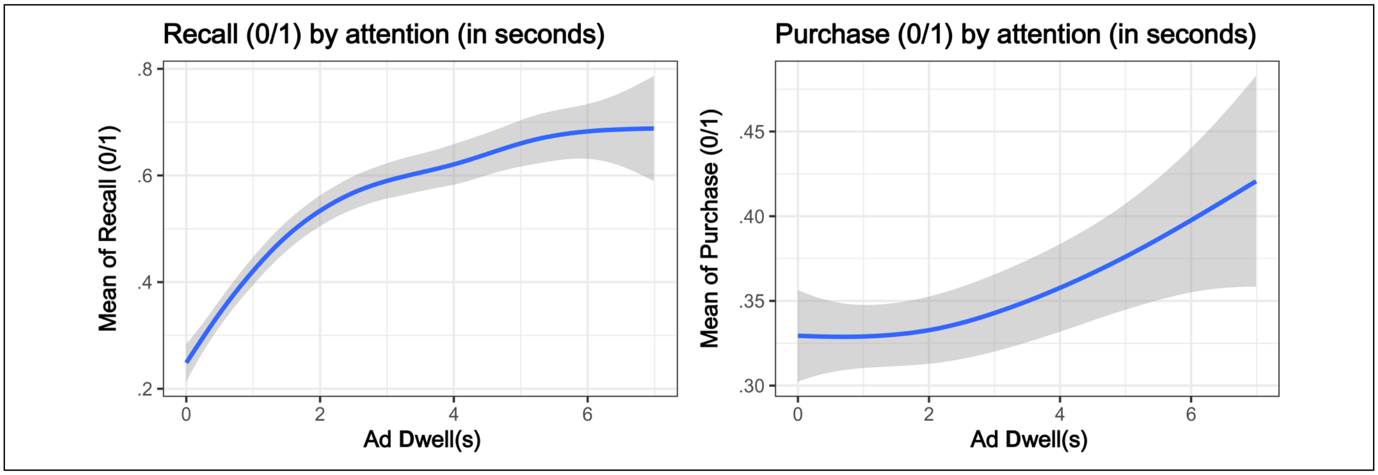

Figure 4. Purchase and Recall Increase in Ad Dwell Time.
Notes: The panels show nonparametric regressions of purchase/recall on Ad Dwell, together with 95% confidence intervals. The automatic optimal bandwidth is used. The range of the x-axis is capped at 7 seconds, which is approximately the 90th percentile of the distribution.

Maximizing utility with respect to x_{art}, x_{ad}, and denoting the solutions as $x^{\star}_{art}$ and $x^{\star}_{ad}$, yields the following first-order conditions:

$$x^{\star}_{ad} = \mathbb{1}(\delta + \gamma x^{\star}_{art}), \tag{2}$$

$$x^{\star}_{art} = \alpha + \mathbb{1}(-\beta + \gamma x^{\star}_{ad}). \tag{3}$$

There are two main coefficients of interest: β and γ. The sign of β reflects whether the reader is an "ad avoider" or "ad lover." It is possible that individuals can be "ad lovers" (e.g., this might be particularly likely in the context of car or beauty magazines; Kaiser and Wright 2006). However, previous literature has found that consumers are more likely to be ad avoiders (e.g., Huang, Reiley, and Riabov 2018; Wilbur 2008, 2016), so we expect $\beta > 0$.

The coefficient γ determines whether articles and ads are substitutes or complements; a priori, both could happen. For instance, as an individual reads the article, small movements of the retina or peripheral attention might allow them to perceive the ad next to it. If so, attention to articles creates positive spillovers of attention to ads ($\gamma > 0$), corresponding to a model of "bottom-up" attention (Cerf et al. 2007; Itti, Koch, and Niebur 1998; Koch and Ullman 1987; Milosavljevic and Cerf 2008; Pieters and Wedel 2007). Alternatively, if articles absorb the individual's attention, high attention to articles would correspond to low attention to ads. Then, attention spillovers are negative ($\gamma < 0$), corresponding to a model of "top-down" attention (Drèze and Hussherr 2003; Simola et al. 2011; Stenfors, Morén, and Balkenius 2003).

Empirical Framework

We now extend the stylized model to our empirical specification. Reader i decides to devote x^{art}_{ijks} seconds of attention to article j, which is paired with an ad for brand k, in experimental step $s = 1, \ldots, 9$. Moreover, reader i also decides to devote x^{ad}_{ijks} seconds of attention to the corresponding ad. Following the model above, we assume that x^{art}_{ijks}, x^{ad}_{ijks} are defined by the following set of simultaneous equations:

$$x^{ad}_{ijks} = \mathbb{1}_{ijks}(\delta_{iks} + \gamma \times x^{art}_{ijks} + \epsilon^{ad}_{ijks}), \tag{4}$$

$$x^{art}_{ijks} = \alpha_{ijs} + \mathbb{1}_{ijks}(-\beta + \gamma \times x^{ad}_{ijks}) + \epsilon^{art}_{ijks}. \tag{5}$$

Notice that, after reintroducing the notation referring to an individual, article, brand, and step order (plus an error term), Equations 4 and 5 correspond directly to the first-order conditions 2 and 3 of the stylized model of attention.

The reader's attention to the ad, x^{ad}_{ijks}, is formed from three components. First, δ_{iks} is individual i's preference for devoting attention to the ad of brand k in step s. We estimate δ_{iks} as a flexible function of individual characteristics, ad FEs, and experimental step FEs. Controlling for individual characteristics accounts for the fact that some types of individuals might be more drawn to ads than others. Ad FEs account for the fact that certain ads might be more appealing than others. We control for the experimental step to account for the potential fatigue of participants as the study progresses.

Second, the attention devoted to an ad can be influenced by the attention devoted to the article, as captured by γ. This corresponds to possible "attention spillovers" between articles and ads. We assume that this effect is homogeneous across individuals, articles, and ads.[18]

Finally, ϵ^{ad}_{ijks} is an idiosyncratic error term that can impact the attention the individual devotes to the ads. Since attention to an

[18] This homogeneity assumption ensures that the direction of attention spillovers is the same for all individuals. This is necessary for using attention to content as an instrument for the attention to ads (Angrist and Imbens 1995; Moshary, Shapiro, and Song 2021), as we do subsequently in this article.

ad is 0 when the ad is not present, Equation 4 is multiplied by $\mathbb{1}_{ijks}$—an indicator that equals 1 if the ad of brand k was shown next to article j for participant i in step s, and 0 otherwise. Therefore, to estimate Equation 4, we use only data for which articles were matched with ads.

Similarly, there are three components that determine the reader's attention to the article, x^{art}_{ijks}. First, α_{ijs} captures reader i's interest in article j during experimental step s. Next, we define α_{ijs} as a flexible function of individual characteristics, article FEs, and experimental step FEs. The variable ϵ^{art}_{ijks} is an idiosyncratic error term that can affect the attention the individual devotes to the article.

Finally, if the ad is present ($\mathbb{1}_{ijks} = 1$), it affects the reader's attention to the article in two ways. First, the coefficient β is the reader's disutility of attention to the article when any ad is shown next to it (or utility if $-\beta > 0$). This captures the fact that ads can be distracting and therefore reduce the amount of attention devoted to articles.[19]

The coefficient γ captures the same "attention spillover" between articles and ads as in Equation 4. For simplicity, our main specifications assume that the attention spillover effect is symmetric—an extra second of attention to the article leads to γ seconds of attention to the ad, and vice versa. This is a natural assumption if attention spillovers are driven by peripheral attention or small movements of the retina due to distractions while looking at page elements. However, all our subsequent results are robust to the spillover from ads to news being of a different order of magnitude than the spillovers from news to ads. We show that the incremental spillover of attention from ads to articles is negligible because an average respondent spends 27 times more time paying attention to news (74.8 seconds) than ads (2.8 seconds), per Table 1.

Identification

There are two main coefficients of interest. The sign of β reflects whether readers are "ad avoiders" or "ad lovers," while γ determines the sign and magnitude of attention spillovers.

The parameter γ can be consistently estimated because of the random matching between articles and ads. For a given ad, our experimental design randomly pairs it with a more or less interesting article. This creates an exogenous shock to the amount of attention a consumer devotes to the content paired with the ad, which we use to estimate the spillover effect of attention to news on the attention to ads.

We estimate γ in two ways. First, to isolate exogenous attention to articles, we estimate Equation 4 instrumenting x^{art}_{ijks} with the average amount of attention devoted to that article by all *other* individuals in the sample. We refer to this IV as the "leave one out" (L1O) mean of article attention.[20]

Second, we show that an OLS regression of x^{art}_{ijks} on x^{ad}_{ijks} in Equation 4 leads to statistically similar estimates of γ as the L1O IV regression. In a general setting, OLS estimates of γ from Equation 4 should be biased due to reverse causality, since γ is also present in Equation 5. However, in our context this simultaneity bias is negligible. This is because the true γ is precisely estimated at around .008, and the average consumer allocates around 27 times more attention to the article (74.8 seconds) than to the ad (2.8 seconds). Thus, the "feedback" of attention spillovers from ads to articles is approximately $.008 \times 2.8 = .022$ seconds, or $.022/74.8 = .029\%$ of the average attention individuals devote to an article.

Given the estimates of γ, the parameter β is identified by comparing attention to articles shown with and without ads after controlling for the estimated $\hat{\gamma} \times x^{ad}_{ijks}$ in Equation 5. Readers' overall tastes for devoting attention to articles and ads (δ_{iks}, α_{ijs}) are identified from the average attention consumers spend on articles and ads at different experimental steps. Article, ad, and individual FEs are not necessary for consistent estimates of γ, β, but we show specifications where they are included to check robustness of the estimates.

Estimation

We estimate the parameters described previously in two steps. First, we use Equation 4 to estimate γ and δ_{iks}. We estimate γ both by using the L1O IV (described previously) and by an OLS regression, including varying sets of FEs (step, brand, and individual) to increase precision and to check the robustness of the estimates. To estimate Equation 4, we use only observations when an ad is present on the page, since otherwise $x^{ad}_{ijks} = 0$ mechanically.

We then use Equation 5 to estimate α_{ij}, β. We estimate an OLS regression of $x^{art}_{ijks} - \mathbb{1}_{ijks} \times \hat{\gamma} \times x^{ad}_{ijks}$ (i.e., attention paid to the article net of spillover effects from the attention to ads) on the indicator $\mathbb{1}_{ijks}$. We use the entire sample including the articles shown without ads. Here, $\hat{\gamma}$ is the estimate of γ from the first step. In our empirical context, we find that the effect of $\hat{\gamma} \times x^{ad}_{ijks}$ on x^{art}_{ijks} is negligible due to both a low estimate of $\hat{\gamma}$ (around .008) and relatively low attention to ads relative to articles, as discussed previously. Our estimates of α_{ij} and β would be virtually identical if we assumed $\hat{\gamma} = 0$ or a value

[19] We assume that β is the same for all individuals and articles. This is a simplification since, in reality, some ads can be particularly distracting. In principle, we could allow β to vary by article and ad. In practice, we are underpowered to estimate those coefficients.

[20] This "jackknife" instrument is similar to the use of article FE as an instrument, but eliminates the bias associated with including the current individual when computing the FE, as discussed by Angrist, Imbens, and Krueger (1999) and Kolesar (2013). This IV approach is similar to the "random judges" instruments used in Dahl, Kostøl, and Mogstad (2014) and Dobbie, Goldin, and Yang (2018). In this case, each article is a "judge," and ads are randomly assigned to articles. Articles that vary in attractiveness play the role of judges who vary in leniency. Our results are also robust to using only attention to articles from individuals for whom the article was *not* paired with the same ad as the target person.

of $\hat{\gamma}$ that is 10 times larger than what we estimate.[21] We include varying sets of FEs (step, article, and individual) for robustness. In both steps, we cluster standard errors at the individual level.

Results

Table 2 presents the estimates under alternative specifications of α_{ijs} and δ_{iks}. Columns 1–3 present the estimates using the L1O IV for estimating γ in Equation 4. The first-stage relationship is highly significant across all specifications, with an incremental F-statistic of 65.9–128.2.

In Column 1, we assume that α_{ijs} and δ_{iks} are only a function of the experimental step. Formally, we assume that $\alpha_{ijs} = \alpha_s$ and $\delta_{iks} = \delta_s$. Parameters $\hat{\alpha}_1$ and $\hat{\delta}_1$ show the attention devoted, on average, to the article and ad shown to each individual in experimental step s = 1. In the first article–ad pair presented, individuals allocate on average approximately $\hat{\alpha}_1 \approx 106$ seconds of attention to the article and $\hat{\delta}_1 \approx 3$ seconds of attention to the ad. An extra second spent looking at the article increases the amount of time individuals look at the ad by $\hat{\gamma} = .008$ seconds. Thus, the 106 seconds spent (on average) looking at the first article creates a total of $106 \times .008 = .848$ seconds of positive spillover attention to the ad, or a $100 \times .848/3 = 28.2\%$ increase in ad attention. The magnitude of the reverse effect is very small: the 3 seconds of attention (on average) devoted to the ad create $3 \times .008 = .024$ seconds extra attention to the article, or a $100 \times .024/106 = .02\%$ increase. Having no ad next to the article increases the amount of time readers devote to the article by approximately $\hat{\beta} \approx 7$ seconds, showing that the average consumer is an ad avoider.[22]

In Column 2 of Table 2, we allow α_{ijs} and δ_{iks} to vary across articles and ads by including article and ad FEs: we assume $\alpha_{ijs} = \alpha_j + \alpha_s$ and $\delta_{iks} = \delta_k + \delta_s$. The baseline levels of $\hat{\alpha}$ and $\hat{\delta}$ are now subsumed by these FEs, so we omit them from Column 2. However, the estimates $\hat{\beta}$ and $\hat{\gamma}$ are nearly identical to those in Column 1.

In Column 3, we further allow α_{ijs} and δ_{iks} to vary across a variety of individual characteristics and controls, denoted X_i. We include country-by-device FEs and sociodemographic variables (e.g., income, age, gender) also included as FEs.[23] We further include a quartic (fourth-order) polynomial of the time each individual spent on an average article (measured by how long each page was visible) to capture the fact that some individuals read more slowly or are intrinsically more engaged by articles than other individuals. In total, we include 31 additional covariates in the regression. Again, the estimates of $\hat{\beta}$ and $\hat{\gamma}$ are statistically indistinguishable from those in Column 1, while their precision is higher.

Further, our results are robust to adding individual FEs that subsume X_i (see Table W22 in Web Appendix F). Adding individual FEs increases the number of controls by around 700 additional covariates, substantially reducing our statistical power in a sample of approximately 3,900 observations. Because of this, for our main analysis, we prefer a specification with individual covariates as controls.[24]

The magnitude of $\hat{\gamma}$ estimated in Columns 1–3 implies that reverse causality—the effect of attention to ads on attention to articles—is negligible. To confirm this further, in Columns 4–6 we present the results of estimating Equation 4 by OLS. The parameter estimates are statistically indistinguishable from those in Columns 1–3.[25]

Determinants of Recall and Purchase

So far we have estimated how individuals devote their attention. After reading the articles, we asked individuals if they recalled the advertised brands. We also asked individuals to make a purchase choice for each brand they saw.[26] Next, we estimate the effect of ad attention on consumers' brand recall and purchase decisions.

Empirical Framework

Consider whether consumer i recalls seeing an ad for brand k, shown next to article j in experimental step s after devoting attention x^{ad}_{ijks}. Let $r_{ijks} \in \{0, 1\}$ be an indicator that takes value 1 when recall is correct, and 0 otherwise. We assume that this recall process follows the following linear probability model (Heckman and Snyder 1997):

$$r_{ijks} = \theta^r_s + \eta^r_k + \mu^{rX}_i + \rho x^{ad}_{ijks} + \epsilon^r_{ijks}. \tag{6}$$

The coefficients θ^r_s are FEs for the experimental step s, capturing the effect on recall of seeing an ad later or earlier in the experiment.[27] The coefficients η^r_k are brand FEs: some brands might be more memorable than others. Finally, X_i adds individual-level controls similar to the ones used in Columns

[21] In particular, if $\gamma = 0$ in Equation 5, we can estimate Equations 4 and 5 simultaneously, avoiding the plug-in estimator and allowing for the correlation in error terms through the seemingly unrelated regression (SUR) model. In our specification, the SUR model leads to identical estimates as separate regressions 4 and 5, since Article Dwell is on the right-hand side in one equation and an outcome variable in another equation, making residuals in two models orthogonal by construction.

[22] We omit the step-order FE estimates from Table 2 to improve readability. Articles and ads shown in later steps of the experiment obtained less attention from participants, as illustrated in Web Appendix Figure W6.

[23] For instance, individuals reported their age in bins of ten years, so we include an indicator for each such bin.

[24] We further note that all our results are robust to a higher- and lower-order polynomial of the time individuals spent on an average article.

[25] For instance, Column 4 reports that an extra second of attention devoted to the article increases the amount of time devoted to the ad by $\hat{\gamma} = .011$ seconds (SE = .002), statistically similar to the estimate of .008 seconds in Column 1 (SE = .003).

[26] We convert U.K. prices to U.S. dollars at purchasing power parity at the time of the experiment (July 2020), £1 = \$1.66. Recall that the price p_{ik} is the random amount of cash offered to individual i as an alternative to choosing the voucher for brand k.

[27] The effect is a priori ambiguous. Ads shown later may receive less attention due to fatigue, but also might be more vivid in the participant's memory at the point when they are asked about their recall.

Table 2. Estimates of Attention Spillovers and Ad Avoidance.

	Ad Dwell					
	IV			OLS		
Panel I	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\hat{\delta}_1$	3.083***			2.715***		
	(.306)			(.197)		
$\hat{\gamma}$	.008***	.007***	.009***	.011***	.011***	.011***
	(.003)	(.003)	(.002)	(.002)	(.002)	(.002)
First-stage incremental F-statistic	65.86	80.15	128.23			
Observations	3,925	3,925	3,925	3,925	3,925	3,925
R^2	.135	.135	.202	.145	.152	.205
	Article Dwell—$\hat{\gamma}$ Ad Dwell					
	OLS					
Panel II	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\hat{\alpha}_1$	105.907***			105.894***		
	(4.521)			(4.521)		
$\hat{\beta}$	7.015*	6.832*	7.906**	7.024*	6.845*	7.913**
	(3.919)	(3.741)	(3.536)	(3.919)	(3.741)	(3.536)
Observations	4,426	4,426	4,423	4,426	4,426	4,423
R^2	.030	.112	.500	.030	.112	.500
FEs						
Step order	Y	Y	Y	Y	Y	Y
Article	N	Y	Y	N	Y	Y
Brand	N	Y	Y	N	Y	Y
Country × Device	N	N	Y	N	N	Y
Demographic controls	N	N	Y	N	N	Y
Poly(Duration, 4)	N	N	Y	N	N	Y

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: Y = yes; N = no. All specifications include step-order FEs, with step order = 1 normalized to 0. Estimates in Panel I represent coefficients from a regression of Ad Dwell on Article Dwell. In the IV specification, Article Dwell is instrumented for by the average amount of attention devoted to that article by all but this individual (L1O IV). Estimates in Panel II represent coefficients from an OLS regression of Article Dwell on an indicator of whether the ad is present on the news article. We subtract $\hat{\gamma}$ Ad Dwell from Article Dwell in Panel II to control for the attention spillover from ad to article. Demographic controls include income, gender, education, age, and self-reported political leaning. Poly(Duration, 4) corresponds to a quartic polynomial in log of average time that an average article was visible for by each individual. Standard errors are clustered at the individual level.

3 and 6 of Table 2—country-by-device FEs, sociodemographic characteristics, and a proxy for each individual's reading speed (a fourth-degree polynomial in the average time taken to read an article). Finally, ϵ^r_{ijks} captures other idiosyncratic shocks that determine consumer i's recall of brand k. Our main parameter of interest is ρ, which captures recall ad effectiveness: the effect of additional attention to the ad of brand k (x^{ad}_{ijks}) on the brand's recall.

Similarly, let $v_{ijks} \in \{0, 1\}$ be an indicator for the individual purchasing the voucher for brand k. We assume that the probability that the individual purchases the voucher at a price p_{ik} after devoting attention x^{ad}_{ijks} to the ad for brand k is:

$$v_{ijks} = \theta^v_s + \eta^v_{k,p_{ik}} + \mu^{vX}_i + \lambda x^{ad}_{ijks} + \epsilon^v_{ijks}. \quad (7)$$

Equation 7 is analogous to Equation 6, with a few small differences. As above, θ^v_s are step-order FEs. In Equation 6, we assume that price does not affect consumer recall. However, in Equation 7, we allow for price to potentially affect purchase decisions. Therefore, $\eta^v_{k,p_{ik}}$ are brand × price FEs, which allow the price elasticity to vary flexibly along the demand curve for each brand and allows demand curves to differ across brands. Finally, ϵ^v_{ijk} captures other idiosyncratic shocks affecting the individual's purchase probability. The parameter λ is the purchase ad effectiveness: the effect of additional attention to the ad of brand k on the decision to purchase that brand.

Identification and Estimation

We are interested in the effects of attention to advertising on consumer recall and purchase decisions, captured by the parameters ρ, λ in Equations 6 and 7. We rely on two empirical strategies to estimate these parameters.

First, we rely on accounting for potential sources of endogeneity biases by including several controls when estimating Equations 6 and 7: step-order FEs, brand FEs, and individual characteristics. These controls account for the same information included in δ_{iks} in Equation 4, capturing the main potential sources of endogeneity—for example, the experimental step might be correlated with both ad recall and attention due to respondents' fatigue, and brand FEs account for potentially higher-quality ads by the more popular brands.[28] With these controls, the residual variation in the amount of time consumers allocate to ads, x^{ad}_{ijks}, is plausibly driven by individuals' idiosyncratic decisions of how much attention to devote to ads that appear randomly throughout our study. If this residual variation in x^{ad}_{ijks} is uncorrelated with the idiosyncratic shocks that influence consumers' recall and purchase outcomes (ϵ^{r}_{ijks}, ϵ^{v}_{ijks}), then OLS produces consistent estimates of $\hat{\rho}$, $\hat{\lambda}$.

Second, we leverage the random pairing of ads and articles in our experiment to further relax the assumption that x^{ad}_{ijks} is uncorrelated with ϵ^{r}_{ijks}, ϵ^{v}_{ijks} conditional on controls. One possible remaining concern is reverse causality: perhaps individuals devote more attention to ads of brands that they are familiar with and particularly like, and therefore are more likely to recall and purchase. Formally, high x^{ad}_{ijks} is due to a high ϵ^{ad}_{ijks}, which in turn might be correlated with ϵ^{r}_{ijks}, ϵ^{v}_{ijks}. This argument is in line with the model of Becker and Murphy (1993) and Tuchman, Nair, and Gardete (2018), where advertising has consumption value and enters viewers' utilities.

To address these concerns, we instrument the amount of attention a reader devotes to an ad (x^{ad}_{ijks}) with the amount of attention they devote to the article randomly paired with that ad (x^{art}_{ijks}). In the previous section, we have shown that there is a strong positive spillover in the consumer's attention from article to ads, making x^{art}_{ijks} a relevant instrument. Moreover, we have also shown that the "feedback" effect of ads on articles is minuscule and robust to using a L1O IV strategy, validating the exogeneity of the instrument. Therefore, this identification strategy uses only the incremental exposure to ads due to positive spillovers of attention from randomly paired articles (which can be more or less interesting to consumers) to measure the effect of ad exposure on recall and purchase decisions. Finally, we assume that attention spillovers are the same for all individuals in our sample, consistent with the monotonicity condition required for standard IV techniques (Angrist and Imbens 1995; Moshary, Shapiro, and Song 2021).[29] In all specifications, we cluster standard errors at the individual level.

[28] While our main specification includes individual demographics as controls, Web Appendix Table W18 shows that the estimates are robust to including individual FEs.

[29] Figure 3 and Web Appendix Figure W11 show that the relationship between attention to articles and ads is positive across various articles, countries, and device types, providing evidence in support of the monotonicity condition.

Results: OLS

We begin by presenting the results of OLS regressions. Table 3 shows the OLS estimates of the effect of ad attention—measured both with Ad Visible and Ad Dwell—on recall and purchase. Column 1 reports the estimates of recall ad effectiveness ($\hat{\rho}$) based on all observations in the sample. Panel I considers attention measured by Ad Visible. If a brand's ad is visible for 1 extra second, this increases the probability of the individual remembering that brand by about .32 percentage points. An increase in Ad Visible of one standard deviation (17.37 seconds, from Table 1) is associated with an increase in recall of $100 \times .0032 \times 17.37 = 5.55$ percentage points. Panel II considers attention measured by Ad Dwell. If the individual devotes an additional second of attention to an ad, this increases the probability of recall by 3.43 percentage points. An increase in one standard deviation of Ad Dwell (3.16 seconds) increases recall probability by 10.83 percentage points (relative to the average recall probability of 48%). In line with intuition, the magnitudes of the estimates are larger when attention is measured using the time individuals actually spend engaging with the ad (which we measure using eye tracking). Ad Dwell explains an additional 5.2% of the variation in recall than Ad Visible: R^2 is .091 in Column 1 of Panel I and .143 in Panel II. This highlights the value of eye tracking as a more direct measure of attention.

Column 6 of Table 3 reports estimates of purchase ad effectiveness, the effect of ad attention on the incentivized purchase behavior ($\hat{\lambda}$). Panel I shows that, if an article is visible for an extra second, purchase probability increases by .13 percentage points. An increase of one standard deviation of Ad Visible increases purchase probability by 2.26 percentage points (relative to the average purchase probability of 35%). If an ad is actually looked at for an extra second, the probability of purchase increases by .73 percentage points. An increase of one standard deviation in Ad Dwell leads to a 2.31 percentage points higher purchase probability. As in the case of recall, Ad Dwell has a better predictive power of the outcome measure than Ad Visible: R^2 increases from .130 in Column 6 of Panel I to .136 in Panel II.

News content type. Columns 4–5 and 9–10 of Table 3 report the estimates of ρ and λ separately for ads that were randomly matched to "hard" and "soft" news articles. As discussed at the outset, industry practitioners are wary of advertising next to "hard news" articles because of the perceived negative effect on their brand. This should imply that, for "hard" news, we should see smaller or even negative estimates of ρ, λ. In contrast, we find that estimates of the recall and purchase ad effectiveness are qualitatively similar across news types. If anything, we find that the magnitudes of the estimates are slightly *higher* for ads shown next to hard news. For instance, a 1 second increase in Ad Dwell for ads next to hard news articles increases purchase probability by .9 percentage points, whereas a similar estimate for ads on soft articles is .5 percentage points.

Table 3. Estimates of Advertising Effects on Recall and Purchase: OLS.

	Recall ($\hat{\rho}$)					Purchase ($\hat{\lambda}$)				
		Device		News Type			Device		News Type	
	All	Mobile	Desktop	Hard	Soft	All	Mobile	Desktop	Hard	Soft
Panel I	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Ad Visible	.003***	.003***	.004***	.004***	.002***	.001**	.002**	.001*	.001**	.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Observations	5,707	2,495	3,212	3,154	2,553	5,707	2,495	3,212	3,154	2,553
R^2	.091	.103	.120	.102	.096	.130	.164	.147	.147	.147
Panel II	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Ad Dwell	.034***	.028***	.036***	.041***	.029***	.007**	.009**	.008**	.009**	.005
	(.004)	(.006)	(.005)	(.004)	(.005)	(.003)	(.004)	(.004)	(.004)	(.004)
Observations	3,925	1,824	2,101	2,165	1,760	3,925	1,824	2,101	2,165	1,760
R^2	.143	.133	.188	.167	.139	.136	.200	.153	.168	.159

*p < .1.
**p < .05.
***p < .01.
Notes: All specifications include a quartic polynomial in log of average time that an average article was visible for by each individual, step order, and device × country FEs, FEs for individual covariates (income, gender, education, age, and self-reported political leaning), and brand (for recall) or brand × price (for purchase) FEs. Standard errors are clustered at the individual level.

Table 4. Attention and Hard News.

	Measure of Attention:			
	Ad Visible (1)	Ad Dwell (2)	Article visible (3)	Article Dwell (4)
Hard news	−.9049***	−.4902***	−10.1627***	−6.7510***
	(.3168)	(.0828)	(2.6201)	(2.0077)
Observations	5,707	3,925	5,707	3,925
R^2	.4187	.1461	.6355	.4705

*p < .1.
**p < .05.
***p < .01.
Notes: FEs for individual covariates (income, gender, education, age, politics), step order, brand, and country × device. Includes a quartic polynomial in total time an average page is visible for each individual. Includes a linear control for number of words in article. Standard errors are clustered at the individual level.

To better understand the interaction between article content, ad effectiveness, and the total amount of ad attention, we regress our four attention variables (Ad Dwell, Ad Visible, Article Dwell, Article Visible) on an indicator of whether the article is classified as hard news. To keep the estimates consistent, we include the same controls as in Table 3. Further, to keep articles comparable, we control for their length by including the number of words.[30] Results are shown in Table 4.

Hard news articles, and the ads randomly shown next to these articles, receive less attention than other ads and articles. Individuals spend less time looking at the ads (Columns 1 and 2), and also less time looking at the article itself (Columns 3 and 4). In terms of Article Dwell, there is a reduction of almost 7 seconds (about 10% of the median), and a reduction of .49 seconds for Ad Dwell (about 15% of the median).

These results should be interpreted with caution. There were many hard news stories on the topics of COVID and BLM in the press at the time of the experiment (July 24–August 6, 2020), so individuals may have already been broadly informed about the topic in the articles we chose (the experiment did not allow testing for preexperiment knowledge). Alternatively, individuals might have grown weary of such stories. We cannot say whether our finding is due to participants disliking hard news or because they were shown articles on topics they were already aware of, resulting in quick skimming.

Importantly, even if we interpret the lower attention that consumers devote to hard news as causal, our results suggest that advertising next to hard news is still at least as effective as advertising next to soft news. To determine this, we combine the negative effects of hard news on the amount of attention readers devote to ads (Table 4) and the positive effect of incremental attention on purchases (Columns 9 and 10 in Part II of Table 3). From Table 1, the average attention to ads (irrespective of news content type) is 2.76 seconds. From Table 3, devoting this amount of attention to ads next to "soft news" articles increases the purchase probability by $.5 \times 2.76 = 1.38$ percentage points. For hard articles, the same effect is $.9 \times (2.76 - .49) = 2.04$ percentage

[30] This addresses the concern that "hard news" articles might systematically be longer or shorter than other articles, which would mechanically affect attention.

points. Hard news articles on average induce .49 seconds less attention to ads but have higher (.9 instead of .5) ad effectiveness per second of devoted attention. On balance, this implies that the benefits of advertising next to hard news are similar to, if not higher than, advertising next to soft news articles.

Device type. Columns 2–3 and 7–8 of Table 3 report $\hat{\rho}$, $\hat{\lambda}$ separately for consumers participating in the experiment from mobile devices and desktop computers. Across all subsamples, estimates of the purchase and recall ad effectiveness are nearly identical, validating the importance of advertising both on mobile and desktop devices.

Robustness. We present three additional robustness checks of the estimates. First, previous work has documented attention fatigue and decay (Ahn et al. 2018; Goldstein, McAfee, and Suri 2011). In Web Appendix Table W17, we test for this by allowing outcomes to be a function of a quartic polynomial in attention in Equations 6 and 7. We indeed find diminishing returns to attention; for all specifications, the quadratic term on the advertising attention is negative. However, within our sample, the nonlinear effects on our main outcome variable (incentivized purchase) are economically and statistically small.

Second, our estimates are similar (although less precise) in a more demanding specification with individual FEs instead of individual-level covariates (Web Appendix Table W18).

Finally, we replicate our main results in Table 3 with a logistic model instead of the linear probability model (Web Appendix Table W19). All estimates are robust and imply marginal effects of similar magnitudes as in Table 3. We discuss the magnitudes in more detail in Web Appendix G.1.

Results: IV

Table 5 presents the estimates of ρ, λ from IV regressions of Equations 6 and 7, where we instrument for Ad Visible and Ad Dwell with Article Dwell.[31] Panel I presents the results with Ad Visible as the measure of attention to ads. The first-stage results are presented in the bottom part of Panel I. For all specifications, we have strong instruments: incremental F-statistics vary from 12.8 to 79. The first-stage regressions confirm strong positive attention spillovers between the article and ads, described in Table 2. The second-stage IV estimates are presented at the top part of Panel I.

For the outcome of recall (Columns 1–5), the estimates $\hat{\rho}$ are too imprecise to conclude that they are different from the OLS estimates or 0. For instance, when we include all observations (Column 1), $\hat{\rho} = .0003$ is smaller than the OLS estimate of .003—but the standard error is .002, making the difference statistically insignificant.[32]

For the purchase outcome (Columns 6–10), the estimates of $\hat{\lambda}$ are positive and statistically significant—the spillover attention to ads due to an interesting article leads to a higher purchase probability of the brand that was advertised. The estimated magnitudes of $\hat{\lambda}$ are larger for the IV case—although differences between the IV and OLS estimates are only marginally significant, due to larger standard errors of the IV estimates. The fact that the IV estimate of $\hat{\lambda}$ is larger than the OLS estimate suggests that reverse causality is not a big concern in this case, since consumer behavior à la Becker and Murphy (1993) and Tuchman, Nair, and Gardete (2018) would lead to an upward bias of the OLS estimates (and we find the opposite).

Panel II of Table 5 presents the results with Ad Dwell as the measure of attention to ads. All conclusions are the same as in the case of Ad Visible. The first-stage results confirm a strong complementarity between attention devoted to articles and ads. Incremental F-statistics are between 10 and 183 across specifications, with the strongest relationship for mobile and the weakest for desktop devices. The estimates $\hat{\rho}$ are imprecise across the specifications (Columns 1–5), while the estimates of $\hat{\lambda}$ are positive and statistically significant (Columns 6–10). The IV estimates of $\hat{\lambda}$ are larger than the OLS estimates, but the difference is not statistically significant.

In Columns 7–10 of Table 5, λ estimates are presented separately for different devices and news types, confirming findings from the OLS analysis. For both mobile and desktop devices, λ estimates show no statistical difference when using Ad Visible or Ad Dwell as attention metrics. Likewise, the impact of advertising on recall and purchase for "hard" and "soft" news is qualitatively similar. Furthermore, the estimated magnitudes are slightly *higher* for ads displayed alongside articles featuring hard news.

Robustness. As an additional robustness check, we use the L1O article attention (the average amount of attention devoted to the article by all *other* individuals in the sample) as an IV to instrument for attention to ads. From Table 2, the L1O attention significantly shifts the amount of time a consumer devotes to the article, which in turn has a positive spillover effect on the attention to ads on the page. We present these results in Web Appendix Table W20. Once again, the first-stage estimates confirm the positive spillover of attention from articles to ads, although the strength of the instrument is weaker (e.g., for Ad Dwell as a measure of ad attention, incremental F-statistics vary from 1.8 to 13.3). Because of the lower statistical power of this instrument, the second-stage (IV) coefficients are also estimated imprecisely, though, reassuringly, they have the same magnitude as previous OLS and IV results.

Finally, we consider an alternative shifter of consumers' attention to articles: the (mis)alignment between consumers' and newspapers' political views. We construct a measure of political alignment of consumers and news outlets by asking participants about their political views. Independently, we classify news outlets as left wing, center, or right wing. A misalignment strongly predicts consumers' attention to articles—going from fully aligned views to completely misaligned views decreases the time people

[31] We cannot use Article Visible as an instrument since it is mechanically influenced by the attention to ads when both article and ad are visible on the page.

[32] Table A1 presents both the IV and the OLS results next to each other, to simplify the comparison of the estimates.

Table 5. Estimates of Advertising Effects on Recall and Purchase: Article Dwell IV.

	Recall ($\hat{\rho}$)					Purchase ($\hat{\lambda}$)				
	All	Device		News Type		All	Device		News Type	
		Mobile	Desktop	Hard	Soft		Mobile	Desktop	Hard	Soft
Panel I	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ad Visible	.0003	.008	−.001	.001	−.0004	.006***	.013**	.004*	.007**	.005*
	(.002)	(.007)	(.002)	(.003)	(.003)	(.002)	(.006)	(.002)	(.003)	(.002)
Observations	3,925	1,824	2,101	2,165	1,760	3,925	1,824	2,101	2,165	1,760
R^2	.105	.097	.138	.122	.103	.123	.128	.146	.148	.149
						First Stage				
Article Dwell	.058***	.024***	.076***	.057***	.059***	.058***	.026***	.075***	.057***	.059***
	(.007)	(.007)	(.009)	(.010)	(.007)	(.007)	(.007)	(.008)	(.010)	(.007)
Observations	3,925	1,824	2,101	2,165	1,760	3,925	1,824	2,101	2,165	1,760
R^2	.459	.282	.566	.430	.516	.467	.307	.582	.447	.531
First-stage incremental F-statistic	75.85	12.83	76.71	31.92	71.4	77.74	14.53	79.01	33.5	70.79
Panel II	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ad Dwell	.001	.008	−.009	.005	−.002	.028**	.015**	.052	.036**	.025*
	(.010)	(.007)	(.032)	(.014)	(.013)	(.011)	(.007)	(.037)	(.016)	(.013)
Observations	3,925	1,824	2,101	2,165	1,760	3,925	1,824	2,101	2,165	1,760
R^2	.107	.122	.117	.130	.100	.119	.199	.079	.145	.143
						First Stage				
Article Dwell	.011***	.022***	.005***	.011***	.011***	.011***	.023***	.005***	.011***	.011***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Observations	3,925	1,824	2,101	2,165	1,760	3,925	1,824	2,101	2,165	1,760
R^2	.205	.476	.129	.208	.232	.220	.500	.156	.235	.262
First-stage incremental F-statistic	48.23	173.37	11.96	34.63	34.09	48.52	183.4	10.41	36.78	34.52

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: All specifications include a quartic polynomial in log of average time that an average article was visible for by each individual, step order and device × country FEs, FEs for individual covariates (income, gender, education, age, and self-reported political leaning), and brand (for recall) or brand × price (for purchase) fixed effects. Standard errors are clustered at the individual level.

read the article by around 15.7 seconds. This, in turn, decreases the attention people devote to ads on the page, with ads becoming visible for 1.25 seconds less (SE = .64 seconds) and attracting .21 seconds less active attention dwell time (SE = .18 seconds). The magnitudes match the previous results on attention spillovers well (e.g., the first-stage results in Table 5 [Column 1] imply that an extra 15 seconds of Article Dwell increase Ad Visible and Ad Dwell by .87 and .17 seconds, respectively). However, the effect of political mismatch on the attention to ads is too imprecise to produce conclusive estimates of ρ, λ. We present details of the analysis and discuss the results in Web Appendix G.3.

Managerial Implications

Our article has four sets of findings with managerial implications. First, attention to ads can be measured and leads to higher ad recall and brand purchases, providing a way to measure ad effectiveness and price display advertising. Second, attention to articles has a positive spillover to ads placed next to them, highlighting the value of high-quality content. Third, "hard news" article content does not make ads less effective, cautioning against the practice of blunt "block lists" of advertisers. Fourth, ad visibility is a more imprecise metric of consumer attention, but still a valuable one for researchers. We consider each of these in turn.

We can use our results to calculate rough estimates of the costs and benefits of online display ads. First, we discuss the benefits. In our experiment, the ads on each page had an average dwell time of about 2.76 seconds per individual (i.e., the time individuals are attentive to the ad). At the mean, this attention increases the probability of purchase by $2.76 \times .007 \approx .02$, or about 2%.[33] In the United States, for instance, the opportunity cost to individuals of acquiring the voucher (the amount of cash individuals had to forgo, or the "price" of the voucher) was on average \$5. Therefore, we take the revenue for the brand from purchase to be \$5. This

[33] Here we use the OLS estimates from Table 3. The IV estimates would imply an even higher value of advertising.

implies that an ad is worth $5 \times .02 = 10$ cents of revenue per person exposed to the ad, or \$100 for 1,000 people.[34] We note that these estimates might overestimate advertising effectiveness of display advertising since individuals make an *immediate* purchase decision following exposure to ads, when information about the brands is more easily retrievable from the memory (Keller 1987).

On the cost side, the advertising industry typically uses the metric of a "cost per mille" (CPM, or cost per 1,000 impressions). For a digital inventory, this is difficult to assess because it is the result of an auction every time an ad is available rather than the setting of a price in general. Things are further complicated because advertisers tend to pay for targeting information (e.g., to ensure that a particular ad is shown to individuals who, based on their known characteristics, are likely to be interested in the brand), which further influences the cost. Still, Lumen Research shared with us its estimate of the cost per *attentive* 1,000 views (aCPM), which is £21.88 (≈ \$30) on desktops and £13.54 (≈ \$19) on mobile devices. On top of this, we would have to include technology and agency fees—that is, the cost of creating the ads and employing marketers. However, on the whole, these figures suggest that advertising is likely worth its cost. The magnitudes of the implied return on investments are larger than those typically reported in the literature (e.g., Kireyev, Pauwels, and Gupta 2016; Lewis and Reiley 2014), likely due to the immediacy of the purchase decision of consumers in our context.

Our second set of results shows that there is a positive attention spillover from articles to ads. These results emphasize the value of good, captivating news content; not only does such content drive more visitors to news outlets and increase their reputation, it also increases the effectiveness of advertising on news outlets' web pages. Thus, by investing in the quality of news content, publishers can charge higher CPM rates to advertisers. These findings provide business justifications against the practice of "clickbait" (using catchy titles or images to entice users to visit low-quality articles that are then immediately skipped). Instead, the result suggests that publishers should be incentivized to invest in more captivating and high-quality news content, even when only considering ad revenue. Our results on the "political mismatch" between outlet and readers further corroborate this idea: newspapers that cater to their audiences attract valuable attention to the article that spills over to the ad.

The third managerial implication that arises from our results is a word of caution when it comes to block lists that often do not allow ads to be placed next to "hard news." In our experiment, these were articles associated with the COVID-19 pandemic and the BLM protests. Our results reject the hypothesis of a negative effect of hard news per se on either ad recall or brand purchase. There may still be other reasons, such as brand safety (Vizard 2017), or preferences and career concerns of brand managers (Gordon et al. 2021), to limit exposure of ads to certain types of content. However, our results suggest that the current system might be too blunt or exhibit excessive risk aversion. Limiting the practice of block lists is particularly important at times of major societal events (e.g., pandemics, wars, the fight against climate change), since block lists penalize news outlets for providing detailed coverage of these important issues and informing citizens.

Our last set of results concerns alternative ways of measuring attention. We used two metrics of attention to articles and ads, visibility and actual dwell time. Dwell time is a more precise and accurate measure, as it measures the amount of time a person actually looks at web page objects. However, to produce that measure, one needs access to (costly) eye-tracking software. We found that the simpler measure, visibility, still produces reliable results when measuring the impact of attention on brand recall and purchase. This is reassuring and has important repercussions. Depending on the question at hand, research teams without access to eye-tracking software can still obtain robust answers by using non-eye-tracking-based measures of attention to ads, such as the time ads are visible on the page.

Our results validate the importance of the attention of website visitors for display advertising effectiveness, which can be "priced in" by the publishers and platforms. This view is aligned with the current thinking in the media industry. For instance, Mail Metro Media, which represents several of the United Kingdom's media brands (such as *The Daily Mail* and *The Telegraph*) created a "high attention" package of advertising, for which they charge a price premium to brands (dmg media 2021). A similar program is run by Ozone, the aggregated selling house used by *The Guardian*. Again, it charges a premium on its advertising inventory, which is justified in part by the higher attention its ads receive because of the intensity of the engagement with the content (The Ozone Project 2021). This does not seem to be only a sell-side or online news phenomenon. Havas, one of the largest media buying networks in the world, has adopted an explicit position that it will pay more for the quality of attention an ad receives (Sagar 2022). Like our method, these pricing strategies and measures of ad effectiveness benefit from a novel approach of leveraging the intensive margin of attention to ads, rather than an extensive margin of showing or not showing an ad on the page. McGranaghan, Liaukonyte, and Wilbur (2022) discuss similar strategies for incorporating attention metrics into the measures of ad effectiveness and pricing for TV ads.

Conclusions

In this article, we used measures of attention obtained with eye tracking to estimate advertising effectiveness in online markets. We ran an experiment that focuses on display advertising online, in which ads are shown next to articles. We showed that more engaging articles generate positive spillovers of attention from the news to the ads. This incremental ad attention increases the probability that the advertised brands are correctly recalled and subsequently purchased.

There are several important caveats to keep in mind regarding the external validity of our results, typical for similar experimental

[34] We are considering only revenue, not profit, since we have no estimate of the cost to the brand of producing and supplying the goods.

settings. First, we asked individuals to make an *immediate* purchase decision, so we are likely overestimating the effect a real ad would have on purchases. We note, however, that the brand-specific vouchers that individuals could obtain were valid for one year or more, so *consumption* does not need to be immediate and hence possibly mitigates this bias.

Second, we may be underestimating the impact of ads, since our ads are not targeted to specific individuals. We relied on the representativeness of the panel selected by a specialist supplier of research and marketing panels, and we chose brands that are of sufficient appeal to large audiences. We cannot estimate the effectiveness of targeted ads (nor was this the goal of our experiment)—doing so would require access to an algorithm that assigns ads to readers online, which we do not possess.

Notwithstanding these limitations, we hope that this work will prompt more research on the drivers and effects of digital attention, including an extended model of the links between attention and recall and a more detailed investigation into the underlying mechanisms. These models can be motivated and informed by the literature in neuromarketing and neuroscience; for example, Plassmann, Ramsøy, and Milosavljevic (2012) discuss advances in the literature and suggest avenues of theory generation that build on consumer neuroscience. Another interesting extension of our work is to measure the heterogeneity of ad effectiveness given the advertised brand and news context match. Tools such as eye-tracking software are now increasingly precise and available at scale in realistic settings to measure this.

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Appendix: Summary of Main Estimates and Results

Table A1. Summary of Main Results.

	First Stage (γ)		Effect on Recall		Effect on Purchase	
	Hard News	**Soft News**	**Hard News**	**Soft News**	**Hard News**	**Soft News**
Panel I (Ad Visible)						
OLS	—	—	.004***	.002***	.001**	.001
			(.001)	(.001)	(.001)	(.001)
Article Dwell IV	.057***	.059***	.001	−.0004	.007**	.005*
	(.010)	(.007)	(.003)	(.003)	(.003)	(.002)
L1O IV	.019	.099***	−.022	.004	.016	−.0002
	(.013)	(.013)	(.031)	(.004)	(.037)	(.004)
Panel II (Ad Dwell)						
OLS	—	—	.041***	.029***	.009**	.005
			(.004)	(.005)	(.004)	(.004)
Article Dwell IV	.011***	.011***	.005	−.002	.036**	.025*
	(.002)	(.002)	(.014)	(.013)	(.016)	(.013)
L1O IV	.009**	.008***	−.050	.046	.030	−.002
	(.004)	(.003)	(.061)	(.057)	(.065)	(.049)

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: This table presents a summary of our main empirical results. It includes estimates of how our two instruments affect attention and the effects of attention on recall and purchase. We separate the effects by news type (hard vs. soft news) in different columns. Standard errors are reported in parentheses below each estimate. The IV regressions for recall controlled for brand FEs, whereas those for purchase controlled for price × brand FEs. For readability, we show only the first stage of the IV regressions for recall, but the coefficients are virtually identical in both first-stage regressions.