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

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Abstract

Using daily data of actual firm advertisements we document a channel through which managers can influence investor attention. Exploiting evidence that firms often advertise at weekly intervals (i.e., every 7 days), we use an instrumental variables analysis to provide causal evidence that ads, especially in weekend and business publications, trigger temporary spikes in investor attention. We further find that ads in business publications trigger increased trading volumes and improved liquidity via greater quoted dollar depth. We contribute to research on both the consequences of advertising and more generally on determinants and financial market consequences of investor attention.

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1 Introduction

Investor attention plays a fundamental role in the acquisition and pricing of information. Limited investor attention is linked to muted responses to information and price drifts (Cohen and Frazzini (2008); Hirshleifer, Lim, and Teoh (2009); DellaVigna and Pollet (2009); Hirshleifer, Lim, and Teoh (2011)), whereas increases in investor attention accelerates the pricing of earnings information (Peress (2008); Drake, Roulstone, and Thornock (2012); Drake, Guest, and Twedt (2014); Drake, Roulstone, and Thornock (2015); Twedt (2016); Madsen (2017)). Investor attention also plays an important role in the dissemination of information, where media coverage and direct-access information technologies (DAITs) improve the dissemination of information, lowering investors' processing costs, reducing information asymmetries, and improving market liquidity (Fang and Peress (2009); Bushee, Core, Guay, and Hamm (2010); Blankespoor, Miller, and White (2014); Peress (2014); Dai, Parwada, and Zhang (2015); Lerman (2016)). Attracting investor attention can thus have significant consequences for a firm's information environment (e.g., liquidity).

This paper examines whether firms can influence investor attention through product market advertisements, and resulting effects of advertisements on financial markets. Advertisements are ubiquitous in modern-day capital markets. Advertising increases firm visibility and plays an important role in the investor recognition hypothesis (Merton (1987); Barber and Odean (2008)). Prior research finds that increased annual advertising, a potential measure of investor recognition, is associated with broader ownership structure and improvements in liquidity (Grullon, Kanatas, and Weston (2004)) as well as higher contemporaneous annual returns (Frieder and Subrahmanyam (2005); Chemmanur and Yan (2011); Lou (2014)). However, these effects may be due to the cumulative and aggregated nature of annual advertising expenditures, omitted variables (i.e., product launches), or reverse causality (i.e., advertising when ownership is broad). It is thus unclear, ex ante, to what extent advertisements actually affect investor attention and financial markets.

Empirically identifying the causal effect of advertising is challenging. Firms endogenously choose when, where, and how much to advertise, thus measuring the causal effects of ads separate from potentially omitted variables using aggregated advertising data (e.g., annual advertising expenditures) is particularly daunting. Although the use of daily advertising data helps reduce some concerns of omitted variables, advertisements can still be timed to coincide with product launches, news events, or other unobserved events, complicating the measurement of a causal effect.

To illustrate this challenge, consider the following two scenarios:

Figure 1

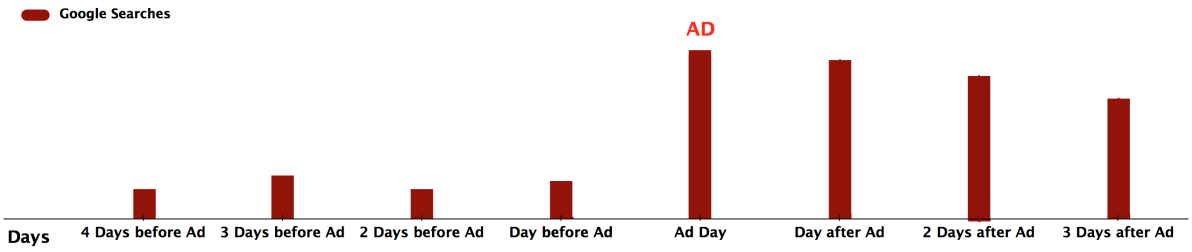

Figure 2

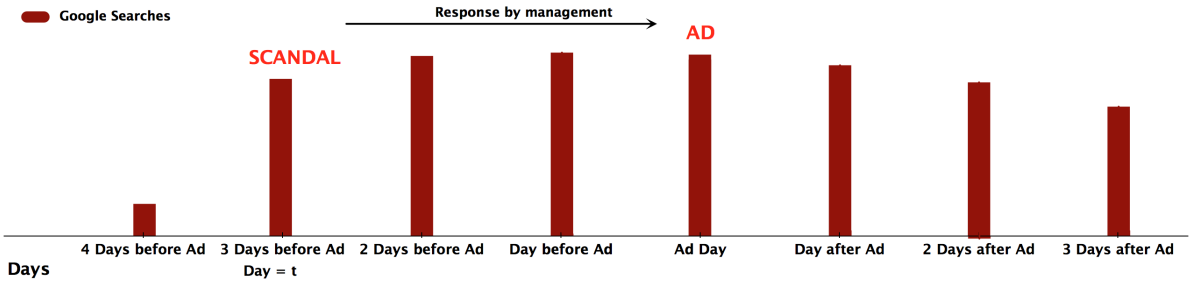

Figure 1 shows a case where advertisements cause increased investor attention. Google searches for company tickers, a commonly accept measure of investor attention, is flat until an ad appears on a randomly selected day, spikes on the day of the ad, and then decreases over several days following the ad. Figure 2 depicts an alternative case where a scandal (e.g., corporate data hack) occurs three days before an ad is published. This scandal causes investors to Google the company's ticker repeatedly over the subsequent week. When an

advertisement subsequently appears, Google searches are already abnormally high, making it difficult to identify the change in attention attributable to the advertisement.

In both scenarios, using annual, monthly, or even weekly advertising expenditures would produce a positive correlation between advertising and investor attention, yet only in figure 1 would there be a positive correlation between measures of daily advertising and investor attention. Using daily advertising data thus has clear advantages over more aggregate advertising data, although it still requires a fairly strong assumption that the ad day was selected randomly for estimating causal effects.

To identify the causal effects of advertising we therefore rely on an instrumental variables analysis, using changes in advertising behavior that are plausibly unrelated to the outcome of interest. To begin, we first examine patterns of advertising activity in search of suitable instrumental variables and model the firm-level decision to advertise on a given day. Using a comprehensive database of all advertisements placed in 39 daily newspapers between 2008 and 2013 by 637 publicly traded companies, we document that these 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 and 14 days earlier. We document that these instrumental variables are significantly associated with the likelihood of advertising on day t and plausibly uncorrelated with investor attention and financial markets on day t.

We thus next use these instrumental variables in two-stage least squares regressions to analyze the effect of advertising on investor attention. Specifically, using daily Google searches for company stock tickers as a measure of investor attention (Da, Engelberg, and Gao (2011); Drake, Roulstone, and Thornock (2012); Madsen (2017)), we find that Google searches spike 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 and company-specific earnings announcements. We furthermore include both firm-year and date fixed effects to implicitly control for unobservable differences across firm-years and days. Tests confirm that the instruments are not weak and that overidentification in these regressions (i.e., correlation between the instruments and error term) is not a concern.

We subject these findings to a battery of robustness tests which collectively suggest that investor attention significantly increases on days with advertisements. We examine variation in the type of advertisement (e.g., full-page ads), placement of the advertisement (e.g., national or business publications), possible information content of the advertisement (e.g., repeat ads), and differences across days of the week (e.g., Mondays versus Saturdays). We find all types of ads elicit increased attention, with weekend ads and ads in business publications (e.g., *The Wall Street Journal*) eliciting the greatest increase in investor attention. To benchmark our results, we find that product releases are associated with a 4.3% increase in investor attention, whereas earnings announcements generate an 18.1% increase, suggesting that ads attract a similar amount of attention as a product release and 27% of the attention associated with an earnings announcement. Falsification tests suggest that Google searches are insignificantly different on the day immediately prior to an advertisement, providing additional evidence that the increased attention is driven by the advertisement rather than a confounding event.

We next examine the effect of advertising on financial markets. Prior research finds that increased investor attention (e.g., improved dissemination) to information (e.g., earnings announcements) results in improved price discovery, reduced information asymmetries, and improved market liquidity (e.g., Bushee, Core, Guay, and Hamm (2010) and Blankespoor, Miller, and White (2014); Twedt (2016)). However, it is unclear how increased investor attention in the *absence* of new information affects financial markets. Advertisements unlikely contain valuable firm-specific information, particularly in our instrumental variables

analysis where we exploit the observable timing frequencies with which firms advertise to elicit plausibly exogenous variation in advertising with respect to financial market outcomes. Thus whether the increases in attention we document in response to advertisements affects financial markets through increased trading activity or liquidity is ultimately an empirical question.

Using the instrumental variables analysis, we find that dollar trading volumes increase by 2.8% and quoted dollar depths increase by 15% on days with ads in a business publication (i.e., the publications that generate the greatest increase in investor attention). Effective spreads (i.e, the realized round-trip cost of executing a trade) do not significantly change. Quoted spreads marginally increase, although the economic magnitude is small (0.8%). Collectively, the evidence suggests that the increased attention driven by advertising results in improved liquidity on ad days.

Our paper relates to a growing literature on the links between product market advertising and financial markets, as well as a broader literature on investor attention and financial markets (Grullon, Kanatas, and Weston (2004); Frieder and Subrahmanyam (2005); Gurun and Butler (2012); Jain and Wu (2000); Cronqvist (2006); Reuter and Zitzewitz (2006)). The closest papers to ours are Boyd and Schonfeld (1977), Chemmanur and Yan (2011), Focke, Ruenzi, and Ungeheuer (2014), and Lou (2014). These papers typically use annual advertising and stock market data and find that stock prices rise in years with high annual advertising expenditures, only to revert over following years.[1] In contrast, we use high-frequency advertising data and an instrumental variables approach to establish a causal link between advertising and investor attention and to examine the effect of increased investor attention (via advertisements) on financial markets.

[1] Focke, Ruenzi, and Ungeheuer (2014) also use daily advertising data, although they use an alternative measure of attention (wikipage views) and do not use an instrumental variables analysis or find evidence of changes in liquidity.

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, 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.[2]

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.[3] 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 $25.57 billion and median market cap $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

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

[3] 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.

on advertising, and generates net profits of $1,539 million. The average firm in our sample spends an estimated $6.4 million each year on 81 print advertisements that appear on 34.9 days for 4 distinct brands placed across 4 newspapers. Conditional on advertising on a given day, the average firm places advertisements in 1.2 publications (99th percentile 3.6), suggesting that ad days often span multiple publications. Although the total amount spent on advertising in our sample is a small proportion of the average firm's annual advertising budget, we find that print advertising is significantly correlated with firm's total advertising activity. After merging our advertising data with monthly advertising expenditures from Kantar Media's Ad$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 general 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.

3 Determinants of Advertising

Researchers face a significant challenge identifying the causal effects of advertising. Firms determine how much and when to 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 practically impossible using *annual* or *monthly* advertising data. Even using daily 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 attention and financial markets, we first attempt to model the determinants of a firm's decision to advertise on a particular date. Given concerns about endogeneity and omitted variables, one approach to empirically identify the casual effect of advertising is to use an instrumental variable which is correlated with the likelihood of placing an ad, but uncorrelated with any other determinants of the outcome of interest (e.g., investor attention or liquidity on the ad day; see Angrist and Pischke (2008)). Patterns in firms' advertising activity provide a useful source for finding such an instrumental variable.

Inspection of the daily advertising data reveals a tendency for firms to advertise at weekly intervals, often 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%). This pattern is not very surprising, as companies often order "ad packages" that include recurrent advertisements over multiple weeks.

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

(*Repeat*), and an ad in a business publication (*Business*).[4] Across all five advertisement types, we find that the days with the highest percent of firms advertising are days $t-7$ (45-60% of firms, depending on the type of ad) and $t-14$ (44-59% of firms). The pattern is particularly striking for business ads, where 45% of firms placed a business ad on day $t-7$, whereas only 11-16% of firms placed a business ad on days $t-1$ through $t-6$.

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,[5] 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").[6] 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.

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

[4] 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*.

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

[6] 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).

conclude that firms and industries exhibit variation in the days of the week on which they most frequently advertise, although there is possible preference for Mondays. To address this and any other potential preferences for certain advertising days, we include in all our analyses date fixed effects.

Based on this pattern of advertising, we analyze the determinants of advertising using as instruments two indicator variables for whether the firm advertised 7 and 14 days earlier. Specifically, we estimate the following linear probability model:

$$\begin{aligned} Ad\,Measure_{i,t} &= \alpha + \beta_1 Ad\,Measure_{i,t-7} + \beta_2 Ad\,Measure_{i,t-14} \\ &+ \gamma_1 News\,Dummy_{i,t} + \gamma_2 News\,Tomorrow_{i,t} + \gamma_3 News\,Yesterday_{i,t} \\ &+ \gamma_4 Product\,Release_{i,t} + \gamma_5 Product\,Tomorrow_{i,t} + \gamma_6 Product\,Yesterday_{i,t} \\ &+ \gamma_7 EA\,Day_{i,t} + \gamma_8 EA\,Window_{i,t} + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t} \quad (1) \end{aligned}$$

where $Ad\,Measure_{i,t}$ is an indicator for one of the five types of advertising discussed previously and zero if firm i did not advertise on day t, and $Ad\,Measure_{i,t-7}$ and $Ad\,Measure_{i,t-14}$ are 7-day and 14-day lagged dependent variables. Based on the observational analysis in table 2, we expect these lag dependent variables to be predictive of firm i advertising on day t, a necessary condition for any instrumental variable.

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 day (i.e., exogenous covariates). Specifically, $News\,Dummy_{i,t}$, $News\,Tomorrow_{i,t}$, and $News\,Yesterday_{i,t}$ are indicator variables equal to 1 if firm i is the focus of at least one news article on day t, $t+1$, and $t-1$, respectively; $Product\,Release_{i,t}$, $Product\,Tomorrow_{i,t}$, and $Product\,Yesterday_{i,t}$ are indicator variables equal to 1 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;[7] $EA\,Day_{i,t}$ is an in-

[7] Media coverage and press release data obtained from Ravenpack.

dicator variable equal to 1 if the firm announced earnings on day t and 0 otherwise; and $EAWindow_{i,t}$ is an indicator variable equal to 1 for the five days before and after an earnings announcement, and 0 otherwise.[8] 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 (rather than firm-year) 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. Both 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 advertisement on day t by 214-233% relative to the sample average,[9] with even larger results for the more specific forms of advertising (e.g., there is 486% increased likelihood an ad is placed in a national newspaper on day t if an ad in a national newspaper was placed 14 days earlier.). Adjusted R^2's are also relatively 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 both on news days and in anticipation of a news day (i.e., significantly positive coefficients on $News\,Dummy$ and $News\,Tomorrow$), but do not appear to advertise in response to a previous news day (insignificant coefficient on $News\,Yesterday$). 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 $Product\,Release$, $Product\,Tomorrow$, and $Product\,Yesterday$). Advertising behavior is not related to actual earnings announcements

[8] Although we have no specific prediction regarding how advertising varies around earnings announcement 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.

[9] Coefficient estimates of 0.256 and 0.235 in column 1 each divided by average dependent variable of 0.110. Sample averages for all dependent variables tabulated in table footnotes.

(insignificant coefficient on EA), but firms on average advertise less in the days leading up to and immediately following an earnings announcement (significantly negative coefficient on $EA\,(t-5, t+5)$).

In the online Appendix table A1 we tabulate a modified version of equation 1 that includes fourteen lagged dependent variables to examine the relative importance of days $t-7$ and $t-14$ relative to 12 other days. Control variables are included but not tabulated for conciseness. The coefficient estimates on $Ad\,Measure_{i,t-7}$ and $Ad\,Measure_{i,t-14}$ are not only positive and statistically significant, but continue to have the highest economic significance of all the lagged variables (e.g., 0.253 and 0.235 for the general advertising specification in column 1). The coefficient estimate on $Ad\,Measure_{i,t-1}$ has the next highest economic significance (0.066), albeit 26% smaller than the coefficient on $Ad\,Measure_{i,t-7}$ in column 1, and suggests the presence of add campaigns with back-to-back advertising. This presence of ad campaigns suggests that $Ad\,Measure_{i,t-1}$ is likely endogenous to the decision to advertise on day t and potentially correlated with outcomes of interest on day t (e.g., investor attention) and thus not a suitable candidate for an instrumental variable. Interestingly, coefficient estimates on lagged variables $t-8$ through $t-13$ are negative and statistically significant, in contrast to the large statistically positive coefficient on the $t-14$ lagged variable.

The combined evidence from tables 2, 3, and A1 suggest a pattern of companies advertising on a weekly basis, with variation in the exact day of the week across companies, and that the variables $Ad\,Measure_{i,t-7}$ and $Ad\,Measure_{i,t-14}$ 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 causal effects of advertising on investor attention and liquidity using these instrumental variables.

4 Advertising and Investor Attention

4.1 General Analysis

In this section we examine the causal effect of advertisements on investor attention. Ads highlight firms' products and services, and typically target current and potential customers. Prior research finds that individuals are more likely to invest in stocks they frequent as customers (Keloharju, Knüpfer, and Linnainmaa (2012)), suggesting that consumers and investors do not necessarily represent distinct groups. The public nature of advertising and overlap between consumers and investors suggests that advertisements can have spillover effects and potentially affect investor behavior.

Advertisements are designed to attract attention. If noticed by current or potential investors, ads might prompt these individuals to check a firm's current stock price, financial performance, or even purchase/sell the stock. We thus empirically examine whether ads attract investor attention to the advertising firm's financial information. Previous research finds evidence that annual advertising expenditures are correlated with annual returns (Lou (2014); Chemmanur and Yan (2011)) and broader ownership structure (Grullon, Kanatas, and Weston (2004)). Although returns and ownership structure may capture some aspect of investor attention, to our knowledge, our paper is the first to provide evidence of a causal link between actual advertising activity and a more direct measure of investor attention.

We measure investor attention using log daily Google search volume index (SVI) for the company's ticker ($Ticker\,SVI$). Prior research demonstrates that $Ticker\,SVI$ is a reasonable and timely measure of investor attention and captures investors' demand for financial information (Da, Engelberg, and Gao (2011); Drake, Roulstone, and Thornock (2012)). We use searches for ticker symbols instead of firm names for two reasons. First, people use many different versions of a company's name. Second, when people search for "Walmart," they are generally not looking for financial information about the company. Using ticker symbols helps alleviate both of these concerns. In the Appendix we describe how we obtain and

construct our daily Google search measure. We use 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 have a causal effect on investor attention we use two-stage least squares (2SLS) regressions, employing the first-stage regression from equation 1 with the instruments $Ad\,Measure_{i,t-7}$ and $Ad\,Measure_{i,t-14}$ and the following second-stage regression:

$$\begin{aligned} log(Ticker\,SVI_{i,t}) &= \alpha + \beta Ad\,Measure_{i,t} + \Gamma Controls \\ &+ \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $Ticker\,SVI_{i,t}$ is the Google search measure for company i's ticker on date t, $Ad\,Measure_{i,t}$ is the instrumented measure of firm advertising activity estimated using equation 1, and controls include the set of exogenous covariates from equation 1. We continue to include firm-year and date fixed effects. To account for time-series and cross-sectional correlation in the residuals, we also continue to cluster standard errors simultaneously by firm and date (Petersen (2009)).

Table 4 panel A presents results from estimating model (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. 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 is economically small (1.7% increase in Google SVI) but statistically significant at the 1% level and consistent with an increase in investor attention on ad days.

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)). 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%).[10] The use of daily data and 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 days, particularly for repeat advertisements which likely contain minimal new 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 a weak instrument and (2) correlation between the instrument 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 43,245 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)).

[10] We directly test for differences across these advertising measures in section 4.3.

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., 1.8% 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 18.1% increase in Ticker SVI, with a smaller but comparably significant increase of 6.8% on days immediately before and after the earnings announcement (Drake, Roulstone, and Thornock (2012); Madsen (2017)). Based on the OLS estimates, advertisements thus trigger approximately the same increase in investor attention as a news story about the company that does not involve a product release, 40% of the increase in investor attention associated with a product release,[11] and 9% of the increase in investor attention related to an earnings announcement.

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 attention to the company name. Because Google searches for company names more likely capture *general* attention, we re-run model (2) (using both OLS and 2SLS) using Google searches for company names ($Name\,SVI$) as the dependent variable and compare the effect of advertising on $Name\,SVI$ with the effect on $Ticker\,SVI$.[12] 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% increase for company tickers versus a 12.8-17.4% increase for company names). The more pronounced effect of ads on searches for company names is unsurprising, as the primary goal of advertising

[11] Coefficient estimate of 0.017 on $Ad\,Measure$ divided by the sum of coefficients 0.018 and 0.025 on $News\,Dummy$ and $Product\,Release$. Relative effects are larger when using the 2SLS estimates.

[12] 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.

is to attract attention to the company and/or its products, and suggests that $Name\,SVI$ more likely captures general 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 general attention. Comparing coefficient estimates on the control variables in panels A and B, we find that news days trigger a larger increase in Google searches for the company's name than searches for the company's ticker (1.8% for company tickers and 3.4% for company names). However, when the news is clearly financial (e.g., an earnings announcement), the pattern reverses. Earnings announcements trigger an 18.1% increase in searches for the company's ticker compared to an 8.6% increase in searches for the company's name, 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.

We perform a number of additional tests with alternative fixed effects, subsamples, and advertising measures to demonstrate the robustness of these results. These results are presented in the online Appendix tables A2 and A3 and discussed here only briefly. We continue to find significant results using firm-year and industry-date fixed effects (defined using the Fama French 12 groupings and clustering standard errors by both firm and industry-date) and alternatively using firm-year, year-month, and day-of-the-week and holiday fixed effects. We also 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), and alternatively examine a specification that requires a Google search for the ticker to produce an info box about the stock. Although sample sizes are significantly diminished with these later two tests, our results are qualitatively unchanged in all of these alternative specifications. Finally, we also estimate models that use continuous measures of advertising

($Log(Ads+1)$, $log(Spend+1)$ and $log(Readership+1)$), rather than indicator variables and continue to find qualitatively similar results.

4.2 Timing Tests

The results in table 4 suggest that ad days are associated with higher levels of Google search for financial information. The combined use of instrumental variables, daily data, controls for media attention and firm-specific events, and an exhaustive fixed effect structure help increase confidence that the effects documented in table 4 are causal in nature. To provide additional insight into whether these effects are likely causal, 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 thus next estimate 2SLS versions of equation (2) using ticker SVI from the previous and subsequent days as the dependent variable (i.e., $Ticker\,SVI_{t-1}$ through $Ticker\,SVI_{t+3}$) and the indicator variable for any advertisement in any publication as $Ad\,Measure$. The results are presented in table 5 and are consistent with our hypothesis that advertisements cause an increase in investor attention on the actual ad day. Specifically, in column 1 we find that advertisements are unassociated with $Ticker\,SVI$ from the previous day, but that attention spikes on the day of the ad in column 2 (which replicates the 2SLS results from table 4 panel A column 2). Examining the duration of this advertising effect, we find in columns 3 and 4 that the effect diminishes by 37% and 55% over days $t+1$ and $t+2$, respectively. By day $t+3$ (column 5) the effect of the ad has reverted to the same insignificant effect documented in column 1 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 5. The incremental effect of a product release in contrast diminishes faster (coefficient on *Product Release*), becoming insignificant by day $t + 2$ (column 4). Attention also diminishes following an earnings announcement, from 18.1% on the actual announcement date, to 15.5% on the subsequent date, 9.8% two days after the event, and 6.8% three days after the event (columns 2 through 5).

4.3 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 (2014)). 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 throughout the week, we estimate the following model:

$$\begin{aligned} \log(Ticker\,SVI_{i,t}) &= \alpha + \beta Ad\,Measure_{i,t} + \theta Ad\,Measure_{i,t} \times DOW_t \\ &+ \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t} \end{aligned} \tag{3}$$

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. θ captures the incremental difference when an advertisement appears on a particular day of the week. To estimate model 3 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 $Ad\,Measure_{t-7}$, $Ad\,Measure_{t-14}$, as well as $Ad\,Measure_{t-7}$ interacted with day-of-the-week dummies, ensuring that the model is not underidentified.

Results for model (3) estimated using both OLS (column 1) and 2SLS (columns 2 through 6) are presented in Table 6. 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 header. 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 are 7.4% and 6.2% higher (estimated using 2SLS in column 2) than Saturdays and Sundays with no advertisement. We find similar effects for repeat ads placed in weekend editions, and a statistically significant main effect for large ads, 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 16.9% increase in investor attention.

The results in table 6 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 determine whether ads were printed during the week or on the weekend, 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:

$$\begin{aligned}
\log(Ticker\,SVI_{i,t}) &= \alpha + \beta_1 Weekday\,Ad_{i,t} + \beta_2 Weekend\,Ad_{i,t} \\
&+ \delta_1 Weekday\,Business\,Ad_{i,t} + \delta_2 Weekend\,Business\,Ad_{i,t} \\
&+ \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t} \qquad (4)
\end{aligned}$$

where $Weekday\ Ad$ captures the effect of any weekday advertisement on $Ticker\ SVI$ (relative to the same 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 (4) estimated using both OLS and 2SLS (with 7-day and 14-day lag versions of each advertising variable used as instruments) are presented in Table 7. 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 6, 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 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 business ads generate greater increases in investor attention than ads in other publications. The 2SLS estimates further suggest that weekend business ads also have an incrementally larger impact, although this effect is insignificant when estimated using OLS.

In summary, tables 4 through 7 support our hypothesis that advertisements attract investor attention. Across multiple measures of daily advertising activity, using an instrumental variables approach we find that ads trigger a temporary 4.9-8% increase in Google searches for the company's stock ticker on the day the ad is published. Results are uniformly smaller but still statistically significant using OLS. We furthermore demonstrate that $Ticker\ SVI$ is a preferable measure of investor attention, and that weekend and business ads generate the largest increases in investor attention. Finally, the granularity of our data,

combined with our fixed effects, control variables, and instrumental variables, suggest that ads cause this increased demand for financial information.

5 Advertising and Financial Markets

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. If there is an increased interest in a firm's stock as a result of an advertisement, then that stock may experience increased trading volumes. Furthermore, if the nature of the increased attention is based on the behavior of uninformed traders, liquidity in the stock may improve. Conversely, if advertising and the increased attention resulting from advertising is informative (to at least some investors), then market makers may respond with decreased liquidity (i.e., price protect).

To examine the effect of advertising on trading volume and liquidity, we estimate the following regression:

$$\begin{aligned} Liquidity_{i,t} &= \alpha + \beta_1 Business\, Ad_{i,t} \\ &+ \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t} \end{aligned} \tag{5}$$

where *Liquidity* is either log dollar trading volume (daily shares traded times share price) for firm i on day t (*vol*), the quoted dollar depth (*qdepth*), share volume-weighted percent effective spread (*espread*), or share volume-weighted percent quoted spread (*qspread*). *qdepth* (total offer depth plus total bid depth divided by 2), *espread*, and *qspread* are computed using TAQ data and the procedure described in Holden and Jacobsen (2014).[13] As described in Holden, Jacobsen, and Subrahmanyam (2014), percent quoted spreads are based on displayed quotes and thus represent "the hypothetical cost of trading," whereas percent

[13] See also Hendershott, Jones, and Menkveld (2011). We thank Craig Holder for providing code necessary to compute these liquidity measures using TAQ data. See http://kelley.iu.edu/cholden/instructions.pdf.

effective spreads are based on the actual trade price and thus capture the "actual round-trip-equivalent cost of trading" (p. 273). All liquidity 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 abnormal liquidity measures.

Our analysis in section 4.3 suggests that business ads have the largest effect on investor attention, and thus we use the indicator variable *Business Ad* to measure the effect of these ads on liquidity. Because markets are closed on weekends, we assume that any effects of weekend advertisements manifest on the next trading day. We therefore set *Business Ad* equal to one on the first trading day of each week if an ad was placed over the previous weekend. We continue to include our set of control variables relating to media coverage and earnings announcement events from table 3, and estimate equation 5 using both OLS and 2SLS (using business advertising on days $t-7$ and $t-14$ as instruments). Standard errors are clustered by firm and date.

Table 8 tabulates coefficient estimates from model 5 using both OLS (columns 1 through 4) and 2SLS (columns 5 through 8). Examining *vol* first, the OLS estimates in column 1 suggest that *vol* increases by 1.1% on days with business ads after controlling for media coverage and earnings announcement events and including our extensive set of fixed effects. The 2SLS estimate in column 2, which accounts for the potentially endogenous decision to advertise, suggests *vol* increases by as much as 2.8%, although the Sargan-Hansen test suggests that overidentification may be an issue in this specification (i.e., Sargan-Hansen p-value of 0.010, suggesting potential correlation between the instruments and error term in the second stage regression). Examining the control variables, we find that news days are associated with increased *vol*, although surprisingly product release days are associated with reduced *vol* (relative to news days without a product release). Earnings announcement windows are associated with significant increases in *vol*.

In columns 2 and 6 we find that *qdepth* also significantly increases on days with business ads, suggesting improved liquidity as market makers increase the number of shares offered at the national Best Bid and Offer (BBO). Both the OLS and 2SLS estimates are statistically and economically significant, suggesting a 6% (OLS) and 15% (2SLS) increase in *qdepth* on days with business ads.[14] Unlike the *vol* specification, overidentification does not appear to be in issue in the 2SLS analysis of *qdepth* (p-value 0.888).

Unlike *qdepth*, *espread* does not appear to increase on days with business ads, suggesting that the increased depth is not associated with either a higher or lower realized cost of trading. Turning to *qspread*, the OLS estimates suggest that *qspread* marginally increases on business ad days, suggesting potentially higher transaction costs and a lower level of liquidity, however the 2SLS estimate in column 8 is insignificant. The increase in *qspread* in column 4 estimated using OLS, although significant, is economically small relative to its mean (0.8%, based on the average *qspread* of 15.7 basis points). Overall, we conclude that liquidity marginally improves through increased volume and depth when firms advertise, consistent with the increased attention associated with the ads resulting in additional uninformed trading in the stock.

6 Conclusion

Although advertising traditionally targets consumers, investors can also take notice. Exploiting the predictable pattern of actual firm advertising behavior, we contribute to prior research on the consequences of advertising and provide a model that both explains the timing of when firms advertise and simultaneously allows us to estimate the likely causal effects of advertising. We contribute to research on the consequences of investor attention by documenting a channel whereby firms can influence that attention, and provide robust

[14] The average dollar depth in our sample is 142.7, tabulated in table footnote.

evidence that advertisements have spillover effects on financial markets through increased attention and improved financial liquidity and trading volume.

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Appendix

Daily Google Search Volume Index

Google Trends, a service run by Google, provides a daily SVI for search volumes above a certain (unspecified) threshold going back to January 2004. The index is not the raw number of searches (i.e., absolute traffic), but the popularity of the term relative to other search terms during the same time period. This adjustment helps normalize the data for general internet usage on that day. Furthermore, Google scales the data by the highest search volume for the given search period. For example, if someone searches for "WMT" during February 2010, and the highest search volume for that period was on February 21, the search index that Google displays has SVI = 100 for February 21, and all other SVIs for that search period are relative to the SVI on February 21. Therefore, results across different search periods are not easily comparable. To get daily search results, we have to search one month at a time. To make daily SVI for a given company comparable across months, we also perform a search over the entire time period (February 2008 - December 2013) at the weekly level for each company. We then scale the daily SVI_d by the weekly SVI_w, using the following formula:

$$SVI = SVI_d * SVI_w/100 \ .$$

Table 1
Summary Statistics

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

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 tabulates averages across indicator variables for five types of advertising: *All* is set to one if the company placed an ad in any publication, *National* is set to one if an ad was placed in any national publication, *Large* is set to one if a full-page ad was placed in any publication, *Repeat* is set to one if an ad was placed for a brand that was previously advertised within the same daily publication within the previous 2 months, and *Business* is set to one if an ad was placed in a business publication. 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*. Panel A tabulates the percent of firms advertising on day $t - X$, conditional on advertising on day t. 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 day of the week with the greatest number of ads), 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, as well as 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	0.39	0.28	0.40	0.16
Ad Measure$_{t-2}$	0.42	0.37	0.27	0.37	0.13
Ad Measure$_{t-3}$	0.40	0.35	0.25	0.35	0.11
Ad Measure$_{t-4}$	0.40	0.35	0.24	0.35	0.11
Ad Measure$_{t-5}$	0.41	0.37	0.26	0.36	0.13
Ad Measure$_{t-6}$	0.43	0.38	0.25	0.38	0.16
Ad Measure$_{t-7}$	0.60	0.59	0.48	0.56	0.45
Ad Measure$_{t-8}$	0.42	0.38	0.25	0.38	0.16
Ad Measure$_{t-9}$	0.40	0.36	0.25	0.35	0.12
Ad Measure$_{t-10}$	0.38	0.34	0.23	0.34	0.11
Ad Measure$_{t-11}$	0.38	0.34	0.23	0.33	0.10
Ad Measure$_{t-12}$	0.40	0.36	0.24	0.35	0.12
Ad Measure$_{t-13}$	0.41	0.37	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
Monday	0.11	0.05	0.04	0.08	0.03
Tuesday	0.11	0.06	0.04	0.08	0.03
Wednesday	0.12	0.06	0.05	0.09	0.03
Thursday	0.13	0.07	0.05	0.09	0.03
Friday	0.12	0.06	0.05	0.08	0.02
Saturday	0.07	0.04	0.02	0.05	0.01
Sunday	0.13	0.09	0.07	0.09	0.00
Overall	0.11	0.06	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 print 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 $Ad\,Measure_{i,t}$ is a measure of firm i's advertising activity on date t, and is 0 if the firm did not advertise. We use five indicator variables of advertising activity as indicated in the column titles and defined in table 2. The main variables of interest are the indicators $Ad\,Measure_{i,t-7}$ and $Ad\,Measure_{i,t-14}$, set equal to one if the firm advertised 7 and 14 days earlier, respectively. Control variables include $News\,Dummy_{i,t}$, $News\,Tomorrow_{i,t}$, and $News\,Yesterday_{i,t}$, indicator variables equal to 1 if firm i is mentioned in at least one news article on day t, $t+1$, and $t-1$, respectively; $Product\,Release_{i,t}$, $Product\,Tomorrow_{i,t}$, and $Product\,Yesterday_{i,t}$, indicator variables equal to 1 if the media coverage on day t, $t+1$, and $t-1$ mentioned a product release, respectively; $EA\,Day_{i,t}$, an indicator variable equal to 1 if the firm announced earnings on day t and 0 otherwise; and $EA\,Window_{i,t}$, an indicator variable equal to 1 for the five days before and after an earnings announcement, and 0 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.

$$
\begin{aligned}
Ad\,Measure_{i,t} &= \alpha + \beta_1 Ad\,Measure_{i,t-7} + \beta_2 Ad\,Measure_{i,t-14} \\
&+ \gamma_1 News\,Dummy_{i,t} + \gamma_2 News\,Tomorrow_{i,t} + \gamma_3 News\,Yesterday_{i,t} \\
&+ \gamma_4 Product\,Release_{i,t} + \gamma_5 Product\,Tomorrow_{i,t} + \gamma_6 Product\,Yesterday_{i,t} \\
&+ \gamma_7 EA\,Day_{i,t} + \gamma_8 EA\,Window_{i,t} + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t}
\end{aligned}
$$

Table 3 (continued)

Dependent variable: $Ad\,Measure_{i,t}$

	(1) All	(2) National	(3) Large	(4) Repeat	(5) Business
Ad Measure$_{t-7}$	0.256***	0.267***	0.254***	0.247***	0.261***
	(30.74)	(21.14)	(21.10)	(29.80)	(16.79)
Ad Measure$_{t-14}$	0.235***	0.277***	0.209***	0.224***	0.253***
	(29.89)	(22.74)	(21.38)	(25.23)	(15.94)
News Dummy	0.004***	0.002*	0.004***	0.003**	0.002***
	(3.01)	(1.88)	(2.98)	(2.04)	(3.02)
News Tomorrow	0.003**	0.002**	0.002**	0.002**	0.002**
	(2.09)	(2.32)	(2.03)	(2.16)	(2.31)
News Yesterday	0.000	-0.000	0.000	-0.000	0.000
	(0.18)	(-0.28)	(0.24)	(-0.11)	(0.65)
Product Release	0.007***	0.005*	0.003	0.006**	0.005***
	(2.67)	(1.81)	(1.14)	(2.36)	(2.98)
Product Tomorrow	0.005**	0.003	0.007***	0.004	0.000
	(2.01)	(1.42)	(2.91)	(1.54)	(0.15)
Product Yesterday	0.005**	0.004**	0.003	0.001	0.005***
	(2.17)	(2.18)	(1.47)	(0.43)	(3.46)
EA	0.003	0.001	0.004	0.001	0.004
	(0.57)	(0.30)	(1.13)	(0.29)	(1.14)
EA (t-5,t+5)	-0.004**	-0.003**	-0.002	-0.004***	-0.002*
	(-2.50)	(-2.47)	(-1.42)	(-2.74)	(-1.72)
Observations	452,376	452,376	452,376	452,376	452,376
Adj R-Squared	0.396	0.407	0.318	0.357	0.270
Mean Dep Var	0.110	0.057	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 Investor 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 ($Ticker\,SVI_{i,t}$), and in panel B we analyze general attention to the firm using Google SVI for the company's name ($Name\,SVI_{i,t}$). 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 model from table 3 with the instruments $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$. 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 the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(SVI_{i,t}) \quad = \quad \alpha + \beta Ad\,Measure_{i,t} + \gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t}$$

Panel A: Ticker SVI

	OLS	2SLS				
	(1) All	(2) All	(3) National	(4) Large	(5) Repeat	(6) Business
Ad Measure	0.017***	0.049***	0.058***	0.064***	0.056***	0.080***
	(2.87)	(3.13)	(3.06)	(2.85)	(3.12)	(3.17)
News Dummy	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***
	(4.15)	(4.11)	(4.14)	(4.10)	(4.12)	(4.11)
News Tomorrow	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(4.77)	(4.70)	(4.72)	(4.71)	(4.71)	(4.73)
News Yesterday	0.015***	0.015***	0.015***	0.015***	0.015***	0.015***
	(5.94)	(5.97)	(5.97)	(5.95)	(5.97)	(5.93)
Product Release	0.025***	0.025***	0.025***	0.025***	0.025***	0.025***
	(3.04)	(3.00)	(3.02)	(3.04)	(3.02)	(2.99)
Product Tomorrow	0.011**	0.011**	0.011**	0.010**	0.011**	0.011**
	(2.32)	(2.26)	(2.31)	(2.23)	(2.28)	(2.37)
Product Yesterday	0.012**	0.011**	0.012**	0.012**	0.012**	0.011**
	(2.56)	(2.52)	(2.53)	(2.55)	(2.55)	(2.46)
EA	0.181***	0.181***	0.181***	0.181***	0.181***	0.181***
	(6.54)	(6.55)	(6.55)	(6.53)	(6.55)	(6.54)
EA (t-5,t+5)	0.068***	0.068***	0.068***	0.068***	0.068***	0.068***
	(6.12)	(6.13)	(6.12)	(6.11)	(6.13)	(6.12)
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	NA	43,245	57,307	37,505	38,555	49,027
Sargan-Hansen p-value	NA	0.855	0.909	0.326	0.890	0.983
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Name SVI

	OLS	2SLS				
	(1) All	(2) All	(3) National	(4) Large	(5) Repeat	(6) Business
Ad Measure	0.059***	0.128***	0.152***	0.132***	0.155***	0.174***
	(6.34)	(5.41)	(4.83)	(4.10)	(6.05)	(4.18)
News Dummy	0.034***	0.034***	0.034***	0.034***	0.034***	0.034***
	(7.36)	(7.33)	(7.39)	(7.40)	(7.36)	(7.37)
News Tomorrow	0.015***	0.015***	0.015***	0.015***	0.014***	0.015***
	(4.48)	(4.41)	(4.46)	(4.47)	(4.37)	(4.49)
News Yesterday	0.016***	0.016***	0.016***	0.016***	0.016***	0.015***
	(5.34)	(5.35)	(5.29)	(5.41)	(5.38)	(5.25)
Product Release	0.023**	0.022**	0.021**	0.022**	0.022**	0.022**
	(2.31)	(2.24)	(2.22)	(2.28)	(2.29)	(2.25)
Product Tomorrow	0.010*	0.009*	0.010*	0.009*	0.010*	0.010*
	(1.85)	(1.71)	(1.85)	(1.71)	(1.77)	(1.92)
Product Yesterday	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
	(3.66)	(3.62)	(3.60)	(3.57)	(3.64)	(3.64)
EA	0.086***	0.087***	0.086***	0.086***	0.087***	0.086***
	(7.24)	(7.24)	(7.21)	(7.20)	(7.25)	(7.19)
EA (t-5,t+5)	0.043***	0.043***	0.043***	0.043***	0.043***	0.043***
	(6.23)	(6.30)	(6.27)	(6.21)	(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	NA	30,660	36,737	25,559	25,207	33,098
Sargan-Hansen p-value	NA	0.094	0.322	0.095	0.766	0.904
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 2SLS versions of the model below, where the first-stage equation is the model from table 3 with the instruments $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$. We use as the advertising measure an indicator for whether firm i placed any ad in any publication on date t. The dependent variable in column 1 is $Ticker\,SVI$ on day $t-1$. Column 2 replicates the results from table 4 panel A column 2. The dependent variables in columns three through five are $Ticker\,SVI$ on days $t+1$, $t+2$, and $t+3$, respectively. Control variables are defined in table 3. 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.

$$\log(Ticker\,SVI_{i,t}) \quad = \quad \alpha + \beta Ad\,Measure_{i,t} + \Gamma Controls + \psi\text{Firm-Year FE} + \eta\text{Date FE} + \epsilon_{i,t}$$

	2SLS				
	(1) SVI_{t-1}	(2) SVI_{t}	(3) SVI_{t+1}	(4) SVI_{t+2}	(5) SVI_{t+3}
Ad Measure	0.008	0.049***	0.031**	0.022	0.008
	(0.59)	(3.13)	(2.23)	(1.55)	(0.64)
News Dummy	0.014***	0.018***	0.010***	0.007***	0.005**
	(5.29)	(4.11)	(4.01)	(2.95)	(2.44)
News Tomorrow	0.005**	0.012***	0.021***	0.015***	0.009***
	(2.28)	(4.70)	(4.68)	(5.15)	(3.85)
News Yesterday	0.024***	0.015***	0.009***	0.005**	0.002
	(5.28)	(5.97)	(3.38)	(2.23)	(0.98)
Product Release	0.010**	0.025***	0.012***	0.002	-0.003
	(2.23)	(3.00)	(2.70)	(0.58)	(-0.80)
Product Tomorrow	-0.003	0.011**	0.027***	0.017***	0.005
	(-0.80)	(2.26)	(2.99)	(2.90)	(1.48)
Product Yesterday	0.026***	0.011**	0.001	-0.004	-0.005
	(2.97)	(2.52)	(0.21)	(-0.89)	(-1.09)
EA	0.081***	0.181***	0.155***	0.098***	0.068***
	(5.68)	(6.55)	(5.60)	(5.30)	(4.93)
EA (t-5,t+5)	0.075***	0.068***	0.075***	0.083***	0.084***
	(6.35)	(6.13)	(6.34)	(6.35)	(6.34)
Observations	452,327	452,376	452,422	452,076	451,723
Adj/Centered R-Squared	0.850	0.850	0.850	0.850	0.849
Cragg-Donald F-Statistic	43,289	43,245	43,275	43,224	43,218
Sargan-Hansen p-value	0.513	0.855	0.428	0.479	0.911
Date FE	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes

Table 6
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 with the instruments $Ad\,Measure_{t-7}$, $Ad\,Measure_{t-14}$, as well as $Ad\,Measure_{t-7}$ interacted with day-of-the-week dummies. Column titles list the ad measure used in each specification (defined in table 2). We include but do not tabulate the control variables from table 3. 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.

$$\begin{aligned}\log(Ticker\,SVI_{i,t}) &= \alpha + \beta Ad\,Measure_{i,t} + \theta Ad\,Measure_{i,t} \times DOW_t \\ &+ \Gamma Controls + \psi\text{Firm-Year FE} + \eta\text{Date FE} + \epsilon_{i,t}\end{aligned}$$

	OLS	2SLS				
	(1) All	(2) All	(3) National	(4) Large	(5) Repeat	(6) Business
Ad Measure	0.005	0.024	0.039	0.068*	0.029	0.041
	(0.58)	(1.13)	(1.49)	(1.91)	(1.28)	(1.29)
Ad Measure × Mon	0.006	0.013	0.001	-0.030	0.026	0.003
	(0.79)	(0.76)	(0.04)	(-1.05)	(1.42)	(0.10)
Ad Measure × Wed	0.002	0.003	-0.009	-0.011	0.001	-0.009
	(0.23)	(0.16)	(-0.33)	(-0.39)	(0.07)	(-0.23)
Ad Measure × Thu	0.004	0.011	-0.005	-0.029	0.004	0.021
	(0.50)	(0.57)	(-0.17)	(-1.04)	(0.21)	(0.46)
Ad Measure × Fri	0.004	0.014	-0.000	-0.037	0.011	0.024
	(0.57)	(0.79)	(-0.01)	(-1.33)	(0.55)	(0.53)
Ad Measure × Sat	0.041*	0.074*	0.051	0.051	0.076*	0.169**
	(1.69)	(1.84)	(0.93)	(0.88)	(1.71)	(2.31)
Ad Measure × Sun	0.042**	0.062*	0.066	0.016	0.081*	
	(2.23)	(1.77)	(1.63)	(0.37)	(1.92)	
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	NA	9,792	12,364	5,427	9,119	7,993
Sargan-Hansen p-value	NA	0.814	0.885	0.374	0.929	0.958
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 7
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 the 7-day and 14-day lag of all four advertising variables as instruments. All regressions include date and firm-year fixed effects. We include but do not tabulate 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. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

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

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Weekday Ad	0.008	-0.000	0.032**	0.010
	(1.35)	(-0.02)	(2.06)	(0.54)
Weekend Ad	0.046***	0.042**	0.089***	0.075**
	(2.80)	(2.49)	(2.91)	(2.41)
Weekday Business Ad		0.027**		0.063**
		(2.41)		(2.00)
Weekend Business Ad		0.047		0.118**
		(1.61)		(2.20)
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	20,290	8,377
Sargan-Hansen p-value	NA	NA	0.925	0.959
Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes

Table 8
Business Advertising and Liquidity

This table examines the effect of advertisements on stock liquidity. We estimate the model below using both OLS (columns 1 through 4) and 2SLS (columns 5 through 8), where *Liquidity* is either log share dollar volume (*vol*), quoted depth (*qdepth*), the share volume-weighted effective spread (*espread*), or share-volume quoted spread (*qspread*) and winsorized at the 1st and 99th percentiles. *qdepth*, *espread*, and *qpsread* are computed using TAQ data and the procedure described in Holden and Jacobsen (2014). Our primary explanatory variable is *Business Ad*, an indicator for an advertisement by firm i in a business publication on day t. If a company advertised over the weekend, we set *Business Ad* equal to one on the following Monday. The 2SLS model uses the first-stage equation from table 3 (using the 7-day and 14-day lag business ad indicators). All variables are defined in 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. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$Liquidity_{i,t} = \alpha + \beta_1 Business\,Ad_{i,t} + \Gamma Controls + \psi \text{Firm-Year FE} + \eta \text{Date FE} + \epsilon_{i,t}$$

Table 8

	OLS				2SLS			
	(1) vol	(2) qdepth	(3) espread	(4) qspread	(5) vol	(6) qdepth	(7) espread	(8) qspread
Business Ad	0.011**	8.718***	0.001	0.133*	0.028*	21.906**	0.004	0.258
	(2.20)	(2.64)	(1.51)	(1.73)	(1.80)	(2.53)	(1.47)	(1.00)
News Dummy	0.097***	2.324***	0.002***	0.010	0.097***	2.315***	0.002***	0.010
	(30.07)	(5.36)	(6.44)	(0.27)	(30.07)	(5.33)	(6.44)	(0.27)
News Tomorrow	0.045***	1.390***	0.001**	0.100*	0.045***	1.349***	0.001**	0.099*
	(19.26)	(3.48)	(2.42)	(1.74)	(19.24)	(3.42)	(2.40)	(1.73)
News Yesterday	0.077***	1.610***	0.001***	-0.105**	0.077***	1.622***	0.001***	-0.105**
	(23.81)	(3.38)	(3.07)	(-2.55)	(23.82)	(3.39)	(3.08)	(-2.55)
Product Release	-0.029***	-0.989	-0.002***	0.019	-0.029***	-1.043	-0.002***	0.019
	(-8.95)	(-1.18)	(-3.32)	(0.40)	(-8.96)	(-1.24)	(-3.34)	(0.39)
Product Tomorrow	-0.021***	0.849	0.001*	0.062	-0.021***	0.872	0.001*	0.062
	(-6.01)	(0.73)	(1.71)	(1.04)	(-6.00)	(0.75)	(1.72)	(1.04)
Product Yesterday	-0.023***	-1.530	-0.001**	0.041	-0.023***	-1.589	-0.001**	0.040
	(-6.33)	(-1.26)	(-2.06)	(0.72)	(-6.35)	(-1.30)	(-2.07)	(0.71)
EA	0.621***	-15.053***	0.020***	0.611***	0.621***	-15.063***	0.020***	0.610***
	(33.89)	(-7.01)	(10.38)	(4.31)	(33.90)	(-7.01)	(10.38)	(4.31)
EA (t-5,t+5)	0.225***	1.409	0.002**	-0.162*	0.225***	1.440	0.002**	-0.162*
	(30.80)	(1.34)	(2.38)	(-1.75)	(30.81)	(1.36)	(2.39)	(-1.75)
Observations	445,763	445,206	445,206	445,206	445,763	445,206	445,206	445,206
Adj/Centered R-Squared	0.959	0.906	0.836	0.871	0.959	0.906	0.836	0.871
Mean Dep Var	17.528	142.719	0.140	15.702	17.528	142.719	0.140	15.702
Cragg-Donald F-Statistic	NA	NA	NA	NA	40,245	40,166	40,166	40,166
Sargan-Hansen p-value	NA	NA	NA	NA	0.010	0.888	0.553	0.749
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A1
Alternative First Stage Regressions

In this table we re-examine the determinants of print advertising (table 3) using fourteen lags of the dependent variable (i.e., $t-1$ through $t-14$). 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.

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

	(1) All	(2) National	(3) Large	(4) Repeat	(5) Business
Ad Measure$_{t-1}$	0.066***	0.024***	0.060***	0.055***	0.007
	(9.76)	(4.18)	(7.14)	(7.48)	(1.18)
Ad Measure$_{t-2}$	0.030***	0.014**	0.036***	0.026***	-0.004
	(6.61)	(2.44)	(6.11)	(5.42)	(-0.54)
Ad Measure$_{t-3}$	0.011***	-0.001	0.014***	0.004	-0.007
	(2.83)	(-0.13)	(3.20)	(1.01)	(-1.30)
Ad Measure$_{t-4}$	0.009**	0.003	0.002	0.006	-0.003
	(2.44)	(0.69)	(0.45)	(1.62)	(-0.56)
Ad Measure$_{t-5}$	0.011***	0.007	0.010**	0.008**	0.004
	(3.00)	(1.37)	(1.97)	(2.07)	(0.72)
Ad Measure$_{t-6}$	0.015***	0.008	0.011**	0.019***	0.013**
	(3.94)	(1.62)	(2.03)	(4.60)	(2.37)
Ad Measure$_{t-7}$	0.253***	0.266***	0.253***	0.244***	0.259***
	(29.82)	(21.07)	(20.57)	(28.90)	(16.88)
Ad Measure$_{t-8}$	-0.014***	-0.006	-0.021***	-0.005	0.005
	(-3.17)	(-1.03)	(-4.18)	(-0.97)	(0.83)
Ad Measure$_{t-9}$	-0.020***	-0.019***	-0.010**	-0.014***	-0.014***
	(-5.77)	(-4.08)	(-2.35)	(-3.88)	(-2.84)
Ad Measure$_{t-10}$	-0.023***	-0.018***	-0.024***	-0.018***	-0.015***
	(-7.11)	(-4.39)	(-5.18)	(-5.16)	(-3.04)
Ad Measure$_{t-11}$	-0.025***	-0.023***	-0.017***	-0.020***	-0.023***
	(-8.27)	(-6.16)	(-4.32)	(-5.73)	(-5.06)
Ad Measure$_{t-12}$	-0.012***	-0.014***	-0.006*	-0.006*	-0.019***
	(-4.13)	(-3.02)	(-1.66)	(-1.89)	(-3.99)
Ad Measure$_{t-13}$	-0.005	-0.011**	-0.016***	-0.003	-0.008*
	(-1.47)	(-2.56)	(-3.34)	(-0.63)	(-1.70)
Ad Measure$_{t-14}$	0.235***	0.277***	0.211***	0.223***	0.252***
	(29.66)	(22.93)	(21.58)	(25.02)	(16.20)
Observations	452,376	452,376	452,376	452,376	452,376
Adj R-Squared	0.401	0.408	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
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*). 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., EPIQ), simultaneously refer to a common object (e.g., SKY), or contain only one letter (e.g., K); and column 5 drops all tickers that do not return an info box using a Google search. All variables are defined in 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. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(Ticker\,SVI_{i,t}) \quad = \quad \alpha + \beta Ad\,Dummy_{i,t} + \gamma Controls + \psi \text{Fixed Effects} + \epsilon_{i,t}$$

	2SLS				
	(1)	(2)	(3)	(4)	(5)
Ad Dummy	0.049***	0.030*	0.047***	0.047***	0.037*
	(3.13)	(1.91)	(2.96)	(2.95)	(1.83)
News Dummy	0.018***	0.014***	0.020***	0.017***	0.020*
	(4.11)	(3.83)	(4.87)	(3.41)	(1.76)
News Tomorrow	0.012***	0.012***	0.015***	0.014***	0.021***
	(4.70)	(5.17)	(5.57)	(4.70)	(3.65)
News Yesterday	0.015***	0.014***	0.017***	0.016***	0.022***
	(5.97)	(5.70)	(7.11)	(5.41)	(4.19)
Product Release	0.025***	0.018***	0.026***	0.023***	0.045***
	(3.00)	(3.12)	(3.19)	(2.79)	(3.50)
Product Tomorrow	0.011**	0.008**	0.012***	0.011**	0.020***
	(2.26)	(2.05)	(2.73)	(2.08)	(2.65)
Product Yesterday	0.011**	0.009**	0.013***	0.011**	0.017**
	(2.52)	(2.09)	(2.78)	(2.27)	(2.55)
EA	0.181***	0.186***	0.184***	0.225***	0.484***
	(6.55)	(6.65)	(6.48)	(6.50)	(6.76)
EA (t-5,t+5)	0.068***	0.071***	0.070***	0.085***	0.186***
	(6.13)	(5.97)	(6.11)	(6.06)	(5.94)
Observations	452,376	433,000	452,376	360,363	118,583
Adj/Centered R-Squared	0.850	0.853	0.850	0.829	0.808
Cragg-Donald F-Statistic	43,245	38,909	43,172	33,677	10,692
Sargan-Hansen p-value	0.855	0.942	0.871	0.871	0.414
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	No	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 A3
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) $log(Ads)$, the natural log plus 1 of ads placed each day, (2) $log(Spend)$, natural log plus 1 of the total dollars spent on advertising each day, and (3) $log(Read)$, natural log plus 1 of the estimated distribution of the publications containing the advertisements. We estimate the model below using two-stage least squares (2SLS), where the first-stage equation is the model from table 3 with the instruments $Ad\,Measure_{t-7}$ and $Ad\,Measure_{t-14}$. All variables are defined in 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. In the footnotes we tabulate the Cragg-Donald F-statistic for weak instruments and Sargan-Hansen p-values testing for overidentification.

$$\log(Ticker\,SVI_{i,t}) \quad = \quad \alpha + \beta Ad\,Measure_{i,t} + \gamma Controls + \psi\text{Firm-Year FE} + \eta\text{Date FE} + \epsilon_{i,t}$$

	2SLS		
	(1)	(2)	(3)
	log(Ads)	log(Spend)	log(Read)
Ad Measure	0.041***	0.006***	0.003***
	(2.90)	(3.17)	(3.04)
News Dummy	0.018***	0.018***	0.018***
	(4.13)	(4.00)	(4.12)
News Tomorrow	0.012***	0.013***	0.012***
	(4.72)	(4.90)	(4.71)
News Yesterday	0.015***	0.016***	0.015***
	(5.96)	(6.17)	(5.97)
Product Release	0.025***	0.028***	0.025***
	(3.02)	(3.25)	(3.01)
Product Tomorrow	0.011**	0.010**	0.011**
	(2.28)	(2.01)	(2.27)
Product Yesterday	0.011**	0.012***	0.011**
	(2.52)	(2.59)	(2.53)
EA	0.182***	0.175***	0.181***
	(6.55)	(6.37)	(6.55)
EA (t-5,t+5)	0.068***	0.068***	0.068***
	(6.11)	(6.07)	(6.12)
Observations	452,376	413,856	452,376
Adj/Centered R-Squared	0.850	0.850	0.850
Cragg-Donald F-Statistic	68,838	41,514	49,716
Sargan-Hansen p-value	0.793	0.609	0.926
Date FE	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes