Is Investor Attention for Sale? The Role of Advertising in Financial Markets*

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Abstract

Prior research documents capital market benefits of increased investor attention to accounting disclosures and media coverage, however little is known about how investors and markets respond to attention-grabbing events that reveal little nonpublic information. We use daily firm advertising data to test how advertisements, which are designed to attract consumers' attention, influence investors' attention and financial markets (i.e., spillover effects). Exploiting the fact that firms often advertise at weekly intervals, we use an instrumental variables approach to provide evidence that print ads, especially in business publications, trigger temporary spikes in investor attention. We further find that trading volume and quoted dollar depths increase on days with ads in a business publication. We contribute to research on how management choices influence firms' information environments, determinants and consequences of investor attention, and consequences of advertising for financial markets.

Keywords: advertising, investor attention, spillover effects

JEL codes: G14, G41, M37, M41

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1 Introduction

This paper examines whether advertisements influence investor attention and financial markets. Investor attention plays an important theoretical role in the acquisition and pricing of information.[1] Prior studies find that increased investor attention to information events (e.g., earnings announcements, media coverage) are associated with improvements in price discovery and liquidity (Hirshleifer, Lim, and Teoh [2009], Bushee, Core, Guay, and Hamm [2010], Drake, Roulstone, and Thornock [2012], Blankespoor, deHaan, and Zhu [2018b]). Aware of these benefits, publicly traded firms often seek to actively manage investor attention through, among other things, the use of investor relations departments (Bushee and Miller [2012], Kirk and Vincent [2014]), the timing of disclosures (deHaan, Shevlin, and Thornock [2015]), and the use of social media (Blankespoor, Miller, and White [2014], Lee, Hutton, and Shu [2015b], Jung, Naughton, Tahoun, and Wang [2017]).

In addition to these deliberate attempts to influence investor attention, firms engage in a myriad of activities that, potentially inadvertently, could also affect investor attention. We investigate whether advertising is one such activity. Advertising is a firm-controlled activity that targets consumers, but has the potential to simultaneously attract investors' attention (Keloharju, Knüpfer, and Linnainmaa [2012], Lou [2014]). In the presence of attention constraints (Kahneman and Tversky [1979]), advertisements plausibly remind current and potential investors about the company and can result in increased search for financial information. However, because ads are typically repetitive and likely reveal little nonpublic information, it is unclear whether ads cause any significant and measurable increase in investor attention. Furthermore, because any advertisement-driven increase in investor attention is unlikely to be information driven, it is unclear whether or how such increased attention affects financial markets.

[1] See Merton [1987]; Hong and Stein [1999]; Hirshleifer and Teoh [2003]; Peng and Xiong [2006]; and Hirshleifer, Lim, and Teoh [2011].

Because firms endogenously choose when, where, and how much to advertise, measuring the effect of advertising separate from correlated omitted variables is challenging. For instance, if firms advertise following an attention-grabbing product announcement, the correlation between advertising and investor attention using annual, monthly, or even weekly advertising expenditures will likely be positive and could be misinterpreted as advertising attracting investor attention. To address such concerns, we exploit variation in firms' daily advertising activity to directly measure effects of advertising on investor attention and financial markets.[2] Our data contain a comprehensive list of print advertisements placed by 637 publicly traded companies in 39 daily newspapers between 2008 and 2013. The granularity of our data allow us to measure changes in investor attention and financial markets on ad days relative to non-ad days.

Despite the clear advantages of using daily data, ad days are a firm-level choice and thus subject to endogeneity concerns. We therefore rely on an instrumental variables approach to generate "quasi-experimental variation" in advertising (Angrist and Pischke [2008], p. 122). We document that firms tend to advertise every 7 days, with variation across firms regarding on which day of the week they typically advertise. For instance, 79% of the 287 ad days for Oracle Corporation in our sample are Fridays, whereas 45% of IBM's 166 ad days are Tuesdays. We thus select as instrumental variables indicators for whether the firm advertised exactly 7 or 14 days earlier. We document that these instrumental variables are significantly associated with the likelihood that the firm advertises on a given day (i.e., relevance condition) and argue that they are also plausibly uncorrelated with omitted variables that also affect investor attention and financial markets on ad days (i.e., exclusion restriction, see Roberts and Whited [2013]).

[2] Our use of ad-level data contrasts with related research which exploits variation in annual advertising expenditures (e.g., Boyd and Schonfeld [1977], Grullon, Kanatas, and Weston [2004], Chemmanur and Yan [2009], Lou [2014]).

We use these instrumental variables in two-stage least squares regressions to analyze the effect of advertising on investor, rather than consumer, attention.[3] Specifically, using daily Google searches for company stock tickers (*Ticker SVI*) as a measure of retail investor attention (Da, Engelberg, and Gao [2011], Drake et al. [2012], Madsen [2017]), we find that *Ticker SVI* spikes by 4.9% on company-specific advertising days relative to non-advertising days. In both the first-stage and second-stage regressions we include controls for media coverage of the firm immediately before, on, and after the advertising day, as well as additional controls for product launches on these days, earnings announcement dates, and Edgar filing dates. We furthermore include both firm-year and date fixed effects to control for unobservable differences across firm-years and dates. Tests confirm that the instruments are not weak and are valid (i.e., uncorrelated with the error term).

We subject these findings to a battery of robustness tests and exploit variation in advertisement type (e.g., full-page ads), placement (e.g., business newspaper), and information content (e.g., repeated ad with little nonpublic information); drop all tickers that refer to a common object or contain only one letter; use only tickers for which a Google search produced a stock-specific information box; and examine alternative fixed effect structures. Collectively, these robustness tests confirm our main results. Furthermore, falsification tests find no increase in *Ticker SVI* on the three days immediately prior to an ad day, providing additional evidence that the increased attention is driven by the advertisement rather than confounding events.

To increase confidence that our results capture increased *investor* attention, we benchmark our findings using Google searches for company names (*Name SVI*), a measure of *consumer* attention. We find that ads trigger a 12.8% increase in *Name SVI*, much larger than the 4.9% increase in *Ticker SVI*. However, this pattern reverses when we examine financial events: *Ticker SVI* increases by 16.8% in response to an earnings announcements,

[3] Importantly, we find qualitatively similar results using ordinary least squares (OLS) regressions, suggesting that our findings are not driven by the use of instrumental varibles.

whereas *Name SVI* increases by 7.6%. Downloads of SEC filings from the EDGAR database, which reflect attention by a variety of investor types and regulators,[4] are insignificantly different on ad days, suggesting that our main results reflect increased interest in stock prices by retail investors. Collectively, our results are consistent with the notion that advertisements elicit increased retail investor attention, as opposed to consumer attention.

We next examine the effect of advertising on financial markets. Advertisements arguably have less nonpublic information than earnings announcements, management forecasts, analyst forecasts, regulatory filings (8k's, 10k's, etc.), and even media coverage. Thus it is unclear how much value investors can extract by analyzing firms' advertising activity.[5] However, even if ads contain no nonpublic information they can potentially affect markets by inducing attention-constrained individuals to pay attention to the company and trade (Barber and Odean [2008], Lou [2014]). Ad-induced trades by retail investors are likely uninformed, and in the market microstructure theories of Admati and Pfleiderer [1988] and Glosten and Milgrom [1985], liquidity is increasing in the proportion of uninformed trading. Thus, if uninformed trading increases relative to informed trading on ad days, then liquidity should increase, or at a minimum not decrease, and both stock prices and stock return volatility should temporarily increase (Greene and Smart [1999], Da et al. [2011], Lou [2014]). However, if informed traders rationally respond to any increase in uninformed trading such that the proportion of uninformed trading is unaltered as in Kyle [1985], then the effects on liquidity are ambiguous.[6]

[4] Prior research suggests that EDGAR downloads reflect attention by institutional investors (Dyer [2017]) and regulators (Bozanic, Hoopes, Thornock, and Williams [2017]), among other interested investor and regulatory groups. See also Drake, Roulstone, and Thornock [2015] and Lee, Ma, and Wang [2015a].

[5] One potentially direct consequence of advertising is increased sales revenue. However, because sales data is typically only available at quarterly frequencies, empirically quantifying the impact of an ad on revenue and brand value is challenging (Assmus, Farley, and Lehmann [1984], Erdem and Sun [2002], Buil, de Chernatony, and Martnez [2013]). Furthermore, it is unclear how any single ad day (the focus in our study) would affect a firm's financial performance.

[6] In this paper we focus on changes in aggregate trading volume and do not distinguish between uninformed and informed trading and their contributions to liquidity. The relation between uninformed and informed trading are studied in a concurrent working paper by Fang, Madsen, and Shao [2018].

We examine the effect of ads on total trading volume, liquidity, and stock returns using ads in business publications, as these are the ads most likely seen by individuals willing to transact in financial markets. We find that dollar trading volumes and quoted dollar depths significantly increase on days with business ads. The analyses suggest that trading volumes increase by $2–5.8 million relative to the sample average of $178 million (a 1–3% increase), and quoted depths increase by 8,200–20,300 shares relative to the sample average of 143,000 shares (a 5–14% increase). We find no significant change in either the effective or quoted spread. The results are consistent with a positive relationship between uninformed trading and liquidity (Lee, Mucklow, and Ready [1993]). Surprisingly, using 2SLS we find marginally significant but economically small negative returns on business ad days (results are insignificant using OLS), and insignificant returns over three-day horizons.[7] We conclude that due to attention constraints, a spillover effect of business ads is a marginal improvement in liquidity, particularly for large trades that benefit from increased depths.

We contribute to research on the economic consequences of advertising. Grullon et al. [2004] use annual ad spending as a proxy for firm visibility and document positive associations between ad spending and a firm's investor base and stock liquidity. Frieder and Subrahmanyam [2005] document that institutional investors tend to invest in stocks with well-recognized brands. Most closely related to this study, Lou [2014] examines the extent to which managers adjust advertising spending to attract investor attention and influence stock returns, and finds that increased annual advertising expenditures are associated with a rise in retail buying and stock returns. Lou [2014] also documents increased advertising expenditures prior to insider sales, consistent with opportunistic advertising by managers to exploit a temporary return effect. We also examine the hypothesis that advertising attracts investor attention, but use more granular ad-level data and a stronger identification strat-

[7] These results contrast with the significant positive returns documented by Greene and Smart [1999] when the number of shares traded increases by a much larger 240% for stocks covered in the *Wall Street Journal's* "Investment Dartboard" column.

egy to identify the immediate and direct effects of advertisements on investor behavior and financial markets.

We also contribute to a growing literature on the mechanisms whereby firms influence and manage investor attention (Bushee and Miller [2012], Kirk and Vincent [2014], Lou [2014], Blankespoor et al. [2014], Lee et al. [2015b], deHaan et al. [2015], Jung et al. [2017], Chapman, Miller, and White [2017], Karolyi and Liao [2017], Brown, Call, Clement, and Sharp [2017]). We find that advertising, a firm-controlled activity that traditionally targets consumers, has significant consequences for both investor attention and financial markets. Our results suggest that advertising is a channel whereby firms (potentially inadvertently) influence their information environment and investors' attention.

Finally, we contribute to a broad literature on investor attention and information dissemination (Hirshleifer et al. [2009], DellaVigna and Pollet [2009], Bushee et al. [2010], Drake et al. [2012], Drake, Guest, and Twedt [2014], Dai, Parwada, and Zhang [2015], Twedt [2016], Rogers, Skinner, and Zechman [2016], Madsen [2017], deHaan, Madsen, and Piotroski [2017], Blankespoor et al. [2018b]). Whereas prior studies generally focus on the effects of attentiveness to and dissemination of information-rich events such as earnings announcements or media coverage, we demonstrate that even frequent and repeated events that reveal little nonpublic information impact the behavior of attention-constrained investors, reducing awareness costs (Blankespoor, deHaan, Wertz, and Zhu [2018a]).

2 Data

We obtain print advertising data from MediaRadar for the sample period February 2008 to October 2013 (based on data availability). The data include information on brand advertised, publication, parent company, ad size, location within the publication, and estimated cost (based on the publication's published rates). We merge these entities by name with the CRSP/Compustat universe and identify 637 public companies which advertised more than once in a total set of 39 daily print publications. We focus on ads in daily publications to precisely identify advertising days.[8]

Because this is the first use of MediaRadar data in an academic research setting, we provide detailed descriptive statistics of these print advertisers (table 1 panels A - D). Table 1 panel A summarizes advertising activity by year. Between 2008 and 2013, these 637 firms placed 190,290 ads costing an estimated $10.8 billion based on the publications' posted rates.[9] These firms advertised 4,879 distinct brands during our sample period, with Macy's advertising the largest number of brands (176). MediaRadar added new titles throughout our sample period as they expanded their business, increasing from 1 daily title in 2008 to 37 in 2013. In our empirical analysis we address this expanding coverage by including both date and firm-year fixed effects to allow for a non-linear time trend and changes in the set of publications containing firm advertisements.

Table 1 panel B summarizes financial data for the firms in our sample. Firm size is skewed towards larger firms (with an average market cap of $25.57 billion and median market cap of $7.72 billion). In 2008 our sample represents 4.7% of the CRSP/Compustat total market capitalization, which increases to 65.5% by 2013. The average firm in our sample has 65% institutional ownership (compared to the average institutional ownership for the CRSP/Compustat universe of 46%), has revenues of $23,284 million, spends $496 million on advertising, and generates net profits of $1,539 million. The average firm in our sample spends an estimated $6.4 million each year on 81 print advertisements that appear on 34.9 days for 4 distinct brands placed across 4 newspapers. Conditional on advertising on a given day, the average firm places advertisements in 1.2 publications (99th percentile 3.6), suggesting that ad days often span multiple publications. Although the total amount spent on print advertisements in our sample is a small proportion of the average firm's total annual adver-

[8] For example the advertising date for *The Economist* is marked on Saturdays, even though *The Economist* goes on sale on Fridays.

[9] We use posted rates as a rough upper bound of total cost. Many companies are likely able to negotiate lower rates based on their volume of advertising.

tising budget, we find that print advertising is significantly correlated with firm's total advertising activity. After merging our advertising data with monthly advertising expenditures from Kantar Media's Ad$pender database (which monitors firms' total advertising activity across print, television, and radio), we find that the correlation between MediaRadar's advertising expenditures and Kantar Media's advertising expenditures is 0.52, suggesting that our measures of advertising activity are representative of at least general monthly advertising activity.

Table 1 panel C tabulates our sample composition by the Fama-French 12 industries. Our sample contains a large number of firms from wholesale/retail (15%) and finance (15%), with wholesale/retail placing 19% of all advertisements and accounting for 59% of the total cost of these advertisements. Panel D tabulates total advertisements by publication title for the 10 most commonly used titles in our sample. *The New York Times* contains over 30,000 advertisements in our sample, followed by *The Los Angeles Times* with 26,466, the *Chicago Tribune* with 16,792, and *The Wall Street Journal* with 14,339 advertisements. These four daily newspapers publish 48% of the total 190,290 advertisements in our sample, and thus a small number of publications carry the vast majority of our sample ads.

There are several trade-offs associated with using print advertising data. Research suggests that individuals are more likely to remember print ads versus digital ads (Agarwal and Ambrose [2008]). Print ads also have a longer shelf life, making it more likely they will be seen by multiple individuals. Advertising companies also argue that to be effective, marketing campaigns need to use multiple media platforms to reach their intended audience, including the use of both print and digital platforms. Although total readership of print newspapers has declined in recent years, readership of the top national newspapers, including *The Wall Street Journal*, has been relatively stable.[10] Furthermore, one implication of recent declines in newspaper readership is that the remaining readers represent the most engaged readers, a desirable feature for advertisers.

[10] https://www.statista.com/statistics/229986/readers-of-the-wall-street-journal-daily-edition.

3 Determinants of Advertising

Researchers face significant challenges identifying the effects of advertising. Firms determine how much and when they advertise (e.g., ads likely coincide with product launches, corporate events, or holiday seasons), making advertising levels inherently endogenous at annual, monthly, and even daily horizons. Disentangling the effects of advertising from the effect of a product launch (or any other potentially omitted variable) is unfeasible using annual or monthly advertising expenditures. Even using daily ad-level data, there are still concerns that an omitted variable would be responsible for any documented effect.

Thus before we analyze the effect of ads on investor attention and financial markets, we first model the determinants of a firm's decision to advertise on a particular date. Given concerns about endogeneity (e.g., omitted variables), we empirically identify the effect of advertising using instrumental variables which plausibly only affect investor attention and financial markets through their effect on the likelihood an ad is placed on a given date. Patterns in firms' advertising activity provide a useful source for finding such an instrumental variable if, having chosen a pattern, the resulting time series reflects the exogenous and predictable part of the advertising decision (Larcker and Rusticus [2010]).

Inspection of the daily advertising data reveals a tendency for firms to advertise at weekly intervals with a preferred advertising day. For example, 226 of the 287 ad days for Oracle Corporation in our sample are Fridays (78%), 74 of the 166 ad days for IBM are Tuesdays (45%), 20 of the 61 ad days for Pepsico are Mondays (33%), and 95 of the 243 ad days for Exxon Mobil are Wednesdays (39%). This pattern is not limited to only a few companies, and importantly is not concentrated on any particular day of the week across firms or industries. The percentages are also significantly greater than what would occur if ads were randomly assigned to days of the week (i.e., 1/7 or 14%).

We more rigorously document the pattern of advertising at weekly intervals in table 2. In panel A we tabulate, conditional on advertising on day t, the percent of firms advertising on day $t-x, \forall x \subset \{1-14\}$. We examine five types of advertising: an ad in any publication (*All*), an ad in a national publication (*National*), a full-page ad (*Large*), an ad for a brand that was previously advertised within the same publication within the previous two months and thus likely reveals little nonpublic information (*Repeat*), and an ad in a business publication (*Business*).[11] Across all five advertisement types, we find that days $t-7$ and $t-14$ contain the highest percent of firms advertising (44-60% depending on ad type). The pattern is particularly striking for business ads, where 45% and 44% of firms placed a business ad on days $t-7$ and $t-14$, respectively, whereas only 11-16% of firms placed a business ad on days $t-1$ through $t-6$ and days $t-8$ through $t-13$.

Panel B tabulates the percent of days of the week with advertisements to provide further evidence that this pattern is not specific to any one day. Although Sunday is the most popular advertising day, all five types of ads appear on each day of the week in comparable frequencies,[12] suggesting that although there is a general pattern of advertising every seven days, each company appears to select its own preferred day of the week.

In panel C we calculate for each day of the week the number of firms that have the highest number of their ads on that day ("preferred ad day").[13] Mondays are the most popular and Sundays the least popular preferred ad day (168 and 34 firms, respectively). We also tabulate, for firms with a given preferred ad day, the average percentage of firm ads that appear on that preferred ad day. For example, for the 168 firms with Monday as their preferred ad day, 53.5% of their ads are on Mondays. Percentages for the remaining days of the week range from 40.4% to 46.6%, suggesting that for most firms there is a clear preference for a specific advertising day of the week and that this preferred day varies by firm.

[11] National publications include *The Wall Street Journal*, *The New York Times*, and *Los Angeles Times.* Business publications include *The Wall Street Journal, Investor's Business Daily, Financial Times, Daily Journal of Commerce,* and *Daily Business Review.*

[12] We note there are no business publications, and thus no business ads, published on Sundays.

[13] Note we allow for ties (e.g., a firm with 10 ads on Mondays and Tuesdays and less than 10 on every other day of the week), thus the sum of these counts (736) does not equal the number of unique firms in our sample (637).

Panel C also tabulates, for each day of the week, the number of firms from each Fama French 12 industry with that preferred ad day. Although there is a preference for Mondays as a preferred day for several industries (e.g., durables, wholesale), for the more populous industries each day of the week is the preferred day for some firms within that industry. We conclude that firms and industries exhibit variation in the days of the week on which they most frequently advertise, although there seems to be a preference for Mondays. To address potential preferences for certain advertising days, we include in all our analyses date fixed effects. Based on this pattern of advertising, we consider as instruments indicators for whether the firm advertised exactly 7 or 14 days earlier.[14]

We analyze the determinants of advertising using the following linear probability model:

$$\begin{aligned}
Ad\,Measure_t &= \alpha + \beta_1 Ad\,Measure_{t-7} + \beta_2 Ad\,Measure_{t-14} \\
&+ \gamma_1 News\,Dummy_t + \gamma_2 News\,Tomorrow_t + \gamma_3 News\,Yesterday_t \\
&+ \gamma_4 Product\,Release_t + \gamma_5 Product\,Tomorrow_t + \gamma_6 Product\,Yesterday_t \\
&+ \gamma_7 Edgar\,File_t + \gamma_8 EA\,Day_t + \gamma_9 EA\,Window_t \\
&+ \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t \qquad (1)
\end{aligned}$$

where $Ad\,Measure_t$ is an indicator for one of the five types of advertising discussed previously and zero if a firm did not advertise on day t, and $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$ are 7- and 14-day lagged dependent variables (i.e., the instrumental variables). Based on the observational analysis in table 2, we expect that these lag dependent variables predict a firm's advertising on day t, which satisfies the relevance condition. Furthermore, the exclusion restriction is unlikely to be violated in this setting. The repeated pattern of advertising

[14] The fact that this pattern stems from the institutional details of ordering ads suggests that these specific lagged variables (i.e., $t-7$ and $t-14$) reasonably capture the exogenous part of advertising. Our focus on specific dates, rather than a general lagged advertising indicator, suggest that the instruments unlikely affect our outcome variables in any way other than through their affect on the likelihood an ad is placed on day t (Larcker and Rusticus [2010]). We tabulate both first- and second-stage diagnostics, and compare and contrast estimates using OLS and 2SLS as recommended by Larcker and Rusticus [2010].

is consistent with companies buying "ad packages" which are typically ordered weeks, if not months, in advance,[15] making it unlikely that the instrumental variables affect investor attention of financial markets on day t except through the increased likelihood an ad is placed on day t.

We include as additional controls several variables related to media coverage of the firm and its reporting environment that also plausibly influence the firm-level decision to advertise on a particular date (i.e., exogenous covariates). Specifically, $News\,Dummy_t$, $News\,Tomorrow_t$, and $News\,Yesterday_t$ are indicator variables equal to one if the firm is the focus of at least one news article on day t, $t+1$, and $t-1$, respectively; $Product\,Release_t$, $Product\,Tomorrow_t$, and $Product\,Yesterday_t$ are indicator variables equal to one if the media coverage on day t, $t+1$, and $t-1$ mentioned a product release, respectively, and thus capture any incremental effect of a product release on a news day (media coverage and press release data obtained from Ravenpack). $Edgar\,File_t$ is an indicator variable equal to one if the firm filed a 10-K, 10-Q, or 8-K with the SEC on day t; $EA\,Day_t$ is an indicator variable equal to 1 if the firm announced earnings on day t; and $EA\,Window_t$ is an indicator variable equal to one for the five days before and after an earnings announcement.[16] We furthermore include firm-year and date fixed effects to account for inherent differences across firms, the changing population of publications in MediaRadar and the firms advertising in those publications, and common time effects (e.g., weekends, weekdays, holidays, etc.). Standard errors are two-way clustered by firm and date to allow for a correlation in the error terms by firm (i.e., a more conservative choice than clustering by firm-year) and date Petersen [2009].

Coefficient estimates of equation 1 are presented in table 3. The instrumental variables are economically and statistically significant, particularly relative to the other control variables. Advertising in any publication 7 or 14 days earlier increases the probability of a general

[15] Per conversation with a *Wall Street Journal* representative.

[16] Although we have no specific prediction regarding how advertising varies around earnings announcement and EDGAR file dates, we include these controls in the first stage 2SLS regressions as they are important exogenous covariates for the second stage regressions we discuss in section 4.

advertisement on day t by 213-233% relative to the sample average,[17] with even larger results for the more specific forms of advertising (e.g., a ten-fold increase in the likelihood an ad is placed in a business newspaper on day t if an ad was placed in a business newspaper 14 days earlier). Adjusted R^2's are also moderately high, with the model explaining 39.6% of the variation in general daily advertising.

Examining the control variables, we find that news days are significantly associated with the likelihood of an advertisement. Firms advertise on news days and in anticipation of news days (i.e., significantly positive coefficients on $News\,Dummy_t$ and $News\,Tomorrow_t$), but do not appear to advertise in response to a previous news day (insignificant coefficient on $News\,Yesterday_t$). If the news is associated with a product release, then there is an incremental increase in the likelihood of advertising both prior to, on, and after these news days (significantly positive coefficients on $Product\,Release_t$, $Product\,Tomorrow_t$, and $Product\,Yesterday_t$). Advertising behavior marginally increases on EDGAR filing dates (significantly positive coefficient on $Edgar\,File_t$), is insignificantly different on earnings announcement dates (insignificant coefficient on EA_t), and is marginally lower on the days leading up to and immediately following an earnings announcement (significantly negative coefficient on $EA\,Window_t$).

In the online appendix table A1 we tabulate a modified version of equation 1 that includes lagged dependent variables $t-1$ through $t-14$ to examine the relative importance of the 7-day weekly interval days to other days. Control variables are included but not tabulated for conciseness. The coefficient estimates on $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$ are not only positive and statistically significant, but continue to have the highest economic significance of all the lagged variables.[18] Interestingly, coefficient estimates on lagged variables $t-8$ through $t-13$ are negative and statistically significant.

[17] Coefficient estimates in column 1 divided by the average dependent variable, tabulated in table footnotes.

[18] The coefficient estimate on $Ad\,Measure_{t-1}$ has the next highest economic significance and suggests the presence of add campaigns with back-to-back advertising, such that $Ad\,Measure_{t-1}$ is likely endogenous to the decision to advertise on day t, potentially correlated with outcomes of interest on day t (e.g., investor attention), and thus not a suitable candidate for an instrumental variable.

The combined evidence from tables 2, 3, and A1 suggests a pattern of companies advertising on a weekly basis, with variation in the exact day of the week across companies, and that lagged weekly advertising indicators (i.e., instrumental variables) generate potentially exogenous variation in the likelihood of a firm advertising on day t. In the next two sections we exploit this variation to estimate the effects of advertising on investor attention and financial markets.

4 Advertising and Investor Attention

4.1 General Analysis

In this section we examine the effect of ads on investor attention using log daily Google search volume index (SVI) for the company's ticker symbol ($Ticker\, SVI$). Prior research demonstrates that $Ticker\, SVI$ is a reasonable and timely measure of investor attention and captures primarily retail investors' demand for financial information (Da et al. [2011], Drake et al. [2012], Madsen [2017]). In Appendix A we describe how we obtain and construct our daily Google search measure, using the natural logarithm of SVI to normalize the distribution. Although SVI cannot be converted into the actual number of Google searches, larger SVIs within a firm are indicative of greater search for financial information.

To estimate whether ads attract investor attention we use two-stage least squares (2SLS) regressions, employing the first-stage regression from equation (1) with the two lagged advertising measures as instruments and the following second-stage regression:

$$\begin{aligned} log(Ticker\, SVI_t) &= \alpha + \beta Ad\, Measure_t + \Gamma Controls \\ &+ \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t \end{aligned} \tag{2}$$

where $Ticker\, SVI_t$ is the Google search measure for a firm's stock ticker on date t, $Ad\, Measure_t$ is the instrumented measure of firm advertising activity (i.e., one of the five ad measures from table 3) estimated using equation (1), and the controls include the set of exogenous covariates from equation (1). We continue to include firm-year and date fixed effects and cluster standard errors by firm and date.

Table 4 panel A presents results from estimating equation (2). In column 1 we estimate equation (2) using OLS (which does not account for the potentially endogenous choice to advertise) and a general advertising indicator, whereas columns 2 through 6 use 2SLS and the five advertising indicators from table 3.[19] The results are consistent with our hypothesis that advertisements attract investor attention to the advertising firm's financial information. Because the dependent variable is measured in logs, we can interpret the coefficients on $Ad\,Measure$ as the percent change in Google searches on an advertising day relative to a day with no ads. The OLS coefficient in column 1 is economically small (1.7% increase in Google SVI) but statistically significant at the 1% level.

When we estimate the same model using 2SLS in column 2, we continue to find a statistically significant increase in investor attention on ad days, although the coefficient estimate is larger (4.9% increase in Google SVI), suggesting that the significant OLS coefficient is not driven by an omitted correlated variable (Angrist and Pischke [2008]).[20] The 2SLS estimates for national, large, repeat, and business (columns 3 through 6) are all slightly larger in magnitude than the general advertising indicator, with business ads generating the largest increase in Google SVI (8.0%).[21] The use of daily data and instrumental variables, combined with the requirement that advertisements must be ordered at least a day in advance, suggest that reverse causality in this setting is highly unlikely (i.e., advertising in response to heightened investor attention). The significant increase in attention to advertisements after including controls for contemporaneous events and accounting for potential endogeneity in advertising

[19] Robustness tests using continuous measures of advertising ($Log(Ads + 1)$, $log(Spend + 1)$ and $log(Readership + 1)$) in both the first and second stage regressions produce qualitatively similar results (see table A2).

[20] Throughout this paper we find that the 2SLS estimates, which capture the 'local average treatment effect' (LATE), are typically larger than the OLS estimates, which capture the 'average treatment effect' (ATE). This pattern is consistent with heterogenous effects in the underlying population (see Angrist and Pischke [2008]).

[21] In the online appendix we find that business ads generate significantly more attention than general ads.

days, particularly for repeat advertisements which likely reveal little nonpublic information, suggests that these effects reflect a spillover from advertising to investor attention rather than a response to an informative advertisement.

Two concerns with 2SLS are (1) the potential for weak instruments and (2) correlation between the instruments and regression error term (i.e., overidentification). The univariate statistics in table 2 and highly significant first-stage results in table 3 suggest that the instruments are not weak. Confirming this inference, the Cragg-Donald F-statistics (tabulated in table footnotes) well exceed the critical values suggested by Stock and Yogo [2005] (e.g., F-statistic of 43,243 in column 2), suggesting that we do not have a weak instrument. To test for possible overidentification (i.e., the instruments could have a direct effect on Google SVI), we compute Sargan-Hansen test statistics (Sargan [1958], Hansen [1982]). For each of the 2SLS specifications in table 4 panel A, we are unable to reject the null hypothesis that the instruments are uncorrelated with the error term (i.e., p-values greater than 0.10), thus providing no evidence of overidentification (see also Garrett, Hoitash, and Prawitt [2014]).

Coefficient estimates on the control variables in table 4 panel A provide natural benchmarks to evaluate the effect of advertising on investor attention. Google searches for company tickers are significantly higher both prior to, on, and immediately after news days (e.g., 1.7% increase on actual news days), and incrementally larger if the news relates to a product release on those days (e.g., an additional increase of 2.5% when new products are announced). Consistent with prior research, earnings announcements trigger a significant increase in *Ticker SVI* (16.8%), with a smaller but comparably significant increase of 6.8% on days immediately before and after the earnings announcement (see Drake et al. [2012], Madsen [2017]). Edgar filing dates are associated with a significant 2.2% increase in *Ticker SVI*.

In table 4 panel A we use $Ticker\,SVI$ to proxy for attention to the firm's financial information. To increase confidence that $Ticker\,SVI$ captures attention to *financial* information, we next examine the effect of ads on Google searches for the company name. Because Google searches for company names more likely capture *general* attention, we re-estimate equation (2) (using both OLS and 2SLS) with Google searches for the company name ($Name\,SVI$) as the dependent variable and compare the effect of advertising on $Name\,SVI$ with the effect on $Ticker\,SVI$.[22] The results are presented in table 4 panel B.

Using the same five types of advertising activity, we find that ads trigger a larger increase in Google searches for company names than company tickers (e.g., a 4.9–8.0% increase in searches for company tickers versus a 12.8–17.4% increase in searches for company names). The more pronounced effect of ads on searches for company names is unsurprising, as the primary goal of advertising is to attract attention to the company and/or its products, and suggests that $Name\,SVI$ more likely captures consumer attention to the company rather than specific attention to the firm's financial information.

The effect of earnings announcements on this alternative Google search measure provides additional evidence that $Ticker\,SVI$ captures attention to financial information whereas $Name\,SVI$ captures consumer attention. Comparing coefficient estimates on the control variables in panels A and B, we find that news days trigger a larger increase in *Name SVI* than *Ticker SVI* (i.e., a 3.3% vs. 1.7% increase in search for company names and tickers, respectively). However, when the news is clearly financial (e.g., an earnings announcement), the pattern reverses. Earnings announcements trigger a 16.8% increase in *Ticker SVI* compared to an 7.6% increase in *Name SVI*, suggesting that individuals (presumably investors) are more likely to search for the company's stock ticker rather than company name on earnings announcement dates. Together, the results in table 4 Panel B suggest that $Ticker\,SVI$ captures investor attention.

[22] We are grateful to Zhi Da, Joseph Engelberg, and Pengjie Gao for providing cleaned up company names. They asked two research assistants to record how they would search for each company based on the company name in CRSP. If there were differences between the reports, they used Google Insights "related search" feature to determine which query is most common.

4.2 Timing Tests

The results in table 4 suggest that ad days are associated with higher levels of Google search for financial information. To provide additional insight into these effects, we exploit the daily aspect of our data to examine changes in investor attention on days before and after ad days. Evidence of insignificant changes in attention prior to ad days (i.e., a falsification test) further helps rule out the effect of correlated omitted variables. We estimate both OLS and 2SLS versions of the following regression:

$$\begin{aligned}
\log(Ticker\,SVI_t) &= \alpha + \beta_1 3DaysBeforeAd_t \\
&+ \beta_2 2DaysBeforeAd_t \\
&+ \beta_3 DayBeforeAd_t \\
&+ \beta_4 AdDay_t \\
&+ \beta_5 DayAfterAd_t \\
&+ \beta_6 2DaysAfterAd_t \\
&+ \beta_7 3DaysAfterAd_t \\
&+ \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t \qquad (3)
\end{aligned}$$

where $Ticker\,SVI_t$ is Google search for a firm's stock ticker on date t, and controls include the set of exogenous covariates from equation 1. $Ad\,Day_t$ is an indicator equal to one if the firm placed an ad on day t, and we separately examine the five types of advertising activity from table 3. $DayBeforeAd_t$, $2DaysBeforeAd_t$, and $3DaysBeforeAd_t$ are indicators equal to one if the firm, as of date t, will place an advertisement in one, two, or three days, respectively, and capture any increase in investor attention prior to the actual placement of an ad on day t. $DayAfterAd_t$, $2DaysAfterAd_t$, and $3DaysAfterAd_t$ are indicators equal to one if the firm, as of date t, placed an ad one, two, or three days earlier, respectively, and capture the duration of any increased attention in response to an advertisement on day t. We continue to include firm-year and date fixed effects. We also continue to cluster standard errors simultaneously by firm and date (Petersen [2009]).

Table 5 presents OLS (panel A) and 2SLS (panel B) coefficient estimates of equation 3.[23] In both panels, across all five advertising measures there are insignificant changes in *Ticker SVI* over the three days prior to ad days. *Ticker SVI* significantly increases on the ad day, with significant but smaller increases over the next one to two days depending on the advertising measure. By day three there is no significant change in *Ticker SVI*. We conduct F-tests, comparing the coefficient on *Ad Day* to each of the six other event days and tabulate p-values for these tests in the table footnotes. The coefficient estimates on ad days are significantly greater then the coefficient estimates on the pre-ad days and the coefficient on $3DaysAfterAd$ at conventional levels. The pattern is consistent with an increase in investor attention linked to the ad day, which persists at most for two days before becoming insignificant.

4.3 Robustness Tests

We perform a number of additional tests with alternative fixed effects, subsamples, and advertising measures to demonstrate the robustness of these results. Table 6 column (1) replicates the main result from table 4 panel A column 2. In columns 2 and 3 we include alternative sets of fixed effects (firm-year and industry-date in column 2 and firm-year, year-month, day-of-the-week and holiday in column 3) and find qualitatively similar results.

A concern with using *Ticker SVI* is that it captures an unknown amount of non-investor search, and in particular may capture search by consumers (e.g., a ticker symbol closely related to the company name). This concern is particularly relevant to this study, as we

[23] Because this model has seven endogenous variables (i.e., each of the ad days) we estimate a first stage regression for each endogenous variable and include as instruments in each first stage the full set of lagged indicator variables (i.e., $Ad\,Measure_{t-4}$ through $Ad\,Measure_{t-17}$) so that each endogenous variable has two lagged instruments at weekly intervals.

find in table 4 that both investors and consumers respond with increased search on ad days. To address this concern, in column 4 we drop all "noisy" tickers that either contain the company's name (e.g., EPIQ), simultaneously refer to a common object (e.g., SKY), or contain only one letter (e.g., K). We also examine an alternative specification in column 5 where we include only those tickers where a Google search produced an info box about the stock.[24] Although sample sizes are significantly diminished with these later two tests, our results are qualitatively unchanged in all of these alternative specifications.[25]

We also examine log downloads of SEC filings (both all filings as well as only the 10K) from the EDGAR website as an alternative measure of investor attention, and find insignificant changes in downloads on ad days (using both OLS and 2SLS, see table A4 of the online appendix). EDGAR downloads more likely represent fundamental research about the company (Lee et al. [2015a], Drake et al. [2015], Bozanic et al. [2017]), whereas *Ticker SVI* presumably represents retail investors' interest in the company's stock price. Daily log EDGAR downloads and *Ticker SVI* are slightly negatively correlated in our sample (-0.07), which contrasts with the positive correlations between the measures documented in prior research around earnings announcements (Drake et al. [2015], deHaan et al. [2015]) and further suggests that the two measures capture different aspects of investor attention.

A remaining concern is that these ads themselves may be informative, and that the increased investor attention is a response to this information content. The use of instrumental variables, as well as analysis of ads for brands which were previously advertised within the same publication within the previous two months (i.e., ads which should contain no nonpublic information), suggests that the increased attention is not information driven. As an additional test, we examine ad images to identify ads that are reprints. We obtain images

[24] Tickers tabulated in table A3 of the online appendix. Google search originally conducted on August 1, 2015. A shortcoming of this test is that we do not know if these tickers produced an info box during our sample period. A subsequent search on March 26, 2018 found that 85% of tickers we originally identified still produced an info box, and an additional 52 tickers produced a ticker box that did not previously. We find it probable that many of the tickers we identify produced info boxes during our sample period.

[25] Untabulated results are also qualitatively similar if we include four or even six weekly lagged advertising indicators as instruments.

for a subset of our sample,[26] and for each firm compute the Hamming distance between any ads that were printed less than one month apart. We flag an ad as "old" if the ad on the more recent date had a Hamming distance of 15 or above. We find that these "old" ads attract similar increases in investor attention, suggesting an unlikely response by investors to nonpublic information (see table A5 of the online appendix).

5 Advertising and Financial Markets

5.1 Business Ads and Liquidity

The previous section provides evidence that advertisements attract investor attention. In this section we examine whether this increased attention to financial information has an effect on liquidity. Advertising-induced attention could potentially motivate investors to buy or sell the advertised stocks (Barber and Odean [2008], Lou [2014]). Furthermore, if the nature of the increased attention and trading is based on the behavior of uninformed traders, liquidity in the stock may improve (Admati and Pfleiderer [1988], Glosten and Milgrom [1985], Lee et al. [1993]). Conversely, if the increased attention resulting from ads is informative (to at least some investors), or if informed investors are able to exploit the increased attention of retail investors as in Kyle [1985], then market makers may price protect against informed trades and the effects on liquidity are ambiguous.

To empirically examine the effect of advertising on liquidity, we estimate the following regression:

$$\begin{aligned} Liquidity_t &= \alpha + \beta_1 Business\,Ad_t \\ &+ \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t \end{aligned} \tag{4}$$

[26] We caution the reader that we cannot be certain that the images we were unable to collect are missing at random.

where $Liquidity_t$ is either log dollar trading volume (vol_t), quoted dollar depth ($qdepth_t$), percent effective spread ($espread_t$), or the percent quoted spread ($qspread_t$) on trading day t. All spreads are share volume-weighted and $qdepth_t$ and each spread measure are computed using TAQ data and the procedure described in Holden and Jacobsen [2014].[27] To facilitate interpretation of the coefficient estimates, we divide $qdepth$ by 1,000 and multiply each of the spread measures by 100. All continuous measures are winsorized at the 1st and 99th percentiles. Due to our use of daily panel data (as opposed to an event study) we continue to include firm-year and date fixed effects, rather than attempt to construct arbitrary daily abnormal liquidity measures.[28]

Our analysis in section 4.1 finds that business ads have the largest effect on investor attention (see also table A8 of the online appendix), and thus we use the indicator variable $Business\,Ad_t$ to measure the effect of these ads on liquidity. We assume that any effects of ads placed on days when the market is closed manifest on the next trading day. We continue to include (but do not tabulate for conciseness) the exogenous covariates from table 3 in both the first and second stage regressions, and include as additional covariates the inverse of share price, log market value of equity (based on the prior fiscal year), and share turnover on day t (except for the analysis of vol_t). Results are virtually identical if we exclude all control variables. Standard errors are clustered by firm and date.

Table 7 tabulates both OLS (columns 1-4) and 2SLS (columns 5-8) specifications of equation (4). Examining vol_t, both the OLS and 2SLS specifications document a significant increase in trading volume on days with business ads, suggesting the attention-grabbing nature of advertisements induce trading. The economic magnitudes suggest a 1.17% (OLS)

[27] Quoted depth captures the average quantity of shares that can be traded at the best price. Percent quoted spreads are based on displayed quotes and thus represent the hypothetical cost of trading, and is a measure of total friction (Stoll [2000]). Percent effective spreads are based on the actual trade price and thus capture the actual round-trip-equivalent cost of trading and are typically smaller than the quoted spread (Holden, Jacobsen, and Subrahmanyam [2014]). See also Hendershott, Jones, and Menkveld [2011]. We thank Craig Holder for providing code necessary to compute these liquidity measures. See http://kelley.iu.edu/cholden/instructions.pdf.

[28] Results are qualitatively similar if we augment equation 4 to include either firm-month or firm-quarter fixed effects to address intra-year or intra-quarter trends in advertising and/or liquidity measures.

and 3.23% (2SLS) increase in dollar trading volumes relative to the average sample trading volume of $178 million.[29]

Turning to $qdepth_t$, we also find significant increases in dollar depth on days with business ads in both the OLS and 2SLS specifications, suggesting improved liquidity as market makers increase the number of shares offered at the national Best Bid and Offer (BBO). The coefficient estimates are economically significant, suggesting a 5.8% (OLS) and 14.3% (2SLS) increase in $qdepth_t$ on days with business ads relative to the average dollar depth of 143,015. Examining the bid-ask spread, using OLS we document insignificant changes in the effective spread, and a marginal increase in the quoted spread. Both estimates are insignificantly different on business ad days in the 2SLS specifications. Overall, we conclude that liquidity marginally improves for large trades, with market makers offering increased market depth in the presence of increased retail investor attention on days with business ads.

5.2 Business Ads and Stock Returns

In this final section we examine the effect of business ads on stock returns and stock return volatility. Prior research suggests that increased investor attention is associated with temporary increases in stock prices and volatility (Greene and Smart [1999], Da et al. [2011], Lou [2014]). However, because our sample consists of predominately large firms and marginal increases in trading volume, the increased retail investor attention could be absorbed by institutional traders (facilitated by the increased depth) with no resulting impact on returns.

To empirically examine the effect of business ads on stock returns and volatility we estimate the following regression:

$$Abret_t = \alpha + \beta_1 Business\,Ad_t + \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t \quad (5)$$

[29] We note the 2SLS Sargan-Hansen p-value is 0.021 suggests that overidentification may be an issue in the 2SLS specification.

where $Abret_t$ is either the daily abnormal firm stock return on day t ($Abret_t$); the cumulative three day abnormal return ($Abret_{(0,3)}$); or the three-day abnormal return volatility ($Vol_{(0,2)}$). Abnormal returns are calculated using individual stock market betas calculated over a rolling one-year window (see detailed variable definitions in Appendix A). Our main coefficient of interest is β_1, which captures the effect of a business ad. We include all control variables from table 7, and continue to include firm-year and date fixed effects and cluster standard errors by firm and date.

Results are presented in table 8. Columns 1 through 3 present OLS estimates and columns 4 through 6 present 2SLS estimates (using two weekly business advertising lags as instruments) of equation (5). Using OLS, we find an insignificant effect of business ads on abnormal returns, three-day cumulative abnormal returns, and abnormal stock return volatility (columns 1–3). After accounting for the potential endogeneity of ad days using the instrumental variables, we find a marginally significant (t=-1.77) but economically small *decrease* in daily stock prices of approximately 11 basis points on days with business ads (column 4). Furthermore, these negative returns appears to be temporary, as the cumulative three-day return is insignificant (column 5). Volatility is insignificantly different on business ad days in column 6. We thus fail to find evidence that the increased attention due to business ads is associated with temporary increases in stock prices, potentially due to changes in the behavior of other investors.

6 Conclusion

This paper examines the extent to which a recurring, low-information-content, attention-grabbing event affects investors and financial markets. Advertisements traditionally target consumers, yet the public nature of advertising suggests that investors will also notice and potentially respond to advertisements. We hypothesize that due to attention constraints (Kahneman and Tversky [1979]), investor attention "jumps" to advertising firms, driving increased interest in financial performance.

Using daily advertising data, we document a recurring pattern in firms' advertising activity: firms frequently select a "preferred advertising day," with a large portion of their ads appearing on this preferred day. We exploit this pattern and introduce instrumental variables based on whether the firm advertised exactly 7 or 14 days earlier. We document that these instruments significantly explain firms' observed advertising activity, yet are likely uncorrelated with omitted variables that are correlated with the outcomes of interest.

Using both OLS and 2SLS regressions, we find significant increases in investor attention on ad days, consistent with ads generating a spillover effect from consumers to financial markets. We also find that ads trigger significant increases in trading volumes and quoted depths, indicating improved liquidity for large trades on ad days. Our results contribute to research on the economic determinants and consequences of advertising, as well as broader research on the consequences of investor attention, particularly with respect to non-financial, low-information-content events.

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Appendix A: Definition of Variables

This appendix describes the calculation of variables used in the core analyses. Firm subscript is omitted for brevity.

Variable	Definition
Indicators for ad days and ad-based instrument	
All_t	An indicator equal to one if the firm placed an ad in any newspaper on day t, and zero otherwise.
$National_t$	An indicator equal to one if the firm placed an ad in any national newspaper on day t, and zero otherwise. National newspapers include *The Wall Street Journal*, *The New York Times*, and *Los Angeles Times*.
$Large_t$	An indicator equal to one if the firm placed a full-page ad in any newspaper on day t, and zero otherwise.
$Repeat_t$	An indicator equal to one if the firm placed an ad on day t for a brand that was previously advertised within the same daily newspaper within the previous 2 months, and zero otherwise.
$Business_t$	An indicator equal to one if the firm placed an ad in a business newspaper on day t, and zero otherwise. Business newspapers include *The Wall Street Journal, Investor's Business Daily, Financial Times, Daily Journal of Commerce,* and *Daily Business Review.*
$Ad\,Measure_t$	One of the five advertising indicators defined above.
$Ad\,Measure_{t-7}$	An indicator equal to one if $Ad\,Measure$ on day $t-7$ equals one, and zero otherwise.
$Ad\,Measure_{t-14}$	An indicator equal to one if $Ad\,Measure$ on day $t-14$ equals one, and zero otherwise.
$nDay(s)BeforeAd_t$	An indicator equal to one if day t is the n^{th} day before an ad day, and zero otherwise, n=1,2,3.
$nDay(s)AfterAd_t$	An indicator equal to one if day t is the n^{th} day after an ad day, and zero otherwise, n=1,2,3.
$Business\,Ad_t$	An indicator equal to one if the firm placed an ad in a business newspaper on trading day t. We align all ads in business newspapers that appear on a non-trading day with the first subsequent trading day.
Outcome measures	
$Ticker\,SVI_t$	Natural logarithm of Google search volume index (SVI) for a company's stock ticker on day t. Daily SVI obtained by searching one month at a time, and standardized across months using weekly SVI (obtained by searching across the entire sample period) as follows: $SVI = SVI_d \times SVI_w/100$.
$Name\,SVI_t$	Natural logarithm of Google SVI for a company's name on day t.
vol_t	Natural logarithm of share dollar volume on day t ($price_t \times volume_t$).

$qdepth_t$	Share volume-weighted quoted depth on day t, divided by 1,000. Calculated using TAQ data and procedure described in Holden and Jacobsen [2014].
$espread_t$	Share volume-weighted effective spread on day t. Calculated using TAQ data and procedure described in Holden and Jacobsen [2014].
$qspread_t$	Share volume-weighted quoted spread on day t. Calculated using TAQ data and procedure described in Holden and Jacobsen [2014].
$Abret_t$	Abnormal return, measured as $Stock\,Return_t - \hat{\beta} \times Market\,Return_t$, where $\hat{\beta}$ is estimated using firm and market returns for days $t-263$ through day $t-1$.
$Abret_{(0,2)}$	Three-day cumulative abnormal return.
$Volatility_{(0,2)}$	Volatility of $Abret_t$ measured over days $0, 1, 2$.
Control variables	
$News\,Dummy_t$	An indicator equal to one if at least one news article on day t mentions the firm, and zero otherwise.
$News\,Tomorrow_t$	An indicator equal to one if, as of day t, at least one news article will mention the firm on day $t+1$, and zero otherwise.
$News\,Yesterday_t$	An indicator equal to one if, as of day t, at least one news article mentioned the firm on day $t-1$, and zero otherwise.
$Product\,Release_t$	An indicator equal to one if media coverage on day t mentions a product release, and zero otherwise.
$Product\,Tomorrow_t$	An indicator equal to one if, as of day t, media coverage on day $t+1$ mentions a product release, and zero otherwise.
$Product\,Yesterday_t$	An indicator equal to one if, as of day t, media coverage on day $t-1$ mentioned a product release, and zero otherwise.
$Edgar\,File_t$	An indicator equal to one if the firm filed an 8-K, 10-K, or 10-Q on day t, and zero otherwise.
$EA\,Day_t$	An indicator equal to one if the firm announced earnings on day t, and zero otherwise.
$EA\,Window_t$	An indicator equal to one for the five days before and after an earnings announcement, and zero otherwise.

Table 1
Summary Statistics

This table shows summary statistics for all publicly traded firms which placed at least two advertisements in a daily newspaper between 2008 and 2013. Advertising data from Media Radar.

Panel A: Total print advertising by year

	Firms	Brands	Titles	Ads	Spend (Mil.)
2008	25	36	1	118	2.1
2009	328	1,076	12	11,090	504.7
2010	444	1,662	18	28,388	747.8
2011	521	2,249	30	52,399	1,866.8
2012	530	2,537	31	54,358	4,043.1
2013	497	2,509	37	43,937	3,675.2
All Years	637	4,879	39	190,290	10,839.6

Panel B: Average annual firm characteristics (2008-2013)

	Mean	Median	SD	P1	P99
Market cap (millions)	25,570	7,720	46,881	28	202,286
Total assets (millions)	86,136	9,632	313,800	65	2,117,605
Revenues (millions)	23,284	6,318	47,010	58	236,286
Net income (millions)	1,539	298	4,902	-5,338	19,024
Adv expense (millions)	496	127	964	0	4,253
Return on assets	0.04	0.04	0.10	-0.32	0.26
Leverage ratio	0.64	0.63	0.27	0.13	1.30
Book/market ratio	0.61	0.51	0.57	-1.26	2.85
Institutional ownership	0.65	0.74	0.28	0.00	0.99
Ad days	34.9	11	60	1	329
Number of ads	81	13	330.4	1	1,146
Print spend (millions)	6.4	0.4	32.0	0.0	133.1
Number of unique brands	4	2	8	1	39
Number of unique titles	4	3	4	1	18
Number of titles per ad day	1.2	1	0.56	1	3.6

Panel C: Industry composition

	% of Firms	% of Total Ads	% of Total Spend
Non-durables	11%	28%	7%
Consumer durables	4%	6%	4%
Manufacturing	10%	1%	0%
Energy	1%	1%	1%
Chemicals	3%	1%	3%
Business equipment	11%	2%	4%
Telephone and TV	5%	15%	9%
Utilities	2%	0%	0%
Wholesale, retail	15%	19%	59%
Healthcare	8%	1%	1%
Finance	15%	12%	8%
Other	14%	12%	4%

Panel D: Number of ads by publication - top 10

	Ads	Start Date	Ad Days
The New York Times	33,134	1/1/2009	1,752
Los Angeles Times	26,466	7/17/2010	1,173
Chicago Tribune	16,792	2/1/2011	956
The Wall Street Journal	14,339	4/1/2009	1,392
The Miami Herald	12,315	1/1/2011	988
Newsday	10,454	4/8/2010	1,279
New York Post	8,934	6/20/2009	1,305
New York Daily News	7,749	1/10/2010	1,053
USA Today	6,798	9/13/2010	751
San Francisco Chronicle	6,558	3/3/2011	906

Table 2
Advertising Patterns Summary Statistics

This table summarizes five advertising variables: All_t, an indicator equal to one if the firm placed an ad in any newspaper on day t; $National_t$, an indicator equal to one if the firm placed an ad in any national newspaper on day t; $Large_t$, an indicator equal to one if the firm placed a full-page ad in any newspaper on day t; $Repeat_t$, an indicator equal to one if the firm placed an ad on day t for a brand that was previously advertised within the same daily newspaper within the previous 2 months; and $Business_t$, an indicator equal to one if the firm placed an ad in a business newspaper. National newspapers include *The Wall Street Journal*, *The New York Times*, and *Los Angeles Times* and business newspapers include *The Wall Street Journal, Investor's Business Daily, Financial Times, Daily Journal of Commerce,* and *Daily Business Review*. Panel A tabulates, conditional on advertising on day t, the percent of firms advertising on day $t - X$. Panel B tabulates the percent of days of the week with advertisements. In panel C we calculate firm-specific preferred advertising days (i.e., the firm-specific day of the week with the greatest number of ads in our sample), and tabulate for each day of the week the number of firms with that preferred ad day, the average percentage of those firms' ads that appear on that day of the week, and the number of firms from each Fama French 12 industry with that preferred day of the week.

Panel A: Percent of firms advertising on day $t - X$, conditional on advertising on day t

	All	National	Large	Repeat	Business
Ad Measure$_{t-1}$	0.45	0.41	0.28	0.40	0.16
Ad Measure$_{t-2}$	0.42	0.39	0.27	0.37	0.13
Ad Measure$_{t-3}$	0.40	0.37	0.25	0.35	0.11
Ad Measure$_{t-4}$	0.39	0.37	0.24	0.35	0.11
Ad Measure$_{t-5}$	0.41	0.39	0.26	0.36	0.13
Ad Measure$_{t-6}$	0.43	0.40	0.25	0.38	0.16
Ad Measure$_{t-7}$	0.60	0.60	0.48	0.56	0.45
Ad Measure$_{t-8}$	0.42	0.39	0.25	0.38	0.16
Ad Measure$_{t-9}$	0.40	0.38	0.25	0.35	0.12
Ad Measure$_{t-10}$	0.38	0.36	0.23	0.34	0.11
Ad Measure$_{t-11}$	0.38	0.36	0.23	0.33	0.10
Ad Measure$_{t-12}$	0.40	0.38	0.24	0.35	0.12
Ad Measure$_{t-13}$	0.41	0.39	0.24	0.37	0.15
Ad Measure$_{t-14}$	0.59	0.59	0.45	0.54	0.44

Panel B: Advertising frequency by day of the week

	All	National	Large	Repeat	Business
Sunday	0.13	0.11	0.07	0.09	0.00
Monday	0.11	0.07	0.04	0.08	0.03
Tuesday	0.11	0.07	0.04	0.08	0.03
Wednesday	0.12	0.08	0.05	0.09	0.03
Thursday	0.13	0.09	0.05	0.09	0.03
Friday	0.12	0.08	0.05	0.08	0.02
Saturday	0.06	0.05	0.02	0.05	0.01
Overall	0.11	0.08	0.05	0.08	0.02

Panel C: Preferred advertising days

	M	Tu	W	Th	F	Sa	Su
# Firms	168	105	88	126	98	117	34
Average Percent of Ads (%)	53.5	42.4	40.4	45.2	46.6	43.9	45.2
By Industry (# firms)							
Non-Durables	30	3	4	6	9	16	4
Consumer Durables	4	3	1	3	6	6	3
Manufacturing	16	13	9	9	12	3	5
Energy	3	1	2	3	0	2	0
Chemicals	7	3	4	4	5	3	0
Business Equipment	4	22	20	13	8	15	3
Telephone and TV	7	2	4	7	3	12	1
Utilities	0	2	1	7	2	0	1
Wholesale, Retail	33	11	9	11	21	15	4
Healthcare	17	7	4	18	4	9	1
Finance	19	18	16	24	16	10	3
Other	17	15	14	13	7	18	7

Table 3
Advertising Determinants: First Stage

In this table we examine the determinants of advertising. The sample includes publicly-traded firms with available print advertising data from MediaRadar and Google SVI for the company's stock ticker and covers the period February 2008 to October 2013 (determined by data availability). We estimate the linear probability model below, where $Ad\,Measure_t$ is one of five indicator variables for different types of advertising activity as indicated in the column titles and defined in table 2. The main variables of interest are $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$, indicators set equal to one if the firm's advertising activity seven and 14 days earlier was positive, respectively (i.e., lags of the dependent variables). Control variables include $News\,Dummy_t$, $News\,Tomorrow_t$, and $News\,Yesterday_t$, indicator variables equal to one if the firm is mentioned in at least one news article on day t, $t+1$, and $t-1$, respectively; $Product\,Release_t$, $Product\,Tomorrow_t$, and $Product\,Yesterday_t$, indicator variables equal to one if the media coverage on day t, $t+1$, and $t-1$ mentioned a product release, respectively; $Edgar\,File_t$, an indicator variable equal to one if the firm filed an 8-K, 10-K, or 10-Q on day t, and zero otherwise; $EA\,Day_t$, an indicator variable equal to one if the firm announced earnings on day t, and zero otherwise; and $EA\,Window_t$, an indicator variable equal to one for the five days before and after an earnings announcement, and zero otherwise. All regressions include date and firm-year fixed effects. The intercepts are not reported. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively.

$$\begin{aligned}
Ad\,Measure_t &= \alpha + \beta_1 Ad\,Measure_{t-7} + \beta_2 Ad\,Measure_{t-14} \\
&+ \gamma_1 News\,Dummy_t + \gamma_2 News\,Tomorrow_t + \gamma_3 News\,Yesterday_t \\
&+ \gamma_4 Product\,Release_t + \gamma_5 Product\,Tomorrow_t + \gamma_6 Product\,Yesterday_t \\
&+ \gamma_7 Edgar\,File_t + \gamma_8 EA\,Day_t + \gamma_9 EA\,Window_t \\
&+ \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t
\end{aligned}$$

Table 3 (continued)

Dependent variable: Ad Measure$_t$	All (1)	National (2)	Large (3)	Repeat (4)	Business (5)
Ad Measure$_{t-7}$	0.256***	0.266***	0.254***	0.247***	0.261***
	(30.74)	(25.01)	(21.10)	(29.80)	(16.79)
Ad Measure$_{t-14}$	0.235***	0.259***	0.209***	0.224***	0.253***
	(29.89)	(26.47)	(21.38)	(25.22)	(15.94)
News Dummy$_t$	0.004***	0.002	0.004***	0.002*	0.002***
	(2.95)	(1.52)	(2.95)	(1.96)	(2.97)
News Tomorrow$_t$	0.003**	0.002**	0.002**	0.002**	0.002**
	(2.06)	(2.11)	(2.01)	(2.12)	(2.29)
News Yesterday$_t$	0.000	-0.000	0.000	-0.000	0.000
	(0.16)	(-0.05)	(0.22)	(-0.14)	(0.64)
Product Release$_t$	0.007***	0.007***	0.003	0.006**	0.005***
	(2.68)	(2.74)	(1.15)	(2.37)	(2.99)
Product Tomorrow$_t$	0.005**	0.002	0.007***	0.004	0.000
	(2.01)	(0.87)	(2.91)	(1.55)	(0.16)
Product Yesterday$_t$	0.005**	0.004**	0.003	0.001	0.005***
	(2.18)	(2.06)	(1.47)	(0.44)	(3.47)
Edgar File$_t$	0.004*	0.001	0.002	0.004**	0.002
	(1.68)	(0.83)	(1.29)	(2.18)	(1.35)
EA$_t$	0.000	0.000	0.003	-0.002	0.003
	(0.09)	(0.03)	(0.77)	(-0.32)	(0.87)
EA Window$_t$	-0.004**	-0.004**	-0.002	-0.004***	-0.002*
	(-2.51)	(-2.29)	(-1.42)	(-2.75)	(-1.73)
Observations	452,376	452,376	452,376	452,376	452,376
Adj R-Squared	0.396	0.421	0.318	0.357	0.270
Mean Dep Var	0.110	0.079	0.051	0.081	0.025
Date FE	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes

Table 4
Advertising and Attention

In this table we examine the effect of ads on attention. In panel A we analyze investor attention to financial information using log daily Google search volume index (SVI) for a company's ticker ($Ticker\,SVI_t$), and in panel B we analyze general attention to the firm using Google SVI for the company's name ($Name\,SVI_t$). We estimate the model below using both OLS (column 1) and two-stage least squares (2SLS, columns 2 - 6), where the first-stage equation is the respective model from table 3. Column titles list the ad measure used in each specification, and all variables are defined in tables 2 and 3. The intercepts are not reported. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate for the 2SLS estimates the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(SVI_t) \quad = \quad \alpha + \beta Ad\,Measure_t + \gamma Controls + \psi\text{Firm-Year FE} + \eta\text{Date FE} + \epsilon_t$$

Panel A: Ticker SVI$_t$

	OLS	2SLS				
	All (1)	All (2)	National (3)	Large (4)	Repeat (5)	Business (6)
Ad Measure$_t$	0.017*** (2.86)	0.049*** (3.12)	0.047*** (2.84)	0.063*** (2.84)	0.056*** (3.11)	0.080*** (3.16)
News Dummy$_t$	0.017*** (4.00)	0.017*** (3.97)	0.017*** (4.00)	0.017*** (3.95)	0.017*** (3.98)	0.017*** (3.97)
News Tomorrow$_t$	0.012*** (4.70)	0.012*** (4.64)	0.012*** (4.67)	0.012*** (4.65)	0.012*** (4.65)	0.012*** (4.67)
News Yesterday$_t$	0.015*** (5.89)	0.015*** (5.91)	0.015*** (5.91)	0.015*** (5.89)	0.015*** (5.92)	0.015*** (5.88)
Product Release$_t$	0.025*** (3.06)	0.025*** (3.02)	0.025*** (3.03)	0.025*** (3.05)	0.025*** (3.03)	0.025*** (3.01)
Product Tomorrow$_t$	0.011** (2.33)	0.011** (2.27)	0.011** (2.33)	0.011** (2.24)	0.011** (2.29)	0.011** (2.38)
Product Yesterday$_t$	0.012** (2.58)	0.012** (2.54)	0.012** (2.56)	0.012** (2.57)	0.012** (2.57)	0.011** (2.48)
Edgar File$_t$	0.022*** (3.39)	0.022*** (3.37)	0.022*** (3.39)	0.022*** (3.38)	0.022*** (3.35)	0.022*** (3.37)
EA$_t$	0.167*** (6.59)	0.168*** (6.59)	0.168*** (6.60)	0.167*** (6.58)	0.168*** (6.60)	0.167*** (6.59)
EA Window$_t$	0.068*** (6.12)	0.068*** (6.13)	0.068*** (6.12)	0.068*** (6.12)	0.068*** (6.13)	0.068*** (6.13)
Observations	452,376	452,376	452,376	452,376	452,376	452,376
Adj/Centered R-Squared	0.850	0.850	0.850	0.850	0.850	0.850
Cragg-Donald F-Statistic		43,243	51,969	37,504	38,553	49,025
Sargan-Hansen p-value		0.859	0.614	0.329	0.889	0.963
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Name SVI_t

	OLS	2SLS				
	All (1)	All (2)	National (3)	Large (4)	Repeat (5)	Business (6)
Ad Measure_t	0.059***	0.128***	0.131***	0.132***	0.155***	0.174***
	(6.34)	(5.41)	(4.70)	(4.09)	(6.05)	(4.17)
News Dummy_t	0.034***	0.033***	0.034***	0.034***	0.033***	0.034***
	(7.29)	(7.26)	(7.29)	(7.34)	(7.29)	(7.30)
News Tomorrow_t	0.015***	0.014***	0.015***	0.015***	0.014***	0.015***
	(4.44)	(4.37)	(4.43)	(4.43)	(4.33)	(4.44)
News Yesterday_t	0.015***	0.015***	0.016***	0.016***	0.016***	0.015***
	(5.30)	(5.31)	(5.30)	(5.37)	(5.34)	(5.21)
Product Release_t	0.023**	0.022**	0.022**	0.022**	0.022**	0.022**
	(2.32)	(2.26)	(2.24)	(2.30)	(2.31)	(2.26)
Product Tomorrow_t	0.010*	0.010*	0.010*	0.009*	0.010*	0.011*
	(1.86)	(1.73)	(1.85)	(1.72)	(1.78)	(1.94)
Product Yesterday_t	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
	(3.67)	(3.62)	(3.62)	(3.57)	(3.65)	(3.64)
Edgar File_t	0.017***	0.016***	0.016***	0.016***	0.016***	0.017***
	(3.51)	(3.46)	(3.46)	(3.47)	(3.45)	(3.53)
EA_t	0.075***	0.076***	0.075***	0.075***	0.076***	0.075***
	(6.27)	(6.27)	(6.25)	(6.23)	(6.28)	(6.21)
EA Window_t	0.043***	0.043***	0.043***	0.043***	0.043***	0.043***
	(6.22)	(6.29)	(6.26)	(6.20)	(6.33)	(6.27)
Observations	320,581	320,581	320,581	320,581	320,581	320,581
Adj/Centered R-Squared	0.778	0.778	0.778	0.778	0.777	0.778
Cragg-Donald F-Statistic		30,659	34,680	25,557	25,206	33,097
Sargan-Hansen p-value		0.094	0.167	0.094	0.758	0.931
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5
Advertising and Investor Attention: Timing

In this table we examine the effect of ads on investor attention using variation in $Ticker\,SVI$ both before and after advertising days. We estimate both OLS (panel A) and 2SLS (panel B) versions of the model below, where $AdDay_t$ is a firm's advertising activity on day t, and is 0 if the firm did not advertise. $DayBeforeAd_t$, $2DaysBeforeAd_t$, and $3DaysBeforeAd_t$ are set equal to whatever the firm's ad measure will be in one, two, or three calendar days, respectively. $DayAfterAd_t$, $2DaysAfterAd_t$, and $3DaysAfterAd_t$ equal the firm's ad measure from one, two, or three days earlier. To estimate this model using 2SLS we use as instruments $Ad\,Measure_{t-4}$ through $Ad\,Measure_{t-17}$ in the first stage models. Column titles list the ad measure used in each specification (defined in table 2). All regressions include date and firm-year fixed effects and the set of control variables from table 3 (not tabulated). Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate two-tailed p-values for F-tests of differences between coefficient estimates, and for the 2SLS estimates in panel B the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\begin{aligned}
\log(Ticker\,SVI_t) &= \alpha + \beta_1 3DaysBeforeAd_t + \beta_2 2DaysBeforeAd_t + \beta_3 DayBeforeAd_t \\
&+ \beta_4 AdDay_t + \beta_5 DayAfterAd_t + \beta_6 2DaysAfterAd_t \\
&+ \beta_7 3DaysAfterAd_t + \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t
\end{aligned}$$

Panel A: OLS

	OLS				
	All (1)	National (2)	Large (3)	Repeat (4)	Business (5)
3 Days Before Ad_t	0.001	0.001	-0.001	0.004	0.005
	(0.19)	(0.21)	(-0.27)	(0.68)	(0.42)
2 Days Before Ad_t	-0.004	-0.006	-0.005	-0.001	-0.009
	(-0.76)	(-0.91)	(-1.02)	(-0.22)	(-0.83)
Day Before Ad_t	0.001	0.001	0.009	0.003	-0.008
	(0.22)	(0.10)	(1.57)	(0.58)	(-0.76)
Ad Day_t	0.016***	0.017***	0.021***	0.018***	0.030***
	(2.96)	(2.63)	(3.12)	(3.02)	(3.11)
Day After Ad_t	0.009**	0.009	0.016***	0.011**	0.025***
	(2.04)	(1.58)	(2.84)	(2.32)	(2.83)
2 Days After Ad_t	0.007*	0.004	0.013**	0.007	0.005
	(1.65)	(0.75)	(2.46)	(1.42)	(0.49)
3 Days After Ad_t	0.005	0.003	0.007	0.005	0.002
	(1.21)	(0.57)	(1.34)	(1.04)	(0.22)
Observations	455,368	455,368	455,368	455,368	455,368
Adj R-Squared	0.850	0.850	0.850	0.850	0.850
Controls	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Two-tailed p-value (3 Days Before = Ad Day)	0.026	0.042	0.003	0.060	0.031
Two-tailed p-value (2 Days Before = Ad Day)	0.007	0.009	0.001	0.020	0.002
Two-tailed p-value (Day Before = Ad Day)	0.002	0.006	0.007	0.007	0.001
Two-tailed p-value (Day After = Ad Day)	0.056	0.065	0.276	0.061	0.355
Two-tailed p-value (2 Days After = Ad Day)	0.132	0.059	0.230	0.077	0.027
Two-tailed p-value (3 Days After = Ad Day)	0.088	0.061	0.053	0.066	0.041

Panel B: 2SLS

	2SLS				
	All (1)	National (2)	Large (3)	Repeat (4)	Business (5)
3 Days Before Ad_t	0.008	0.004	-0.003	0.014	0.013
	(0.64)	(0.28)	(-0.20)	(0.99)	(0.43)
2 Days Before Ad_t	-0.010	-0.017	-0.022	-0.005	-0.028
	(-0.77)	(-0.98)	(-1.44)	(-0.34)	(-0.89)
Day Before Ad_t	0.005	0.004	0.021	0.005	-0.017
	(0.42)	(0.24)	(1.21)	(0.40)	(-0.59)
Ad Day_t	0.046***	0.047***	0.059***	0.053***	0.078***
	(3.32)	(2.88)	(2.94)	(3.34)	(3.07)
Day After Ad_t	0.024**	0.022	0.039**	0.027*	0.057**
	(1.99)	(1.49)	(2.51)	(1.95)	(2.35)
2 Days After Ad_t	0.019	0.012	0.042**	0.013	0.004
	(1.52)	(0.75)	(2.54)	(0.95)	(0.15)
3 Days After Ad_t	0.012	0.008	0.023	0.008	0.001
	(1.05)	(0.53)	(1.38)	(0.61)	(0.03)
Observations	450,551	450,551	450,551	450,551	450,551
Centered R-Squared	0.850	0.850	0.850	0.850	0.850
Cragg-Donald F-Statistic	5,044.9	4,885.8	4,350.7	4,342.3	4,180.5
Sargan-Hansen p-value	0.332	0.529	0.634	0.770	0.341
Controls	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Two-tailed p-value (3 Days Before = Ad Day)	0.032	0.034	0.007	0.061	0.036
Two-tailed p-value (2 Days Before = Ad Day)	0.005	0.006	0.001	0.015	0.002
Two-tailed p-value (Day Before = Ad Day)	0.003	0.004	0.006	0.004	0.001
Two-tailed p-value (Day After = Ad Day)	0.022	0.023	0.188	0.009	0.083
Two-tailed p-value (2 Days After = Ad Day)	0.066	0.033	0.381	0.022	0.009
Two-tailed p-value (3 Days After = Ad Day)	0.036	0.033	0.084	0.017	0.031

Table 6
Advertising and Investor Attention: Robustness

In this table we conduct a series of robustness tests and modify the base-line specification from table 4 using 2SLS and our general advertising indicator ($Ad\,Dummy_t$). Column 1 replicates our main finding from table 4 panel A column 2; column 2 includes firm-year and industry-date fixed effects; column 3 includes firm-year, year-month, day-of-week, and holiday fixed effects; column 4 drops all "noisy" tickers that either contain the company's name (e.g., AOL), simultaneously refer to a common object (e.g., SKY), or contain only one letter (e.g., K); and column 5 drops all tickers that did not return a stock-specific info box using a Google search that was conducted on August 1, 2015. List of noisy tickers and tickers producing an info box are tabulated in the Online Appendix. The intercepts and control variables from table 4 are not reported. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(Ticker\,SVI_t) = \alpha + \beta Ad\,Dummy_t + \gamma Controls + \psi \text{Fixed Effects} + \epsilon_t$$

	2SLS				
	(1)	(2)	(3)	(4)	(5)
Ad Dummy$_t$	0.049***	0.030*	0.047***	0.048***	0.043**
	(3.12)	(1.90)	(2.95)	(2.97)	(2.00)
Observations	452,376	433,000	452,376	358,583	116,569
Centered R-Squared	0.850	0.853	0.850	0.828	0.809
Cragg-Donald F-Statistic	43,243	38,908	43,171	33,526	8,131.2
Sargan-Hansen p-value	0.859	0.948	0.873	0.873	0.328
Controls	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	No	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Industry-Date FE	No	Yes	No	No	No
Day-of-Week FE	No	No	Yes	No	No
Year-Month FE	No	No	Yes	No	No
Drop Noisy Tickers	No	No	No	Yes	No
Returns Box	No	No	No	No	Yes

Table 7
Business Advertising and Liquidity

This table examines the effect of advertisements on stock liquidity. We estimate the model below, where $Liquidity_t$ is either log share dollar volume (vol_t), share volume-weighted quoted depth $\times 10^{-3}$ ($qdepth_t$), share volume-weighted percent effective spread ($espread_t$), or the share volume-weighted percent quoted spread ($qspread_t$). All variables are computed using TAQ data and the procedure described in Holden and Jacobsen [2014]. Our primary explanatory variable is $Business\,Ad_t$. If a company advertised on a day the market was closed, we set $Business\,Ad_t$ equal to one on the subsequent trading day. We estimate the model using OLS (columns 1 through 4) and 2SLS (columns 5 through 8). The 2SLS analyses use seven and 14-day lag indicators as instruments in the first stage regressions. We include all controls from table 4 and additional controls for the inverse of share price, log market cap (based on the previous fiscal year), and share turnover (except in column 1 where we drop share turnover). Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$Liquidity_t \quad = \quad \alpha + \beta_1 Business\,Ad_t + \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t$$

	OLS				2SLS			
	vol_t	qdepth_t	espread_t	qspread_t	vol_t	qdepth_t	espread_t	qspread_t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Business Ad_t	0.0117**	8.2409**	0.0012	0.0013*	0.0323*	20.3829**	0.0024	0.0016
	(2.16)	(2.47)	(1.27)	(1.67)	(1.83)	(2.35)	(1.01)	(0.69)
Observations	439,841	439,841	439,841	439,841	439,841	439,841	439,841	439,841
Adj/Centered R-Squared	0.958	0.907	0.847	0.881	0.958	0.907	0.847	0.881
Mean Dep Var	17.544	143.015	0.136	0.152	17.544	143.015	0.136	0.152
Cragg-Donald F-Statistic					39,523	39,521	39,521	39,521
Sargan-Hansen p-value					0.021	0.807	0.343	0.370
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8
Business Advertising and Stock Returns

This table examines the effect of advertisements on stock returns. We estimate the model below using both OLS (columns 1 through 3) and 2SLS (columns 4 through 6), where the dependent variable is either the abnormal daily return ($Abret$), three-day cumulative abnormal return ($Abret_{(0,2)}$), or the three-day abnormal return volatility ($Volatility_{(0,2)}$). Our primary explanatory variable is $Business\,Ad$. If a company advertised on a day the market was closed, we set $Business\,Ad$ equal to one on the subsequent trading day. The 2SLS analyses use seven and 14-day lag indicators as instruments in the first stage regressions. We include all controls from table 4 and in addition control for the inverse of share price, log market cap (based on the previous fiscal year), and share turnover (except in columns 3 and 6 where we drop share turnover). Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$Ret_t \quad = \quad \alpha + \beta_1 Business\,Ad_t + \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t$$

	OLS			2SLS		
	Abret_t	$\text{Abret}_{(0,2)}$	$\text{Volatility}_{(0,2)}$	Abret_t	$\text{Abret}_{(0,2)}$	$\text{Volatility}_{(0,2)}$
	(1)	(2)	(3)	(4)	(5)	(6)
Business Ad_t	-0.0001	-0.0000	-0.0186	-0.0011*	-0.0013	0.0245
	(-0.48)	(-0.13)	(-1.60)	(-1.77)	(-1.47)	(0.77)
Observations	439,841	439,774	439,774	439,841	439,774	439,774
Adj/Centered R-Squared	0.024	0.035	0.413	0.024	0.035	0.413
Cragg-Donald F-Statistic				39,521	39,511	39,513
Sargan-Hansen p-value				0.587	0.435	0.079
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Is Investor Attention for Sale? The Role of Advertising in Financial Markets

Online Appendix

Alternative Timing Tests

In this section we discuss an alternative timing test. We estimate 2SLS versions of equation 2 from the paper using ticker SVI from the previous and subsequent days as the dependent variable (i.e., $Ticker\,SVI_{t-2}$ through $Ticker\,SVI_{t+3}$) and the indicator variable for an advertisement in any publication as $Ad\,Measure$. The results are presented in table A6 and are consistent with our hypothesis that advertisements cause an increase in investor attention on the actual ad day. Specifically, in columns 1 and 2 we find that advertisements are not associated with $Ticker\,SVI$ from the previous two days, but that attention spikes on the day of the ad in column 3 (which replicates the 2SLS results from table 4 panel A column 2). Examining the duration of this advertising effect, we find in columns 4 that the coefficient estimate is reduced by 63%. By day $t+2$ and $t+3$ (columns 5 and 6) the effect of the ad on $Ticker\,SVI$ is insignificant, reverting to the same insignificant effect documented in column 2 on day $t-1$.

The shifting dependent variable also allows us to examine how media and earnings announcements affect attention over different horizons. Although the effect of media coverage diminishes over subsequent days (coefficient on $News\,Dummy$ in each column), there remains a significant increase in investor attention even three days after the initial media coverage in column 6. The incremental effect of a product release in contrast diminishes faster (coefficient on $Product\,Release$), becoming insignificant by day $t+2$ (column 5). Attention also diminishes following an earnings announcement, from 16.8% on the actual announcement date, to 14.8% on the subsequent date, 9.8% two days after the event, and 7.0% three days after the event (columns 3 through 6).

Cross Sectional Variation

Prior research suggests that investor attention to financial information varies by the day of the week and, in particular, is lower over weekends and holidays (Niessner [2015]). However, individuals have more leisure time to read newspapers on weekends and holidays, and therefore might be more likely to respond to weekend advertisements. To examine whether the effect of advertisements on investor attention varies by day of the week, we estimate the following model:

$$\begin{aligned}\log(Ticker\,SVI_t) &= \alpha + \beta Ad\,Measure_t + \theta Ad\,Measure_t \times DOW_t \\ &+ \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t \end{aligned} \quad (6)$$

where DOW_t are dummy variables for each day of the week (e.g., Monday, Tuesday) and other variables are as previously defined. Because we use date fixed effects, the DOW main effects are subsumed in our model, and θ captures the incremental difference when an advertisement appears on a particular day of the week. To estimate model (6) using 2SLS requires an instrument for both the main effect of advertising and each of the interaction terms (i.e., each interaction term is also a potentially endogenous variable). We thus supplement the set of instruments to include $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$, as well as each of these variables interacted with the day-of-the-week dummies, ensuring that the model is not underidentified.

Results for model (6) estimated using both OLS (column 1) and 2SLS (columns 2 through 6) are presented in Table A7. For parsimony we do not tabulate the control variables. Similar to table 4, we use five measures of advertising activity as indicated in the column title. The omitted day-of-week variable is Tuesday. When we use $Business\,Dummy$ we exclude Sundays as there are no business publications on Sundays in our data. Using both OLS and 2SLS, we find in columns 1 and 2 that the effect of advertisements on investor attention appears concentrated in the weekends. Coefficients on $Ad\,Measure$ and the interaction terms show that advertisements published Monday through Friday do not generally affect investors' attention. However, if an ad is published on a Saturday or Sunday, then Google SVI for that company's ticker is 7.3% and 6.1% higher (2SLS estimate in column 2) than Saturdays and Sundays with no advertisement. We find a similar weekend pattern for national ads and repeat ads; the main effect for large ads is also statistically significant, suggesting that these full-page ads elicit a significant increase in attention when placed in a Tuesday edition (the omitted group) and that these effects are similar on weekdays and weekends (i.e., insignificant coefficients on each interaction term). Ads appearing in business publications on Saturdays elicit a significant 17.2% increase in investor attention.

The results in table A7 suggest that the effect of advertisements on increased investor attention is primarily driven by weekend advertisements, particularly when placed in a business publication (which presumably investors are more likely to read). We next examine whether the larger effect of ads in business publications is statistically significant. We separate ads into weekday and weekend ads, and estimate the incremental impact (relative to a general publication) of having a weekday (weekend) ad in a business publication. Specifically, we estimate the following model:

$$\begin{aligned}\log(Ticker\,SVI_t) &= \alpha + \beta_1 Weekday\,Ad_t + \beta_2 Weekend\,Ad_t \\ &+ \beta_3 Weekday\,Business\,Ad_t + \beta_4 Weekend\,Business\,Ad_t \\ &+ \Gamma Controls + \psi\text{Firm-Year FE} + \eta\text{Date FE} + \epsilon_t \qquad (7)\end{aligned}$$

where $Weekday\,Ad$ captures the effect of any weekday advertisement on $Ticker\,SVI$ (relative to a weekday without an advertisement) and $Weekend\,Ad$ is similarly defined over weekends. $Weekday\,Business\,Ad$ captures the incremental effect of a weekday advertisement on $Ticker\,SVI$ if that ad appeared in a business publication and $Weekend\,Business\,Ad$ is similarly defined over weekends. Controls and fixed effects are as previously defined. Standard errors are clustered by firm and date.

Results for model (7) estimated using both OLS and 2SLS (with 7- and 14-day lag versions of each advertising variable used as instruments) are presented in Table A8. We estimate both the full model (columns 2 and 4), as well as a simplified version that omits the business advertisement indicators (columns 1 and 3). Similar to the results in table A7, in column 1 using OLS we find that ads printed on weekdays do not increase attention to the firm's financial information (insignificant coefficient on $Weekday\ Ad$) but that weekend ads result in a significant 4.6% increase. In contrast, the 2SLS estimates in column 3 find that weekday ads are associated with a significant 3.2% increase in investor attention, and that the increase is even larger in magnitude for weekend ads (8.9%). In columns 2 and 4 we examine the incremental effect of business ads, and find consistent evidence using both OLS and 2SLS that weekday and weekend business ads generate greater increases in investor attention than ads in other publications.

Table A1
Alternative First Stage Regressions

In this table we re-examine the determinants of print advertising (table 3 of the paper) using fourteen lags of the dependent variable: $t-1$ through $t-14$ (inclusive). All regressions include date and firm-year fixed effects and the control variables from table 3. The intercepts are not reported. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively.

$$Ad\,Measure_t = \alpha + \Sigma_{j=1}^{14}\beta_j Ad\,Measure_{t-j} + \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t$$

	All (1)	National (2)	Large (3)	Repeat (4)	Business (5)
Ad Measure$_{t-1}$	0.066***	0.042***	0.060***	0.055***	0.007
	(9.76)	(7.06)	(7.14)	(7.48)	(1.18)
Ad Measure$_{t-2}$	0.030***	0.022***	0.036***	0.026***	-0.004
	(6.61)	(4.91)	(6.11)	(5.42)	(-0.54)
Ad Measure$_{t-3}$	0.011***	0.007*	0.014***	0.004	-0.007
	(2.84)	(1.72)	(3.20)	(1.01)	(-1.30)
Ad Measure$_{t-4}$	0.009**	0.005	0.002	0.006	-0.003
	(2.44)	(1.21)	(0.46)	(1.62)	(-0.56)
Ad Measure$_{t-5}$	0.011***	0.009**	0.010**	0.008**	0.004
	(3.00)	(2.48)	(1.97)	(2.07)	(0.72)
Ad Measure$_{t-6}$	0.015***	0.011***	0.011**	0.019***	0.013**
	(3.94)	(2.59)	(2.03)	(4.60)	(2.37)
Ad Measure$_{t-7}$	0.253***	0.264***	0.253***	0.244***	0.259***
	(29.82)	(24.83)	(20.57)	(28.90)	(16.88)
Ad Measure$_{t-8}$	-0.014***	-0.013***	-0.021***	-0.005	0.005
	(-3.17)	(-2.74)	(-4.18)	(-0.97)	(0.83)
Ad Measure$_{t-9}$	-0.020***	-0.018***	-0.010**	-0.014***	-0.014***
	(-5.77)	(-5.21)	(-2.35)	(-3.88)	(-2.84)
Ad Measure$_{t-10}$	-0.023***	-0.024***	-0.024***	-0.018***	-0.015***
	(-7.11)	(-6.88)	(-5.18)	(-5.16)	(-3.04)
Ad Measure$_{t-11}$	-0.025***	-0.023***	-0.017***	-0.020***	-0.023***
	(-8.27)	(-6.86)	(-4.32)	(-5.73)	(-5.06)
Ad Measure$_{t-12}$	-0.012***	-0.014***	-0.006*	-0.006*	-0.019***
	(-4.13)	(-4.22)	(-1.66)	(-1.89)	(-3.99)
Ad Measure$_{t-13}$	-0.005	-0.012***	-0.016***	-0.003	-0.008*
	(-1.47)	(-2.98)	(-3.33)	(-0.63)	(-1.70)
Ad Measure$_{t-14}$	0.235***	0.261***	0.211***	0.223***	0.252***
	(29.66)	(26.80)	(21.58)	(25.02)	(16.20)
Observations	452,376	452,376	452,376	452,376	452,376
Adj R-Squared	0.401	0.424	0.323	0.361	0.272
Controls	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes

Table A2
Google Searches: Continuous Advertising Measures

In this table we examine the effect of advertising on Ticker SVI using three continuous measures of advertising activity: (1) $log(Ads_t + 1)$, the natural log of one plus the number of ads placed by a firm on day t; (2) $log(Spend_t + 1)$, the natural log of one plus total dollars spent on advertising by a firm on day t; and (3) $log(Read_t + 1)$, the natural log of one plus the estimated distribution of the publications containing a firm's ads on day t. We estimate the model below using both OLS (columns 1 through 3) and 2SLS (columns 4 through 6), where the first-stage equation is the model from table 3 of the paper. All variables are defined in table 3 of the paper. All regressions include date and firm-year fixed effects. The intercepts are not reported. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(Ticker\,SVI_t) = \alpha + \beta Ad\,Measure_t + \gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t$$

	OLS			2SLS		
	log(Ads) (1)	log(Spend) (2)	log(Read) (3)	log(Ads) (4)	log(Spend) (5)	log(Read) (6)
Ad Measure$_t$	0.018***	0.002***	0.001**	0.041***	0.006***	0.003***
	(2.70)	(3.38)	(2.52)	(2.89)	(3.16)	(2.72)
News Dummy$_t$	0.018***	0.017***	0.018***	0.017***	0.017***	0.017***
	(4.07)	(3.86)	(4.08)	(3.99)	(3.86)	(4.00)
News Tomorrow$_t$	0.012***	0.013***	0.012***	0.012***	0.013***	0.012***
	(4.76)	(4.96)	(4.78)	(4.66)	(4.84)	(4.68)
News Yesterday$_t$	0.015***	0.016***	0.015***	0.015***	0.016***	0.015***
	(5.95)	(6.08)	(5.95)	(5.90)	(6.11)	(5.91)
Product Release$_t$	0.025***	0.028***	0.025***	0.025***	0.029***	0.025***
	(3.07)	(3.26)	(3.07)	(3.04)	(3.26)	(3.04)
Product Tomorrow$_t$	0.011**	0.011**	0.011**	0.011**	0.010**	0.011**
	(2.37)	(2.31)	(2.38)	(2.29)	(2.02)	(2.31)
Product Yesterday$_t$	0.012***	0.013***	0.012***	0.011**	0.012***	0.012**
	(2.62)	(2.75)	(2.64)	(2.54)	(2.61)	(2.56)
Edgar File$_t$	0.022***	0.022***	0.022***	0.022***	0.022***	0.022***
	(3.50)	(3.44)	(3.51)	(3.38)	(3.29)	(3.39)
EA$_t$	0.167***	0.163***	0.167***	0.168***	0.161***	0.167***
	(6.60)	(6.47)	(6.60)	(6.60)	(6.35)	(6.59)
EA Window$_t$	0.068***	0.068***	0.068***	0.068***	0.068***	0.068***
	(6.10)	(6.05)	(6.10)	(6.12)	(6.07)	(6.12)
Observations	456,829	437,326	456,829	452,376	413,856	452,376
Adj/Centered R-Squared	0.850	0.850	0.850	0.850	0.850	0.850
Cragg-Donald F-Statistic				68,837	41,513	51,590
Sargan-Hansen p-value				0.788	0.606	0.952
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A3
Noisy Tickers and Google Search Returns Info Box

Columns 1 and 2 list the 78 tickers for which a Google search on August 1, 2015 returned a stock-specific info box. Columns 3 through 5 list the 82 tickers we flag as containing only a single letter, part of the company's name, or a common word or phrase.

Returns Box		Noisy Tickers		
(1)	(2)	(3)	(4)	(5)
AAPL	HPQ	AIG	HIT	VALE
ALU	INTC	AMR	HOG	WCI
AMZN	IRM	AN	IBM	WIN
AVY	JPM	ANN	ICON	WWW
BAC	KO	AOL	IDT	
BAX	KR	AVID	ITT	
BHI	LMT	BAY	JEN	
CAG	LTM	BIG	K	
CB	LUV	C	KBR	
CHK	LVS	CA	KEY	
CME	MAR	CAB	KIND	
CMG	MCD	CAND	L	
CMI	MDT	CAR	LEG	
COH	MMM	CARB	LO	
COST	MON	CAT	LOW	
CSCO	MSFT	CD	M	
CVX	NOK	CLUB	MAN	
DE	NSC	CNA	MAT	
DECK	NUE	COST	MGM	
DEO	NVS	CREE	MORN	
DF	PFE	CVS	NEWT	
DHR	PG	DELL	PENN	
DIS	PRU	DISH	PG	
DLX	PWR	DISK	PNC	
DOW	RIO	DOW	POST	
DUK	SBUX	EAR	PVH	
DVA	SRE	EAT	R	
ETFC	STT	EBAY	RATE	
ETN	TMO	EMC	RENT	
EXC	TPX	EPIQ	RUTH	
GD	TSCM	F	SAM	
GILD	TXT	FAST	SAP	
GOOG	VVUS	FD	SO	
GS	VZ	FIG	TJX	
HAL	WFC	FMC	TOY	
HAS	WINN	FUN	TRY	
HD	WMT	GE	TXT	
HIG	XOM	GOLF	UPS	
HMC	YHOO	GPS	URS	

Table A4
Advertising and Edgar Downloads

In this table we examine the effect of ads on downloads of all Edgar filings from the SEC website ($ESVI$). We estimate the model below using OLS (column 1) and 2SLS (columns 2 through 6) using the first stage model from table 3 of the paper. All regressions include date and firm-year fixed effects. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(ESVI_t) \quad = \quad \alpha + \beta Ad\,Measure_t + \gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t$$

	OLS	2SLS				
	All (1)	All (2)	National (3)	Large (4)	Repeat (5)	Business (6)
Ad Measure$_t$	-0.003	0.002	-0.005	0.019	-0.016	0.046
	(-0.43)	(0.09)	(-0.20)	(0.54)	(-0.67)	(1.37)
News Dummy$_t$	0.113***	0.113***	0.113***	0.112***	0.113***	0.112***
	(21.63)	(21.63)	(21.62)	(21.55)	(21.65)	(21.66)
News Tomorrow$_t$	0.046***	0.046***	0.046***	0.046***	0.046***	0.046***
	(11.78)	(11.78)	(11.78)	(11.77)	(11.80)	(11.79)
News Yesterday$_t$	0.100***	0.100***	0.100***	0.100***	0.100***	0.100***
	(22.11)	(22.11)	(22.11)	(22.11)	(22.11)	(22.10)
Product Release$_t$	-0.074***	-0.074***	-0.074***	-0.074***	-0.074***	-0.074***
	(-9.65)	(-9.66)	(-9.64)	(-9.70)	(-9.65)	(-9.72)
Product Tomorrow$_t$	-0.015**	-0.015**	-0.015**	-0.015**	-0.015**	-0.015**
	(-2.44)	(-2.45)	(-2.44)	(-2.48)	(-2.44)	(-2.42)
Product Yesterday$_t$	-0.050***	-0.050***	-0.050***	-0.050***	-0.050***	-0.051***
	(-7.91)	(-7.92)	(-7.91)	(-7.95)	(-7.91)	(-7.97)
Edgar File$_t$	0.250***	0.249***	0.250***	0.249***	0.250***	0.249***
	(18.17)	(18.16)	(18.16)	(18.15)	(18.17)	(18.16)
EA$_t$	0.507***	0.507***	0.507***	0.507***	0.507***	0.507***
	(21.19)	(21.19)	(21.19)	(21.18)	(21.20)	(21.18)
EA Window$_t$	0.149***	0.149***	0.149***	0.149***	0.149***	0.149***
	(15.69)	(15.69)	(15.69)	(15.69)	(15.68)	(15.71)
Observations	450,486	450,486	450,486	450,486	450,486	450,486
Adj/Centered R-Squared	0.777	0.777	0.777	0.777	0.777	0.777
Cragg-Donald F-Statistic		42,429	49,281	31,227	38,257	44,661
Sargan-Hansen p-value		0.968	0.409	0.221	0.340	0.869
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A5
Images

This table estimates the effect of ads on investor attention using a subset of ads in 27 publications for which we have ad images. $Ad\,Dummy_t$ is an indicator equal to one if we have an ad image for a firm on day t and zero otherwise. $Old\,Dummy_t$ is an indicator equal to one if a firm's ad on day t has a Hamming distance of 15 or greater when compared to all ads placed by the firm within the previous month. Columns 1 through 3 estimate OLS and columns 4 through 6 estimate 2SLS regressions. We tabulate in the footnotes of columns 3 and 6 the p-value of an F-test that $Ad\,Dummy_t$ and $Old\,Dummy_t$ are jointly positive. T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Ad Dummy$_t$	0.029***		0.024***	0.081***		0.031
	(3.55)		(3.01)	(3.96)		(0.70)
Old Dummy$_t$		0.030***	0.010		0.120***	0.081
		(3.30)	(1.26)		(4.07)	(1.28)
Observations	232,359	232,359	232,359	232,359	232,359	232,359
Adj/Centered R-Squared	0.853	0.853	0.853	0.852	0.852	0.852
p-value (Ad + Old = 0)			0.001			0.000
Cragg-Donald F-Statistic				25,942	15,356	928
Sargan-Hansen p-value				0.431	0.640	0.832
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A6
Advertising and Investor Attention: Alternative Timing Tests

In this table we examine the effect of ads on investor attention using variation in $Ticker\,SVI$ both before and after advertising days. We estimate 2SLS versions of the model below, where the first-stage equation is the model from table 3 of the paper with the instruments $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$. We use as the advertising measure an indicator for whether the firm placed an ad in any publication on date t. The dependent variable in columns 1 and 2 are $Ticker\,SVI$ on days $t-2$ and $t-1$, respectively. Column 3 replicates the results from table 4 panel A column 2 of the paper. The dependent variables in columns four through six are $Ticker\,SVI$ on days $t+1$, $t+2$, and $t+3$, respectively. Control variables are defined in table 3 of the paper. All regressions include date and firm-year fixed effects. The intercepts are not reported and standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(Ticker\,SVI_t) \quad = \quad \alpha + \beta Ad\,Measure_t + \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t$$

	2SLS					
	SVI_{t-2} (1)	SVI_{t-1} (2)	SVI_t (3)	SVI_{t+1} (4)	SVI_{t+2} (5)	SVI_{t+3} (6)
Ad $Measure_t$	-0.011	0.008	0.049***	0.031**	0.022	0.008
	(-0.71)	(0.59)	(3.12)	(2.23)	(1.55)	(0.64)
News $Dummy_t$	0.006***	0.013***	0.017***	0.010***	0.007***	0.005**
	(2.73)	(5.19)	(3.97)	(3.88)	(2.98)	(2.47)
News $Tomorrow_t$	0.007***	0.005**	0.012***	0.021***	0.015***	0.009***
	(2.77)	(2.24)	(4.64)	(4.65)	(5.14)	(3.86)
News $Yesterday_t$	0.018***	0.024***	0.015***	0.009***	0.005**	0.002
	(5.66)	(5.25)	(5.91)	(3.36)	(2.23)	(0.99)
Product $Release_t$	-0.003	0.011**	0.025***	0.012***	0.002	-0.003
	(-0.77)	(2.25)	(3.02)	(2.72)	(0.58)	(-0.81)
Product $Tomorrow_t$	-0.005	-0.003	0.011**	0.027***	0.017***	0.005
	(-1.16)	(-0.78)	(2.27)	(2.99)	(2.90)	(1.47)
Product $Yesterday_t$	0.015**	0.026***	0.012**	0.001	-0.004	-0.005
	(2.48)	(2.97)	(2.54)	(0.23)	(-0.89)	(-1.10)
Edgar $File_t$	0.010**	0.014**	0.022***	0.012**	0.000	-0.002
	(2.35)	(2.37)	(3.37)	(2.31)	(0.04)	(-0.65)
EA_t	0.059***	0.072***	0.168***	0.148***	0.098***	0.070***
	(5.00)	(5.58)	(6.59)	(5.66)	(5.45)	(5.19)
EA $Window_t$	0.071***	0.075***	0.068***	0.075***	0.083***	0.084***
	(6.31)	(6.35)	(6.13)	(6.34)	(6.35)	(6.34)
Observations	452,274	452,327	452,376	452,422	452,076	451,723
Centered R-Squared	0.850	0.850	0.850	0.850	0.850	0.849
Cragg-Donald F-Statistic	43,336	43,288	43,243	43,274	43,223	43,217
Sargan-Hansen p-value	0.761	0.515	0.859	0.430	0.479	0.910
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A7
Advertising and Investor Attention: Searches by Day of the Week

In this table we examine how the effect of advertising on investor attention varies by day of the week. We estimate the model below using both OLS (column 1) and 2SLS (columns 2 - 6), where the first-stage equation is the model from table 3 of the paper with the instruments $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$, as well as each of these instruments interacted with day-of-the-week dummies. Column titles list the ad measure used in each specification (defined in table 2 of the paper). We include but do not tabulate the control variables from table 3 of the paper. All regressions include date and firm-year fixed effects. The intercepts are not reported. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\begin{aligned}\log(Ticker\,SVI_t) &= \alpha + \beta Ad\,Measure_t + \theta Ad\,Measure_t \times DOW_t \\ &+ \Gamma Controls + \psi\text{Firm-Year FE} + \eta\text{Date FE} + \epsilon_t\end{aligned}$$

	OLS	2SLS				
	All (1)	All (2)	National (3)	Large (4)	Repeat (5)	Business (6)
Ad Measure$_t$	0.005	0.024	0.014	0.063*	0.027	0.045
	(0.57)	(1.16)	(0.61)	(1.81)	(1.23)	(1.37)
Ad Measure$_t$ × Mon	0.006	0.011	0.001	-0.032	0.021	-0.004
	(0.78)	(0.70)	(0.04)	(-1.17)	(1.19)	(-0.11)
Ad Measure$_t$ × Wed	0.002	0.004	0.003	-0.001	0.005	-0.020
	(0.23)	(0.26)	(0.13)	(-0.03)	(0.25)	(-0.50)
Ad Measure$_t$ × Thu	0.004	0.007	0.010	-0.025	0.006	0.019
	(0.50)	(0.42)	(0.44)	(-0.95)	(0.32)	(0.44)
Ad Measure$_t$ × Fri	0.004	0.017	0.020	-0.032	0.018	0.026
	(0.59)	(0.99)	(1.02)	(-1.18)	(0.93)	(0.59)
Ad Measure$_t$ × Sat	0.041*	0.073*	0.094**	0.060	0.079*	0.172**
	(1.70)	(1.80)	(2.04)	(1.02)	(1.75)	(2.53)
Ad Measure$_t$ × Sun	0.042**	0.061*	0.084**	0.021	0.082*	
	(2.23)	(1.76)	(2.27)	(0.51)	(1.95)	
Observations	452,376	452,376	452,376	452,376	452,376	388,418
Adj/Centered R-Squared	0.850	0.850	0.850	0.850	0.850	0.853
Cragg-Donald F-Statistic		5,734	6,825	3,554	5,296	6,068
Sargan-Hansen p-value		0.795	0.434	0.855	0.427	0.898
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A8
Advertising and Investor Attention: Business Ads vs. General Ads

In this table we examine how the effect of advertising on investor attention varies by publication type. We estimate the model below using both OLS (columns 1 and 2) and 2SLS (columns 3 and 4). $Weekday\,Ad$ is a dummy variable equal to 1 for weekdays with an advertisement and $Weekend\,Ad$ is an indicator variable equal to 1 for weekends with an advertisement. $Weekday\,Business\,Ad$ and $Weekend\,Business\,Ad$ are defined similarly, except we only look at ads placed in business publications. We estimate 2SLS using as instruments the 7- and 14-day lagged variables of the advertising measures used in each specification. All regressions include date and firm-year fixed effects. We include but do not tabulate the control variables from table 3 of the paper. The intercepts are not reported. Standard errors are robust to heteroskedasticity and account for within-cluster correlation by both firm and date (two-way clustered standard errors). T-statistics are reported in parentheses, and *,**, and *** indicate 10%, 5%, and 1% two-tailed statistical significance, respectively. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\begin{aligned}\log(Ticker\,SVI_t) &= \alpha + \beta_1 Weekday\,Ad_t + \beta_2 Weekend\,Ad_t \\ &+ \delta_1 Weekday\,Business\,Ad_t + \delta_2 Weekend\,Business\,Ad_t \\ &+ \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_t\end{aligned}$$

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Weekday Ad	0.008	-0.000	0.032**	0.010
	(1.34)	(-0.03)	(2.05)	(0.54)
Weekend Ad	0.046***	0.042**	0.089***	0.075**
	(2.80)	(2.49)	(2.91)	(2.40)
Weekday Business Ad		0.027**		0.062**
		(2.40)		(1.99)
Weekend Business Ad		0.047		0.118**
		(1.62)		(2.21)
Observations	452,376	452,376	452,376	452,376
Adj/Centered R-Squared	0.850	0.850	0.850	0.850
Cragg-Donald F-Statistic	NA	NA	20,289	8,377.3
Sargan-Hansen p-value	NA	NA	0.927	0.960
Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes