Background Noise? TV Advertising Affects Real Time Investor Behavior*

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Abstract

Using minute-by-minute television advertising data covering approximately 326,000 ads, 301 firms, and \$20 billion in ad spending, we study the real-time effects of TV advertising on investor search for online financial information and subsequent trading activity. Our identification strategy exploits the fact that viewers in different U.S. time zones are exposed to the same programming and national advertising at different times, allowing us to control for contemporaneous confounding events. We find that an average TV ad leads to a 3% increase in SEC EDGAR queries and an 8% increase in Google searches for financial information within 15 minutes of the airing of that ad. Such advertising effects spill over through horizontal and vertical product market links to financial information searches on closest rivals and suppliers. The ad-induced queries on the advertiser and its key rival lead to higher trading volumes of their respective stocks. For large advertisers, around 0.8% of daily trading volume can directly be attributed to advertising. This suggests that advertising, originally intended for consumers, has a sizable effect on financial markets.

Keywords: Advertising; Limited Attention; Information Acquisition; Investor Behavior

JEL Classification: G11, G12, L15, M37

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1 Introduction

Prior research has widely recognized that investors exhibit limited attention when considering their investment opportunities (e.g., Barber and Odean (2008); Abel et al. (2013)). However, the empirical literature studying the causal effects of exposure to and reminders about firms on investor behavior is scant. This may be due in part to the challenge involved in designing or finding experimental settings that expose investors to firms, holding the larger context (e.g., news coverage) in which a firm operates constant. In this paper, we consider that within a sufficiently short time frame TV advertising can be interpreted as an attention shock that puts an advertising firm on investors' radars. Such an attention shock may carry an informative signal about the firm's financial position (Nelson, 1974; Kihlstrom and Riordan, 1984) or serve simply as a non-informative reminder making advertisers more salient to investors with limited attention (Merton, 1987).

Using high-frequency data on TV advertising[1] with real-time geography-based identification, which allows us to control for contemporaneous news about a firm, we find a causal link between advertising and the search for an advertiser's financial information. Such ad-induced searches on advertising firms are linked to the increased trading volume of their respective equity securities. Specifically, we find that each dollar spent on advertising translates to 51.3 cents of additional trading activity for the advertiser's stock. Ad-induced searches are associated with positive overnight stock returns but these returns partially reverse during the next trading day. Importantly, we show that such advertising carries both informative and non-informative signals. Furthermore, to our knowledge, our paper is the first one to show the causal effect of a firm's advertising on the investor interest in the advertiser's closest rival. Taken together, the evidence presented in this paper suggests that the advertising effect on investor actions is more immediate and far-reaching than has previously been documented.

[1] TV is the dominant advertising medium by expenditure, constituting around 40% of total corporate advertising expenses (eMarketer, 2016). In addition, TV consumption is associated with multitasking, which allows us to capture its immediate effects. Nielsen (2010) reports that 34% of all Internet usage time occurs simultaneously with TV consumption, whereas Council for Research Excellence (2014) finds that 69% of TV viewers consume one or more additional media platforms concurrently.

Firm advertising is a good proxy for how visible a firm is to investors beyond their participation in financial markets (Grullon et al., 2004) and thus studying advertising effects on investment behavior can help explain how investors react to attention shocks. However, given confounding events that might affect both investor interest and advertising (Cohen et al., 2010; Lou, 2014; Fich et al., 2017), co-determination of profitability (and thus stock returns) and advertising (Comanor and Wilson, 1967; Schmalensee, 1976, 1983), as well as the dual nature of investors as consumers (Keloharju et al., 2012), discerning the causal effect of ads on investor actions is challenging.

In this paper, we are able to overcome the aforementioned endogeneity concerns by utilizing a novel quasi-experimental identification approach. We examine how real-time TV advertising affects contemporaneous investor interest in the advertiser within a narrow time window after their ad. We rely on minute-by-minute data at the ad insertion level representing 301 publicly listed US firms over a sample period that runs from 2015 through 2017.[2] Studying the effect within a narrow time window ensures that firms cannot strategically time their ads within that time window due to institutional constraints of TV advertisers not being able to pick the exact timing for their ads (Wilbur et al., 2013). The use of such high-frequency data also mitigates the concern that the effect of advertising is systematically confounded with other actions undertaken by the firm or news about it and also enables us to measure the immediate effect of advertising on investor behavior.

In addition to using real-time data, we also exploit a unique feature of broadcast network TV programming. Most network TV programs and the associated national advertising are first broadcast in the Eastern Standard Time (EST) and Central Standard Time (CST) zones simultaneously, after which the signal is held and broadcast on a three-hour delay in the Pacific Standard Time (PST) zone. Thus, when a particular advertisement is broadcast in the easterly time zones (in EST or CST rather than in PST), we can analyze the behavior of investors in these exposed time zones, using the behavior of investors in the contemporane-

[2] Our sample includes all of the publicly listed companies that advertised during our studied time period. These companies together represent 64% of overall TV advertising expenditures.

ously unexposed time zone as the control. In this way, we control for any other confounding real-time effects involving the advertiser.

In particular, we study how TV advertising affects financial information acquisition via the SEC EDGAR database. We match the internet protocol (IP) addresses from SEC EDGAR visitation logs to geographic locations, allowing us to identify the timezone from which the visitation originated. We then construct a *firm×time zone×15 minute interval* panel and control for fixed effects that capture contemporaneous confounding signals about the advertising firm such as news, fixed effects that capture differences in Internet searching or TV viewing behavior across time zones at a particular time, and fixed effects that capture non-time-varying differences in investor information sets about an advertising firm such as local bias based on the firm's location of operations.

After controlling for the potential confounders, we find that, on average, a TV ad leads to an immediate 3% increase in queries about the advertising firm on SEC EDGAR and an 8% increase in Google searches. The effect is stronger during primetime viewing hours and for more expensive ads, and also on days of major firm financial events, in particular M&A transactions and earnings announcements. We also find that this effect is the strongest for the advertisers in the financial sector followed by firms in pharmaceuticals and consumer staples. For instance, the effect rises to 11% in the case of ads of financial firms during primetime TV hours. We do not find that our ad-related queries are influenced by automated bot traffic and the effect disappears completely in a timing falsification test wherein we insert placebo ads in time intervals preceding actual ads.

We further show that these advertising effects spill over through horizontal and vertical product market links. Specifically, we find that advertising can be causally linked to real-time financial information acquisition about an advertiser's primary rival and major supplier, suggesting that, as a function of an attention shock to a specific firm, investors also seek further information to evaluate the competitive environment of that advertiser.

Zooming in on the IP addresses that follow up with SEC EDGAR searches on an advertiser after its TV ad in a treated timezone, we find that over our sample period 164,000 distinct, non-bot IP addresses search within 15 minutes after the airing of an ad, suggesting a widespread effect. The IP addresses that search immediately after ads air are notably more frequent users of the SEC EDGAR database relative to a typical SEC EDGAR user, implying a certain degree of user sophistication.

We further reconfirm that the effects of advertising on investor information search are not confined to queries on the SEC EDGAR database but are also present in financial information searches on Google. Comparing ad-induced SEC EDGAR queries with ad-induced Google financial searches, we find that the Google effect is greater in magnitude and is statistically significant for more firms. Given a larger economic effect on Google searches, it is likely that our estimates pertaining to SEC EDGAR searches constitute a lower bound of the TV ad effect on investor information search behavior.

Next, we show that searching for financial information is related to trading activity. Specifically, we show that higher ad-induced search during primetime TV hours (which occur after trading hours) leads to higher trading volume of the advertiser's stock during the following day. In particular, a one-standard-deviation increase in daily real-time SEC EDGAR searches increases the trading volume by 0.49%. This effect comes solely from the intensive margin, i.e., high ad-induced searches, rather than the extensive margin, i.e., any ad airing. When looking at the trading activity of an advertiser's rivals and suppliers, we find that ad-induced information search on the closest rival translates to higher trading volume of the rival's stock, but find no such effect for the advertising firm's suppliers.

We finish by studying the heterogeneity of the effect, which allows us to investigate when TV advertising affects investors by serving as an informative and when as a non-informative attention signal. As a result of being exposed to an advertisement, investors might anticipate consumer reaction[3] and the subsequent effect of this reaction on firm financials. Thus, ads

[3] This holds even if ads seemingly lack informative content for consumers as long as investors anticipate that advertisements can change consumer behavior by altering their preferences (e.g., by making demand for the advertised product less elastic).

might send an informative signal to investors, inducing them to act promptly.[4] Alternatively, ads might have no informative content for investors but simply raise salience about the firm.[5] To differentiate these informative and non-informative attention shocks, we investigate how the effect varies with the time that elapses since the first airing of a given advertisement, arguing that the first time a specific ad creative is shown should be the most informative. We find that older ads are followed by smaller financial information search effects, suggesting that there exists an informative signal that dissipates as the novelty of the advertisement wears off. On the other hand, such a negative relationship is absent when a firm's advertising is in the timezone in which the firm's headquarters are located; in these cases the non-informative attention effect dominates.

Our study contributes to several strands of literature. We primarily relate to research on the effects of product advertising on investor behavior and firm financial decisions (Grullon et al., 2004; Srinivasan and Hanssens, 2009; Gurun and Butler, 2012; Lou, 2014; Madsen and Niessner, 2016). The literature has suggested multiple reasons why advertising can be endogenous to investor behavior.

First, firms strategically choose where, when, and how often to advertise. Advertising campaigns have been shown to coincide with earnings announcements, product launches, equity issuances, stock option exercises, and M&A transactions (Cohen et al., 2010; Lou, 2014; Fich et al., 2017). Firms might also strategically adjust their advertising in response to external events that are independently correlated with investor interest. They might increase advertising to offset negative media coverage of product recalls or corporate scandals (Gao et al., 2015). Other confounding signals about a firm, such as news about product market rivals can be correlated with both advertising and investor interest.

[4]Recent anecdotal evidence suggests that investors increasingly rely on diverse information sources that help them unlock potential trading signals and give them an 'information edge'. For instance, Financial Times (2018) writes that in the past two years investment groups have more than doubled their spending on alternative data sources that could potentially provide information on future fundamentals. Such alternative data sources (see, e.g., www.alternativedata.org) include social media feeds, product reviews, satellite images, credit card sales, and geolocation data, among other data.

[5]This is a similar distinction to the one discussed in DellaVigna and Gentzkow (2010) that distinguishes between belief- and preference-based persuasion models.

Yet another potentially confounding factor is that both higher advertising spending and more active investor interest in a firm's stock might be co-affected by the firm's recent positive stock performance. Increasing stock prices might grab the attention of, say, momentum traders, but would also simultaneously increase firm valuation, which in turn could reduce financial constraints on marketing expenditures. Similarly, advertising and profitability are simultaneously determined and positively related to omitted variables that induce large markups (Comanor and Wilson, 1967; Schmalensee, 1976, 1983), thus the relationship between advertising and investor actions might simply reflect its relationship with profitability.

Finally, advertising might affect investor behavior indirectly by increasing product sales and thus raising the probability that an investor is personally familiar with an advertised product (Keloharju et al., 2012). In such a case, the investment decision is affected by investor-consumer familiarity with the advertiser rather than directly by advertising.

All of the abovementioned factors complicate the study of the relationship between advertising and investor behavior. Thus, the advertising expenditure data that are aggregated annually, monthly, or even daily are unlikely to provide satisfying evidence of the causal effect. Meanwhile, our paper uses high frequency data, focuses on the advertising medium with the widest reach, and relies on a quasi-experimental research design to overcome identification challenges present in prior research.

More broadly, our paper contributes to the literature on investor attention (Peng and Xiong, 2006; Barber and Odean, 2008; Abel et al., 2013) and, in particular, we relate to the work on investor information acquisition from media and web sources (Da et al., 2011; Ben-Rephael et al., 2017; Loughran and McDonald, 2017). Additionally, Chen et al. (2018) present compelling evidence that investors use the information from SEC EDGAR and show that this information in turn has implications for portfolio choices. In a way, our estimation approach captures a shock to investor attention and provides evidence that exogenously generated investor attention translates into searching for financial information on SEC EDGAR and Google. We also find that such salience shocks spread to a firm's rivals and suppliers, i.e., increased attention to a stock affects information collection pertaining to a given sector more generally, thus relating to predictions in Peng and Xiong (2006).

In this respect, our paper is also related to the studies of the effects of media on investor attention (e.g., Chan (2003); Tetlock (2007); Engelberg and Parsons (2011)). While both advertising and media are likely to attract the attention of investors, these two attention-grabbing channels are substantially different. For example, financial media is strongly associated with the dissemination of information intended for investors (Fang and Peress, 2009; Peress, 2014). On the other hand, TV advertising is directed primarily at consumers and has indirect effects on investors. Moreover, a given company is rarely fully in control of its media coverage, whereas advertising is a firm's strategic choice and therefore is less influenced by the interests and incentives of other parties such as media companies and journalists. Our research thus provides evidence that a channel that is under a firm's control does affect investor actions.

2 Empirical Methodology

2.1 Institutional Details

Our identification strategy relies on different geographic locations being exposed to the same TV commercials at different times. Five U.S. national network TV broadcast-over-the-air channels (ABC, CBS, CW, FOX, and NBC) use only one feed for all of their affiliate local partners scattered around the country.[6] When the broadcast feed goes out, each station picks up the signal to broadcast it immediately (EST or CST time zones) or they hold the feed for broadcast at a later time (MST or PST time zones). For example, when New York airs the feed live at 8pm EST, Chicago airs the same feed live at 7pm CST. Meanwhile, Denver receives the feed at 6pm local time and broadcasts it 7pm MST and Los Angeles receives

[6] These channels are also by far the most watched TV channels in the U.S. with the most expensive advertising slots, constituting 80% of the daily TV viewership (Nielsen, 2016).

the feed at 5pm local time and broadcasts it to their viewers at 8pm PST. We refer to these programs and ads that are shown at different times in different time zones as *time-shifted* programs and ads.[7]

Time-shifted programs include national TV shows broadcast in primetime TV hours (8pm-11pm), late night shows, news shows (6:30pm-7pm), and morning shows (7am-9am). The remaining programming is local or includes live shows such as sporting and election events that are shown simultaneously in all time zones. We manually cross-verify all program categories with TVGuide.com to make sure that we are not attributing live events to time-shifted programs in our analysis.

Finally, an important institutional detail for our identification strategy is that firms can choose what program to advertise on, but they cannot pick the exact time when to advertise. Advertising contracts require networks to assign commercials to slots within commercial breaks on an *equitable basis*, which is commonly understood to mean quasi-random (Wilbur et al., 2013). This assertion has been verified in our advertising dataset by McGranaghan et al. (2018) who show that the empirical distribution of average ad position placements within advertising breaks is consistent with a random placement of ads.

Our novel double difference identification approach is more robust and more appropriate for financial market contexts (where the primary concern is about confounding contemporaneous effects) than the single difference identification approach used in marketing literature by Du et al. (2017), Joo et al. (2014), and Lewis and Reiley (2013), who show that TV commercials cause internet search spikes, and Liaukonytė et al. (2015) who show that this search effect also extends to online sales of the advertised products.

[7]Given that local stations in EST and CST broadcast the feed at the same time, in our analysis we consider these time zones together and further refer to both EST and CST time zones as EST. Section 4.3 presents robustness tests with EST and CST time zones considered separately. In order to reduce the possibility that some of TV viewers can observe multiple feeds, we remove MST from the analysis. Figure 1 shows the map how we assign the states into two time zones – EST and PST.

2.2 Specification

Given that only some geographic locations are treated at a given time, our identification strategy can control for contemporaneous confounding events. At each quarter of an hour interval[8], we record two observations for each of 301 publicly traded firms that had at least one ad during the time-shifted programming in our sample period. One of these two observations includes the number of searches for the firm's filings on SEC EDGAR database coming from the EST time zone in this 15 minute interval while the second one of these observations records the number of searches coming from the PST time zone in the same 15 minute interval.[9] Note that if a commercial is aired in the EST time zone in that 15 minute interval, only "EST observation" is treated while the "PST observation" acts as a control, and this is reversed 3 hours later when "PST observation" becomes treated and "EST observation" becomes a control.

Our specification is thus estimated at a firm × 15 minute interval × time zone level:

$$Ln(EdgarIPSearches)_{itk} = \beta \times Ad_{itk} + \gamma_{it} + \kappa_{ik} + \theta_{tk} + \epsilon_{itk} \tag{1}$$

where i indexes the firms, t indexes time at a 15 minute interval, k indexes the time zones (EST or PST). $Ln(EdgarIPSearches)_{itk}$ refers to the log number of times that firm's i filings were accessed on the SEC EDGAR database in a t 15-minute time interval from the IP addresses that are associated with the time zone k. Ad_{itk} refers to a dummy whether at least one broadcast channel aired a commercial of the firm i during t 15-minute time interval in the time zone k.

We control for three sets of fixed effects. First, γ_{it}, a fixed effect constructed at a 15

[8]The choice of 15 minute interval balances between providing enough response time after an ad airing (e.g., 5 minutes might be too short, especially if an ad falls towards the end of the interval) and having confounding effects if the interval is too long. In Section 4.3, we provide robustness by considering 10 minute and 20 minute intervals.

[9]Due to an uneven average distribution of ads within different 15 minute intervals, we define our intervals starting at 5 minutes past each hour. Internet Appendix 1 details the rationale of this methodological choice. In Section 4.3 we show that our results are robust to alternative interval definitions.

minute interval × *firm level*, controls for what is happening nationally with the firm i in this 15 minute time interval t. That is, this effect captures any contemporaneous confounding signal about the firm, e.g., news about the firm itself or general news that might affect the firm. Given γ_{it}, our advertising effect can only be identified on the time-shifted commercials.

Second, κ_{ik}, a fixed effect constructed at a *firm* × *time zone* level, controls for differences in the baseline interest about the firm i across time zones k. For instance, it controls for the differences in the non-time varying investor information set about the firm or local bias based on the firm's location of operations.

Third, θ_{tk}, a fixed effect constructed at a 15 *minute interval* × *time zone* level, controls for any events happening in the time zone k at a particular time t that is unrelated to the firm. For instance, this fixed effect would capture the differences in the time of the day habits, or the differences in internet browsing patterns, or TV watching behavior across time zones k at time t (e.g., baseline search differences at February 15, 2017, 9:15AM EST versus February 15, 2017, 6:15AM PST).

3 Data

3.1 Information Acquisition

Our main measure of information acquisition is based on how often firm's SEC filings were accessed via SEC EDGAR database from the IP addresses associated with each time zone. SEC EDGAR database hosts all mandatory filings by public companies such as 10-K filings, 8-K filings, as well as forms 3 and 4, and other filing documents. SEC EDGAR database has been frequented by over $100,000$ unique daily users on average in our sample period of 2015-2017Q1.[10] As suggested by Drake et al. (2017), SEC EDGAR users are more likely to

[10] This financial information is also disseminated by the data providers such as Bloomberg, Morningstar, or Thomson Reuters and thus our estimates provide a lower bound of the effect of advertising on financial information search. See Li and Sun (2018) for the discussion on what investors might see as SEC EDGAR advantages over other information sources. For example, other sources often condense financial statements into pre-specified formats and thus some components of firms' financial information may be misrepresented.

be higher income and more educated individuals than the rest of population.

We obtain the server request records from the EDGAR Log File dataset available on the SEC's web servers. This dataset maintains a log file of all activity performed by users on EDGAR such as the client IP address, timestamp of the request, and page request. IP addresses in the dataset are partially anonymised using a static cypher (e.g., 24.145.236.jcf). In mapping IP addresses to the geographic locations, we consider all 256 possible IP addresses in the anonymised range (e.g., 24.145.236.0 − 24.145.236.255). We then map all the addresses in this range to the geographic locations (at a zipcode level), using Maxmind data. Maxmind periodically tests the accuracy of the data used in their databases by checking known web user IP address and location pairs against the data within their databases. The reported location accuracy falling within 150 miles of the true location is 91%.[11]

After we perform the matching, we check whether all matched zipcodes fall within the same continental US time zone (either EST/CST, or MST, or PST). If that is the case, we attribute this query to that time zone. If some of the 256 possible addresses map to different time zones, we exclude this access event from our analysis.[12] We then aggregate the matched geographic location IP searches for each time zone at the 15 minute intervals.

Following past literature (e.g., Lee et al. (2015)), we exclude IP addresses that have performed more than 500 queries on SEC EDGAR database during a day as these are likely to be automated searches. As we report in Section 4.3, our results are consistent if we exclude IP addresses that have performed more than 50 queries during the day.

3.2 TV Advertising

Our TV advertising data come from Kantar Media. Kantar monitors all TV networks in the U.S. It identifies national commercials using codes embedded in networks' programming

Also, some accounting information such as operating leases as well as qualitative information contained in 10-K filings are not easily available in these data consolidators (Loughran and McDonald, 2011).

[11] Given our broad definition of geographic areas, i.e., at the time zone level, the relevant accuracy metric is likely to be much higher than 91%.

[12] We lose fewer than 5% of observations in this step. If there remains any measurement error after these steps, it is likely to be very small and unlikely to systematically bias our treatment effect.

streams. We observe every commercial at the ad "insertion" level, defined as a single airing of a particular advertisement on a particular television channel at a particular date and time. For each such insertion, the database reports the advertised brand, the parent company of the advertised brand, the date and start time (in hours, minutes, and seconds), and an estimated insertion cost. The data also include the characteristics of the programming where the ad was inserted, i.e., the channel (e.g., CBS) and the program name (e.g., "Survivor").

We manually match the name of the ultimate owner of each advertiser to the CRSP/ Compustat and SEC CIK databases. In the rare cases of joint commercials (i.e., when multiple firms are listed as advertisers for the same ad), we create entries for both advertising firms. Our final sample includes 301 publicly listed firms that advertise on the five channels in the time-shifted national programs in the years 2015-2017 Q1.

3.3 Descriptive Statistics

Table 1 provides descriptive statistics for our data. Panel A provides summary statistics for the advertising data on the time-shifted ads of 301 publicly listed firms. Our dataset covers $326,745$ unique ad insertions with an average estimated cost of \$61k and the total cost of \$20bn. As expected, primetime TV ads are more expensive, costing \$87k on average. These $181,266$ primetime TV ads constitute 78.4% of total ad expenditure in our data.

Panel B reports the representation of firms in our data across different industry sectors. We group firms into broad industry sectors, using Global Industry Classification Standard (GICS), developed by MSCI and S&P. Most of the firms in our sample are in the consumer discretionary sector, followed by consumer staples. We see few firms from materials, utilities, energy, and real estate. Consumer discretionary sector constitutes the largest share of the total advertising expense, contributing 39% of total advertising expenditure in our data.

Panel C provides the summary statistics of our sample firms' financial information based on Compustat, CRSP, and Thomson Reuters 13f data. We report the 2014 fiscal year data.

In Panel D we report the total number of SEC EDGAR queries for the firms in our sample over 2015-2017Q1. We also separately report the split of the searches coming from EST and PST time zones. Here in column (1) we exclude IP addresses that have performed more than 500 queries on SEC EDGAR database during the day and in column (2) we exclude IP addresses that have performed more than 50 queries. In column (3), we provide the number of searches for the queries related to the firm's financial position and the annual reports (forms 10-K, 10-Q), in column (4) – the filings on material events (form 8-K), in column (5) – firm's insiders and beneficial ownership (forms 3, 4), and in column (6) – other filings. In column (7), we only look at the SEC EDGAR queries that come from the IP addresses with more than 500 queries during the day that we call automated bot queries, which in our sample constitute around 90% of all of the traffic on SEC EDGAR and which we further exclude from the analysis.

Overall, we see that approximately 80% of the queries originate from EST and CST, which is consistent with the East Coast being the main region of financial activity.

4 Main Findings

4.1 Univariate Analysis

We start with the univariate analysis. Our identification strategy relies on search variation being present (i) in short time intervals when an ad was aired as compared to when an ad was not aired in one time zone and (ii) such patterns being different across treated and untreated time zones. Figure 2 illustrates an example of such variation with a specific Citigroup ad on March 3, 2017. Panel A illustrates SEC EDGAR queries in both time zones before and after the ad is shown in EST (but not yet in PST), whereas Panel B illustrates the pattern when the same ad is shown 3 hours later in PST.

We look at whether such patterns exist, on average, across all ads in our sample. In particular, we calculate the effect on SEC EDGAR queries by taking a double-difference, where the first difference is taken between the average log of number of queries during 15 minutes when an ad was aired and when an ad was not aired in the time zone that was exposed to that ad (EST or PST) and the second difference is taken over the corresponding intervals in the other time zone that has not been exposed to that ad:

$$AdLift_{ckt} = [ln(EdgarIPSearches_{ik}|ad = 1) - ln(EdgarIPSearches_{ik}|ad = 0)] - [ln(EdgarIPSearches_{ik'}|ad = 1) - ln(EdgarIPSearches_{ik'}|ad = 0)] \quad (2)$$

where c indexes commercials of firm i, t indexes time at a 15 minute interval with $(ad = 1)$ or without $(ad = 0)$ an ad. For non-treated $(ad = 0)$ 15 minute intervals, we consider only the hours of the day that have timeshifted ads in our sample, i.e., only the hours that have corresponding treated 15 minute time periods $(ad = 1)$. k refers to one of the time zones (EST or PST) where the c is broadcast at t and k' refers to the other time zone where the c is not contemporaneously broadcast. $ln(EdgarIPSearches_{ik})$ refers to the log of number of times that firm's i filings were accessed on the SEC EDGAR database in 15 minute time interval from the IP addresses that are associated with the time zone k.

We thus compare the SEC EDGAR queries for the firm i during the 15 minutes when an ad was aired and when an ad was not aired in the time zone that was exposed to the ad and then difference out any potential confounding effect happening contemporaneously in both time zones by subtracting a level of SEC EDGAR queries for the same firm but in the other time zone where the commercial was not broadcast during the same 15 minute interval.

In Table 2, Panel A, we report both the first difference only, and the double difference that controls for the contemporaneous effects. We find that the effect is much smaller when looking at double difference relative to the single difference, further reinforcing the importance of our identification strategy and highlighting the fact that not controlling for contemporaneous interest in a firm might overestimate the advertising effect. When looking at the double differences, we find that on average there has been a positive and statistically significant effect of the commercial broadcast on SEC EDGAR searches. Column (1) shows results for the whole sample. In column (2), we refine the analysis by only focusing on the ads with an estimated cost of $50k. TV commercial's estimated cost is known to correlate with the possible reach of TV audiences and thus these more expensive ads should command a higher economic effect. Column (3) focuses on the commercials over primetime hours (8PM-11PM), where we expect the largest effect due to the larger audience reach in general but also because financial market participants are more likely to be exposed to TV during the primetime hours than during the trading hours. While columns (1)-(3) provide the estimates for 15 minute intervals, in columns (4) and (5) we also show that the effect is present but smaller if it is calculated for 10 minute and 20 minute intervals.

These univariate tests reported in Table 2, Panel A are suggestive of advertising affecting investor search, however, there might still be confounding factors remaining due to different search intensities and patterns at any given time across the analyzed timezones. We address this in the Section below with our full econometric model.

4.2 Baseline Regression Results

Next, we move to the regression analysis where we adopt our baseline specification (1). Here, contrary to the univariate tests in the previous Section, we rely on the balanced panel setting with fixed 15 minute intervals.

Table 2, Panel B, presents our results where we estimate the contemporaneous effect of TV ads on the queries about the firm on the SEC EDGAR website. Parallel to univariate analysis, we provide results for four specifications. In column (1), we show the effect of any TV commercial being broadcast. In column (2), we refine the analysis by only focusing on the ads with an estimated cost of $50k that have a wider reach. We find consistent results. In column (3), we only look at the ads during primetime that are the most coveted ad slots due to their broad audience reach. We find that the point estimate is larger when we consider only primetime ads. Finally, in column (4), we look at the log value of the total estimated cost of TV commercials of the advertising firm in a particular 15 minute interval. Here we see that the effect size is increasing with the estimated ad cost. This result is consistent with the fact that ad cost is highly correlated with the audience reach.

In terms of the economic significance, our results suggest that, on average, a TV ad leads to 2.5% more queries about the advertising firm on SEC EDGAR database in a 15 minute time window, and this number increases to 3.2% if we look only at ads during the primetime hours of TV broadcasting. As a comparison, Madsen (2016) finds that earnings announcements increase daily SEC EDGAR queries by 36%, while news events about the firm increase daily searches by 20%.

4.3 Robustness

We perform a number of robustness tests where we study the sensitivity of our results to the definition of our outcome variable and also to how we capture ad insertions, especially with regards to their timing. We report them in Table 3.

We start with the robustness tests with respect to the definition of the outcome variable. Our first test narrows down the definition of automated queries. In the baseline analysis, we exclude IP addresses that have performed more than 500 queries on SEC EDGAR database during the day. In Panel A, column (1), we report the results if we exclude IP addresses that have performed more than 50 daily queries. We see that our effect is both statistically and economically stronger with a stricter automated bot traffic definition.

Our second test reverses the exercise. Here we only look at the SEC EDGAR queries that come from the IP addresses that we have flagged as automated bots in our previous analysis. Presumably, the bots that perform automated queries should not react to the TV ads (although one could imagine an algorithm that would condition on the TV ad insertions). Thus, we perform a falsification test where we reverse the analysis and only look at the SEC EDGAR access from the IP addresses that have more than 500 queries during the day. The absence of the identified effect, as reported in column (2), suggests that our result is not mechanical and is not driven by any correlated patterns between SEC EDGAR and Kantar

Media databases.

In our third robustness test, we only look at the first search by each IP address for each advertising firm. In particular, for each IP address that is searching about an advertiser within 15 minutes of its ad, we determine whether that IP address has accessed SEC EDGAR reports on that advertiser at any time since 2012, and only record new searches. As shown in column (3) we find a statistically significant, albeit smaller, ad effect on such "virgin" searches. This suggests, that advertising not only acts as a reminder to continue investigating previously explored firms, but also induces new searches for previously unexplored firms.

The fourth and fifth robustness checks focus on narrower geographic regions. First, in column (4) we exclude CST and only compare searches originating from the actual EST timezone to searches from PST. Second, in column (5), we impose an even stricter geographic definition and compare searches from the states of Connecticut and New York to searches from California. Indeed, when we focus on regions where investors are more likely to be located, the advertisement effect is more statistically significant and larger in magnitude.

In column (6), we report the results of the specifications where we exclude the dates when advertising firms announced their earnings, i.e., those days that might see an increased activity of SEC EDGAR searches. We rely on Compustat and IBES on earnings announcement dates. Where these two sources disagree we take a conservative approach and exclude both sets of dates. We find that advertising effect is not concentrated on the days when firms announce their earnings.[13]

In Panel B, we report the tests with respect to the timing of the effect. First, we look at how ad effect carries over into the future time intervals. That is, in addition to looking at the ad effects in the same 15 minute interval, we study whether the effect persists in the subsequent intervals. We do find a statistically significant one-period lagged effect of an ad, as reported in column (1), but the size of the estimate is much smaller than that of a contemporaneous effect. The effect of two-period lag is not statistically significant,

[13]In additional tests, we also exclude three days before earnings announcements and three days after and we continue to find a similar and significant effect.

suggesting that the ad lift dies off over approximately 30 minutes.[14]

Further, we perform another type of falsification test, where we insert a placebo ad one 15 minute interval before the actual ad. This exercise is equivalent to checking whether a future event (advertisement) affects current outcomes (searches). When doing so, we make sure that there are no commercials by the same firm at least 30 minutes before this interval, i.e., by choosing a placement of a placebo ad, we do not want to capture any spillover effects from the previous commercials. The results are reported in column (2) and, as expected, show that there is no effect for placebo ads.

Our next specification tests whether our results are robust to how we define the start of our intervals. Instead of starting them at 5 minutes past the hour as in our main set of analysis, here we start them exactly at the hour (X:00-X:14; X:15-X:29; X:30-X:44; X:45-X:59, where X is a particular hour). As shown in column (3), as expected, based on the ad distribution patterns provided in the Internet Appendix Figure IA1, we get consistent, albeit marginally weaker, results.

Finally, we redefine the intervals to be constructed at 10 minute and 20 minute intervals instead of 15 minutes that we consider in our baseline specifications. As shown in columns (4) and (5), we find that results are slightly stronger for 10 minute interval and weaker for 20 minute interval.

In all our specifications we cluster standard errors by advertising firm. In the results, available at request, we find that the statistical significance of the effect is virtually identical if we double-cluster standard errors by firm and time or firm and timezone x time.

4.4 Heterogeneity

We further perform a number of descriptive heterogeneity tests. We first analyze the effects of advertising on the type of the information that users seek on SEC EDGAR, i.e., we look

[14]One other paper that studies real time TV exposure effects is Busse and Green (2002) who analyze CNBC news show coverage on the stock market and finds that the market responds within 15 minutes to the stock coverage, with the highest effect manifesting itself within the first 5 minutes.

at the content of the filings that are being accessed. We group them into four categories: (a) filings on the firm's financial position and its annual reports (forms 10-K and 10-Q); (b) filings on material events (form 8-K); (c) filings on firm's ownership (forms 3 and 4); (d) all other filings. We perform the analysis separately where our outcome variable is defined to be queries for each of these four filing categories. As reported in Table 4, Panel A, while the effect is statistically significant across all form types, it is the strongest for the queries related to the firm's financial position and the annual reports (column (1)), as opposed to the filings on material events (column (2)), ownership (column (3)), and other filings (column (4)).

Our second set of tests studies the heterogeneous effects across different contexts. We look at the ad effects on the days when advertising firms had major announcements. In particular, we study M&A announcement effects for both target and acquirer as well as earnings announcement days. We draw M&A announcement days from SDC Platinum database and earnings announcement days from Compustat and IBES. In Panel B, we report our specifications where we interact ad exposure variables with the dummies if on that particular day it was announced that the firm will engage in an M&A transaction as either an acquirer, or a target, or it announced its earnings. For the sake of brevity, we only report the results for the primetime ads.

We find that the advertising effect is stronger on the earnings announcement days (column (1)) but does not vary by the earnings surprise, estimated based on the analyst earnings forecasts (column (2)). The effect is also stronger for the advertising target in the M&A transaction (column (3)) but not for the acquirer (column (4)). Overall, given that the ad effects are magnified during the significant corporate events with wider media coverage, our results suggest that advertising might act as a reminder for investors.

Third, we look at the heterogeneity of the effect at the ad creative level. Specifically, we investigate three ad characteristics where we uncontroversially expect a stronger effect. In particular, we analyze how the effect varies with an advertised brand name similarity to their parent company's name (e.g., *Wendy's* (brand) and *The Wendy's Co* (parent company) versus *Taco Bell* (brand) and *Yum! Brands Inc* (parent company)), the ad position within an ad break, and the ad creative length. The results are reported in the Internet Appendix Table IA1. We find that advertisements for brands that sound similar to their parent company name lead to significantly more searches. We also find that the first ad in an ad break leads to significantly more searches. This is consistent with the first ad receiving the most audience attention due to attention depreciation throughout an ad break (see e.g., McGranaghan et al. (2018)). Finally, we also find a strong positive relationship between the number of searches and an ad length.

Our fourth set of tests looks at how the effect varies across different industries. We report them in the Internet Appendix Table IA2.[15] As before, we estimate four separate regressions: general effect (column (1)), more expensive ads (column (2)), primetime (column (3)), and the log value of the total estimated ad cost (column (4)).

We find that the effect is stronger among consumer staples, financial sector, and pharmaceutical firms, as compared to the other sectors. The effect is the strongest for the financial sector and during the primetime hours. One way to speculate about the reason for these variations in the effect size is that ads for products in different sectors carry different informativeness. For instance, Nelson (1974) has argued that ads for search goods contain more product-oriented information than do experience goods advertisements. We further discuss informative and non-informative aspects of ads in Section 5.4.

Finally, we perform heterogeneity tests where we estimate the effect separately for each firm. Internet Appendix 2 discusses the procedure, while Internet Appendix Tables IA3-IA4 and Figures IA3-IA4 report the results. We find that out of 301 firms in our sample, 124 firms have a statistically significant positive response to the TV advertising at a 5% level.

[15]We provide the distribution of firms in different sectors in Table 1, Panel B. Given limited number of observations in Telecommunications sector, we group it together with Information Technology sector. Moreover, we group Real Estate and Financial sectors together. Since the vast majority of the companies in our sample falling under the larger Healthcare GICS sector belong to Pharmaceuticals, Biotechnology & Life Sciences sub-sector (the other sub-sector being Health Care Equipment & Services), we refer to this sector as Pharmaceuticals. Finally, we define materials, utilities, and energy as “Other”.

4.5 Google Searches

Our SEC EDGAR results provide evidence that investors respond to the TV commercials when searching for the firm financial information. We further look at whether our effect extends beyond SEC EDGAR queries and whether it is also present in the search for firm financial information in Google.

The recent literature on investor attention has used Google searches for companies' ticker symbols as a proxy for investor interest in that company's securities (e.g., Da et al. (2011)). We expand upon this approach. In particular, in addition to Google search volume on tickers, we also collect information on related keywords that lead to the same financial information websites as the searches for tickers. Google AdWords Keyword Planner tool provides total search volume estimates for every keyword, as well as suggests alternative search keywords that lead to the same type of websites. For example, Google AdWords Keyword Planner suggests that users who search for the keyword "MSFT", ticker symbol for Microsoft, go to similar websites as people who search for the keywords "Microsoft Stock" or "MSFT Stock". We manually gather all of these related keywords for every ticker symbol in our sample. We only include related keywords that generate at least 10k searches per month to ensure that we do not include obscure keywords that would add noise to search volume estimates.

Given the complexity and restrictions in downloading the Google Trends data and its sheer volume, we only focus on one month of data[16] and on the most populous states: California, Connecticut, Florida, Illinois, New Jersey, New York, North Carolina, Oregon, Pennsylvania, Texas, Virginia, and Washington. Since search volume index (SVI) is normalized within each Google Trends query, we include a control keyword in every query and ensure that at least one minute of the query overlaps with the subsequent query. Furthermore,

[16]For the highest frequency, i.e., minute-by-minute data, Google only allows downloads in four-hour blocks for up to five search terms. To make this exercise manageable, we thus need to limit the time period for our analysis. We download the data for one full month for the same stocks that we use in the analysis of SEC EDGAR queries. We pick August, 2016, as 2016 Summer Olympics were taking place in this month and Summer Olympics are known to attract wide TV viewership. The main Olympics coverage during primetime was time-shifted. Our sample consists of 156 publicly traded firms. The sample is smaller than before since not all of 301 firms we use over 2015-2017Q1 advertised in the time-shifted programs in August, 2016.

given that Google SVI data is reported at the state level and the index is normalized at this level and thus cannot be compared across states, we do not aggregate the searches across the time zones but we add state fixed effects to directly control for state level normalization in Google Trends SVI algorithm. Our specification follows the one for SEC EDGAR searches and is thus estimated in a panel, constructed at a *firm* × 15 *minute interval* × *state level*:

$$Ln(GoogleSearches)_{its} = \beta \times Ad_{itk} + \gamma_{it} + \kappa_{ik} + \theta_{tk} + \psi_s + \epsilon_{its} \tag{3}$$

where i indexes the firms, t indexes time at a 15 minute interval, k indexes the time zones (EST or PST), and s indexes the states. $Ln(GoogleSearches)_{its}$ refers to the log SVI for firm's i ticker and other related Google keywords in a t 15 minute time interval from the state s in the time zone k. Ad_{itk} refers to a dummy whether at least one broadcast channel aired a commercial of the firm i during t 15 minute time interval in the time zone k.[17]

The results are reported in Table 5. We find a statistically significant increase in the searches for ticker and other related keywords after the ad is broadcast in a treated time zone, as compared to searches in the contemporaneously non-exposed time zone. As before, we report the general effect of the ad in column (1), focus on ads with an estimated cost greater than $50k in column (2), primetime in column (3), and the log value of the total estimated cost of TV ad in column (4). The estimates point in the same direction and follow similar patters with SEC EDGAR search results: TV ads increase firm financial information search on Google and more expensive ads lead to more Google financial information searches.

Given a higher economic effect on Google searches, these results suggest that our estimate on SEC EDGAR searches constitutes a lower bound of the TV ad effect on investor information search.[18]

[17] We also perform an alternative specification where we control for all fixed effects at the state level rather than time zone level, i.e., we add firm × state and 15 minute interval × state fixed effects:

$$Ln(GoogleSearches)_{its} = \beta \times Ad_{itk} + \gamma_{it} + \kappa_{is} + \theta_{ts} + \epsilon_{its}$$

The estimates are identical to those from specification (2). We report them in Internet Appendix Table IA5.

[18] Since our advertising data is at the product-level, as a comparison we also evaluate the effect of advertising on Google searches for advertised product names. That is, for example, upon airing of the Apple

5 Investors and Markets

In this Section, we further discuss the implications of our main results presented above. We start with addressing the question of whether the response comes from sophisticated or unsophisticated investors. We then study the effect of ad-induced search on the trading volume and stock returns. Finally, we discuss a framework that allows us to evaluate whether ad related attention shocks can be considered as informative or non-informative, and provide the corresponding evidence.

5.1 Investor Sophistication

Since the IP addresses provided by SEC are partially anonymized, we cannot identify the actual investors who are affected by the TV advertising nor their professional affiliations. These could be professional investors who look for more information about the firm after their work hours, or retail traders.

In an attempt to understand investor sophistication, we look at the unique IP addresses that search for the advertised firm's financial information on SEC EDGAR immediately after the ad airing in their timezone. We see that over 2015-2017Q1 period $164,000$ distinct users searched for advertising firms within 15 minutes after the ad airing; $129,000$ users searched within 10 minutes; and $89,000$ users searched within 5 minutes, out of 8.3m total number of distinct non-bot IP addresses present in our sample.[19] Absent an ad, we would expect that average per minute distribution of searches on any company should be approximately even. The above pattern, on the other hand, suggests that the average per minute search for firm financial information decays after an ad and that a disproportionate number of investors react within a very narrow time window of an ad, which is consistent with ads inducing near

IPhone commercial, we can compare the Google searches for the firm's ticker ("AAPL") and other financial keywords to searches for firm's advertised product name ("IPhone"). Such product-level analysis suggests that the treatment effect of an ad on the financial information search constitutes 30%-40% of the effect of an ad on the product name search.

[19] These numbers provide the upper bound of the treatment effect as we do not know which of these particular IP addresses would have searched for the firm absent its ad.

real-time reaction of investors.

We investigate investors' sophistication further by comparing browsing patterns of the IP addresses that ever searched for an advertiser after an ad with the browsing patterns of an average SEC EDGAR user. Figure 3, Panel A, depicts the distribution of overall frequency of queries during our sample period on SEC EDGAR that come from the IP addresses that searched within 15 minutes after an ad airing relative to the overall sample. We see that the IP addresses that search for firm's information after an ad airing are much more active on SEC EDGAR in general, suggesting their relative sophistication compared to other participants on SEC EDGAR. In Panel B we also see that the users that search within the first 5 minutes (relative to the users who search within the second or third 5 minute interval after an ad) are even more active SEC EDGAR users, suggesting that the most sophisticated users of SEC EDGAR react to the ads the fastest.

We also check the time of the day activity patterns for the IP addresses that react after the ads as compared to the average activity patterns of all IP addresses. We find that IP addresses that react after the ads have on average 68% of their activity in the evening (6pm-12am), as compared to 48% in the case of all IP addresses. This asymmetry is particularly pronounced for the browsing activity during the primetime hours, i.e., 36% versus 18%, and it suggests that a lot of ad-induced searches are happening on the devices with the IP addresses that are primarily used during the evenings.

Given this high number of distinct IP addresses and also that we find consistent results when we look at both SEC EDGAR and Google searches, it is likely that at least some of this rise in search activity is driven by the sophisticated retail investors.[20]

5.2 Trading Volume

Additional signals coming from advertising and then later from the information collection through SEC EDGAR are likely to generate dispersion in the opinions among investors and

[20]Retail trading volume results presented in Section 5.2 are also consistent with this assertion.

thus facilitate trading.

Absent geographic trading data and the fact that most of the commercials in our sample are aired outside of the trading hours, we are unable to apply the same identification strategy to see whether TV commercials lead to higher trading volumes of the shares of the advertising firms. That said, in this Section we provide evidence consistent with the interpretation that TV commercials affect not only the search for financial information, but that this search predicts increases in trading volume.

In particular, we look at the trading of a firm's shares on the day after the firm's ads are broadcast. We focus our analysis only on primetime ads to limit ourselves to the time of the day after the trading hours. We look at the impact of the ads based on how significant their effect is on the firm's queries on SEC EDGAR.

For each TV commercial broadcast during the primetime TV hours, we estimate the effect of each ad on the SEC EDGAR searches, according to our econometric specification represented in equation (1), where we difference out γ_{it}, κ_{ik}, and θ_{tk} from total searches during the 15 minute time interval with an ad. This step estimates how many SEC EDGAR searches are directly attributable to each ad after it aired in EST and then in PST and then adds them up to get the total effect. Next, in case an advertiser had multiple ads during the primetime hours in a given day, we sum ad-induced search lifts across all of the ads of that advertiser. The resulting measure is the total searches due to firm's advertising during the primetime in a given day. We then relate this measure to the next day's trading volume of the firm's stock.[21] We add date fixed effects to control for any unusual market events as well as firm fixed effects to control for the baseline differences across firms. Our specification is:

$$Ln(Volume)_{id} = \alpha + \beta \times PrimeAdLift_{id-1} + \gamma_i + \theta_d + \epsilon_{id} \tag{4}$$

[21] Our estimation has a flavor of instrumental variables specification whereby the first stage would estimate the advertising effect on SEC EDGAR search and the second stage would estimate the instrumented SEC EDGAR effect on trading. However, the exclusion restriction in the instrumental variables estimation is unlikely to hold since advertising might affect trading directly or through other indirect channels.

where i indexes the firms and d indexes date. $Ln(Volume)_{id}$ refers to the trading volume on firm's i stock on d, as extracted from CRSP database. $PrimeAdLift_{id-1}$ is the total ad-induced search lift over primetime for firm i on $d-1$ day as described above. In these regressions we also control for the overall daily search on a given firm on SEC EDGAR during the prior day. Such control is intended to remove any overall daily variation in the interest in the firm's financials, further assuring that what we are capturing is the advertising effect.

As reported in Table 6, Panel A, we find a strong positive relationship between a significant ad lift in the evening during the primetime and the trading volume the next day. That is, these results suggest that our earlier finding that TV advertising causes information search on SEC EDGAR also carries over into the trading behavior. Column (1) shows the baseline effect for ads aired in primetime hours while column (2) shows the effect for all ads aired throughout the prior day. In terms of the economic effect, for one standard deviation increase in total daily SEC EDGAR searches over 15 minute interval during the primetime hours, the trading volume increases by 0.49%. Further, in column (3), to get at the intensive margin, we condition the sample if ads were at all aired for the firm during the prior day while in column (4) to get at the extensive margin, we separately estimate the effect of any ad airing. We show that this effect comes exclusively from the intensive and not the extensive margin. That is, the effect on trading volume is not driven just by the airing of any ad but rather by the magnitude of advertising-induced searches on SEC EDGAR.

Next, we explore the retail trading activity. We follow Boehmer et al. (2017) who have suggested an algorithm to identify retail trades from TAQ data. Most marketable retail orders are executed either by wholesalers or via internalization. Because of the institutional arrangements, such orders are given a small amount of price improvement relative to the National Best Bid or Offer. Thus, transactions with a retail seller tend to be reported on a FINRA Trade Reporting Facility at prices that are just above a round penny due to the small amount of price improvement, while transactions with a retail buyer tend to be reported on a FINRA Trade Reporting Facility at prices just below a round penny. According to Boehmer et al. (2017), such approach can identify the majority of overall retail trading activity.

We present the retail investor trading results following Boehmer et al. (2017) methodology in Panel B of Table 6. Again, column (1) presents the baseline effect on retail trading for ads aired in primetime hours during the prior day, column (2) presents the effect for all ads aired throughout the prior day, column (3) shows the intensive margin, and column (4) shows the extensive margin. We find consistent and in fact marginally stronger effects as compared to the overall trading volume results presented in Panel A, suggesting that retail investors are responsible for a significant fraction of the ad-induced trading activity. In terms of the economic effect, one standard deviation larger total daily SEC EDGAR searches over 15 minute interval during the primetime is associated with 0.70% larger retail trading volume.

In Table IA6, we provide robustness for both total trading volume (Panel A) and retail trading volume (Panel B) results. First, in columns (1) we show that the magnitude of this effect is even larger when the above specification is estimated over the 10 minute interval. The comparison of the effects based on 15 minute versus 10 minute intervals suggests that the trading volume increase is disproportionately driven by the investors who quickly react to the TV ads by searching for financial information about the advertising firm. In Section 5.1, we showed that the IP addresses that react to ads quickly tend to also be more active users of the SEC EDGAR. Taken together, both of these results suggest that a significant fraction of the ad related trading activity can be attributed to retail investors, who are also sophisticated users of SEC EDGAR.

Importantly, a larger effect coming from a narrower time window also gives significantly more confidence to the assertion that the effect on trading is directly attributable to advertising and not to any other factors that might influence stock trading. In the same Table IA6 we provide additional evidence suggesting that these trading volume increases are not driven by alternative factors. In columns (2) and (3), we show that this effect is robust to the exclusion of earnings announcement days as well as the days if the firm was announced to be an acquirer or a target in a merger deal. In columns (4), instead of firm fixed effects, we control for the one-day lagged volume. In all cases our main result remains robust. Our overall conclusion from the results presented in this Section is that the ads that induce higher SEC EDGAR search are associated with higher trading volume.

These estimates also allow us to perform a back-of-the-envelope calculation of what fraction of the overall daily trading volume is attributable to advertising. Based on our ad-induced search estimates, we find that the dollar elasticity of TV ad spending is \$0.513, i.e., \$1 spent on advertising translates to 51.3 cents of trading activity.[22] Extrapolating this elasticity to the total annual advertising expenditures of these firms of \$150bn and the annual trading volume of \$18.1tr, we can estimate that approximately 0.42% of the daily trading volume can be directly attributed to advertising. For large advertisers such as AT&T, this number rises to 0.8%.

5.3 Stock Price Reaction

Similar to the analysis on the trading volume, we study the effects on the stock price returns. The prediction on the stock returns is a priori ambiguous. On one hand, advertising might provide investors a positive information signal about the financial health of the company, its expected future sales and cash flows, or attract the attention of investors who further take a positive view on the firm's prospects after collecting more financial information, thus leading to increased stock prices. On the other hand, advertising (and subsequent information collection) might induce some investors to update their forecasts negatively. For instance, they could infer from the ads that the firm's sales are lower than expected and the firm is increasing advertising to facilitate a higher consumer reaction. Further, the investors might not believe that the particular ad content might be successful in generating sales. If some investors react positively and others negatively due to ads, absent strong short-sale constraints, it is possible that positive trading volume effect might lead to no changes in stock price (see, e.g., Kandel and Pearson (1995) who find that earnings announcements

[22] This calculation is based on our regression estimates, the average primetime ad expenditures (\$87k, see Table 1), and the average daily trading volume of our analyzed stocks (\$252m).

lead to an increase in trading volume but have no associated stock price reaction).

Our analysis parallels the one described in the previous sub-section on trading volume. Specifically, we relate $PrimeAdLift_{id-1}$, the total primetime daily ad lift for firm's queries on SEC EDGAR, to the stock price return on the next trading day d. Our specification is:

$$Return_{id} = \alpha + \beta \times PrimeAdLift_{id-1} + \gamma Return_{id-1} + \theta_d + \epsilon_{id} \quad (5)$$

where i indexes the firms and d indexes date. $Return_{id}$ refers to the return on firm's i stock on day d, as extracted from CRSP database. We control for the overall daily search on a given firm on the SEC EDGAR during the prior day and the lagged return. We also add day fixed effects to control for general market movements.[23]

Table 7 reports the results. Column (1) shows that there is no overall relationship between the level of ad-induced searches during the primetime and stock price return on the subsequent day. We further follow Lou et al. (2018) and separate these daily returns into the overnight returns, estimated as the return between the opening stock price in the next trading day d and the closing stock price in the previous trading day $d-1$, and the intraday returns, estimated as the return between the closing stock price in the next trading day d and the opening stock price in the next trading day d. We separately report the effect on overnight returns and intraday returns in columns (2) and (3), respectively. We find that $PrimeAdLift_{id-1}$ is associated with positive overnight stock returns but these partially reverse during the trading hours. Such cross-period reversal effect is consistent with Lou et al. (2018) who suggest that overnight and intraday trading attract different clienteles. One standard deviation increase in total daily SEC EDGAR searches over 15-minute interval during the primetime hours is associated with 0.86bp higher overnight returns and 0.34bp lower intraday returns during the next trading day, and while the overall return is positive,

[23]This specification is similar to the one in Tetlock (2007). Because of the particular event we study, we choose to focus on one-day lags rather than longer periods as in Tetlock (2007). The results are qualitatively similar if we replicate this analysis using Fama-Macbeth methodology to rule out that the effect is not purely driven by the time-series component but is present in the cross-sectional dimension.

it is not statistically significant.

5.4 Informative or Non-informative Attention Shocks?

So far our findings described above are consistent with a strong causal relationship between the TV advertising and immediate investor behavior, but we have not suggested a reason or a mechanism through which these effects manifest themselves. Next, we look at whether any of the patterns in our data are consistent with advertising carrying informative or non-informative signals to investors.

With respect to the advertising effect on consumers, economics and marketing literature distinguishes between two types of advertising effects: messages that affect behavior because they update receivers' beliefs (informative advertising role) and messages that affect the behavior independent of beliefs (non-informative advertising role).[24]

In terms of the role that advertising plays on investors, its informativeness will depend on investors' beliefs on how advertising affects consumers and eventually the firm financials, e.g., through product sales. Even if consumers do not find ads informative but investors infer that these ads alter consumer preferences and change their purchase behavior, investors might be able to update their beliefs. Ad content might also be informative to investors but not to consumers if ads, for instance, carry a signal about the financial health of the company. We refer to this type of ad content as carrying *informative* signals, whereby investor's beliefs are updated with a given piece of new information due to an ad.

Some ads, however, might not update investor beliefs but still contribute to changes in their actions. These ads could carry signals that are already incorporated in investor beliefs (e.g., repeatedly observed ads, when even the fact that they are repeated does not provide additional information to investors), or signals that have too much noise to update investor beliefs (e.g., the ads in a foreign language), or signals that carry only the information that is

[24] See, e.g., DellaVigna and Gentzkow (2010) who label them as belief-based models and preference-based models, respectively. The key aspect that distinguishes preference-based models from belief-based models is that in preference-based models the messages may affect behavior even when they convey no information. See also the survey of the literature by Bagwell (2007).

irrelevant to investor beliefs. In these cases the effect on investor behavior would be driven by ads increasing the salience about the firm. We refer to such ad content as carrying *non-informative* signals to investors as they do not alter their beliefs about the firms' performance.

In most contexts both informative and non-informative attention effects are likely to be present simultaneously. In this Section, we explore the heterogeneity of the ad effect in order to discern whether the changes in investor behavior are driven by informative or non-informative signals.

In particular, we rely on the advertising literature, which beginning with Shryer (1912) has shown that informativeness of the signal has diminishing returns to repeating the advertisement. Multiple empirical studies have shown that in situations where product advertising contains informative signals for consumers, the advertising effects are largest at the beginning of the advertising campaign and for individuals that have little experience with the advertised products (see, e.g., Simon and Arndt (1980); Ackerberg (2001, 2003); Simester et al. (2009); Tellis et al. (2000)). We argue that investors' priors should also be decreasingly affected with repeated exposures to same ads and thus the informative signal of an ad should decrease with the time since the first observed advertisement. Thus, we look at whether the estimated ad effect varies with advertisement age.

In particular, we study how the effect varies with the time since the first airing of a specific advertisement creative. We plot the results in Figure 4 by showing the relationship between the log of length of time (in days) since a specific ad was aired for the first time and the ad-induced search lifts. Panel A illustrates that the linear fit line between the log of ad age and ad-induced search lift is negative and statistically significantly different from zero. The slope of the relationship is -0.0285 (p=0.001) and implies that older ads, on average, have smaller ad-induced financial information search effects, suggesting that there exists an informative signal that dissipates over time with the decrease in the novelty of the ad.

Second, we relate this to the phenomenon documented in finance literature that investors are more informed about the firms that are located geographically closer to investors (e.g., Coval and Moskowitz (1999, 2001)) and look at whether the relationship between the ad effect and ad age varies by whether the ad is broadcast in the areas that are closer geographically to their headquarters (HQ) as compared with those further away. Presumably, the investors who are located closer to the advertising firms have more information about them and thus the sensitivity of searches to the novelty of an ad is weaker.

We look at the relationship between ad age and search lifts separately for firms with HQ in the same versus a different timezone. We define same timezone HQ firms as those that are headquartered in the same timezone where the ad is broadcast, i.e., either (i) its HQ are in EST and ad is broadcast in EST, or (ii) its HQ are in PST and ad is broadcast in PST. As we show in Panel B, the average effect for same timezone HQ firms is statistically significantly larger than the effect for different timezone HQ firms, with the difference increasing with the ad age. More importantly, the slope of the same timezone HQ advertising is not statistically significantly different from zero (p=0.753) but the slope for different timezone HQ firms is negative and statistically significantly different from zero (p<0.000).

We find similar patterns when exploring the relationship between the ad-induced search lifts and advertisement length. Holding everything constant, longer ads have a capacity to contain more information. Overall, as reported before in our tests exploring the heterogeneity of the effect, we find that longer ads are associated with significantly higher search lifts (p<0.000). In addition, when we look at the geographic variation, we find that this positive effect is primarily driven by queries for the firms with HQ locations in a different timezone than locations of investors. Specifically, we find a strong positive relationship for different timezone investors (slope of 0.0034, p<0.000) and a flat relationship for investors from the same timezone as a firm's HQ (slope of −0.0012, p=0.379).

While both informative and non-informative ad effects are likely to coexist simultaneously, the above results suggest which effect might dominate in which circumstances. Specifically, for firms located further away from investors, the sensitivity to new and longer advertisements is strong, suggesting that informative effect dominates. In contrast, for firms that are geographically closer to investors, the ad effect is independent of its age and length, suggesting that non-informative attention effect dominates, e.g., ads increase advertiser's salience or act as a reminder about the advertiser.

6 Product Market Information Spillovers

In the previous Section, we explored the heterogeneity of the ad effect to discern whether it is consistent with ads being informative to investors or whether investors are rather affected by the non-informative attention shocks. In this Section, we explore whether such information generated by advertising spills over through the horizontal and vertical product market links. We investigate two types of such relationships. First, we look at firm's rivals. Second, we study suppliers to whom the advertising firm was a major customer. If an ad is informative about the firm's position in the product markets, it is also likely to be informative about the rivals' relative performance as well as the supplier's future sales.[25]

We start with the product market rivals. Here we rely on the classification developed by Hoberg and Phillips (2010, 2016) and for each advertising firm we look at the product market rival that is closest to the firm based on the firm-by-firm pairwise similarity scores, constructed by parsing the business descriptions of 10-K annual filings. The resulting data include SEC EDGAR queries for 219 unique firms for which our original sample advertising firms are the primary rivals (106 of these firms advertise themselves). As reported in Table 8, Panel A, we find that the magnitude of the rival ad effect amounts to around a third of the own ad effect on the financial information search.

We further look at the firms that are linked through vertical relationships. Firms are required to disclose the customer's identity as well as the amount of sales to the customer if a customer is responsible for more than 10% of the firm annual revenues. The Compustat

[25]Previous literature has looked at the tight link between the firms' information provision to the product markets and the information provision for the investors, and how such information is further transmitted through the economic links (see, e.g., Darrough (1993); Gigler (1994); Evans III and Sridhar (2002); Cohen and Frazzini (2008); Madsen (2016); Bourveau et al. (2018)).

Segment database gathers information on the sales to and identities of customers from the firms' original filings with the SEC.[26] We use this information on the firms that have advertising firm as a major customer to see if the suppliers that are dependent on the firm's sales are affected by the firm's advertisements. The resulting sample tracks SEC EDGAR queries for 715 unique suppliers who have our advertising firms as major customers (92 of these suppliers advertise themselves). We report the results in Table 8, Panel B. We find that the effect is limited to the most expensive and, to a lesser degree, primetime ads.[27]

Finally, we investigate whether such spillover advertising effect on rival and supplier information search translates to additional trading activity for these related stocks. Similarly to Table 6, we construct ad-induced search lift on rival or supplier firms as a response to a given ad. As reported in Table 9, we find a statistically significant effect on rival firm trading but no such effect on the supplier firms. In terms of the economic effect, for one standard deviation increase in total daily SEC EDGAR searches of rival firm over 15 minute interval during the primetime hours, the trading volume of rival firm increases by 0.60%.

Indirectly, these findings on product market spillovers also speak towards an informative role of advertising in the financial markets. While it is plausible that some advertising acts as a reminder for investors with limited attention, our results suggest that advertising might provide an indirect information signal. The results on the trading volume spillovers also suggest that these are likely to be more sophisticated investors who are aware of product market links and after further investigation trade rival firms' stock.

[26]We thank the authors of Cen et al. (2016) for kindly providing us with the recent match of this data to Compustat database.

[27]We also explore an alternative data source on rivals and customer-supplier links. We rely on the industry taxonomy built by Factset, an information service provider, and replicate our estimation. Factset does not provide the sales figures and so we cannot evaluate the importance of each product market connection. As reported in the Internet Appendix Table IA7, Panel A, our results on the investor attention to the rival ads are consistent when we base analysis on the alternative definition of rivals and estimate the effect on *all* rivals. In Panel B, we estimate the effect on *all* suppliers of the advertising firm based on Factset data. We do not find a statistically significant effect on suppliers, suggesting that investors take into account if the customer is very important to the supplier (as reported in Table 8, Panel B).

7 Conclusion

Advertising in product markets inadvertently affects financial markets but showing the causality has been challenging given the inherently strategic nature of when and how the firm places its advertising. In this paper, we look at the TV advertising and exploit a unique institutional feature that relies on the U.S. national broadcast TV channels using the same programming and advertising feed across different US time zones but at different times. This allows us to control for any contemporaneous events happening with the advertising firm.

We find a statistically significant effect of TV ads on the search for financial information on SEC EDGAR database coming from the IP addresses associated with the time zone where the commercial is aired as compared to the time zone where the commercial is not contemporaneously aired. In a smaller sample we also show the advertising effect with minute-by-minute Google Trends data which has also been collected on a regional basis. Our results also highlight substantial heterogeneity in the response by different industry sectors and firms. Finally, these ad-induced lifts in search volumes are associated with the increased trading volume on the firm's stock in the day following the advertisement airing.

Our findings suggest that the link between marketing actions and investor behavior is more direct and immediate than previously thought. Indeed, advertising plays an important role in financial markets and our results have implications for firm advertising strategies: namely, the content of an ad should not only be geared to generate the direct effect on consumers but should also take into account how that will be internalized by firm's financiers.

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Figure 1: U.S. States Across Time Zones and Broadcast Network TV Feeds

This figure highlights the U.S. states falling into different time zones and different broadcast network TV feeds (states that fall into two time zones are highlighted in the color of the time zone that the majority of the state falls in). In our analysis, we combine search activity in CST and EST and disregard states falling into MST time zone as well as Alaska and Hawaii.

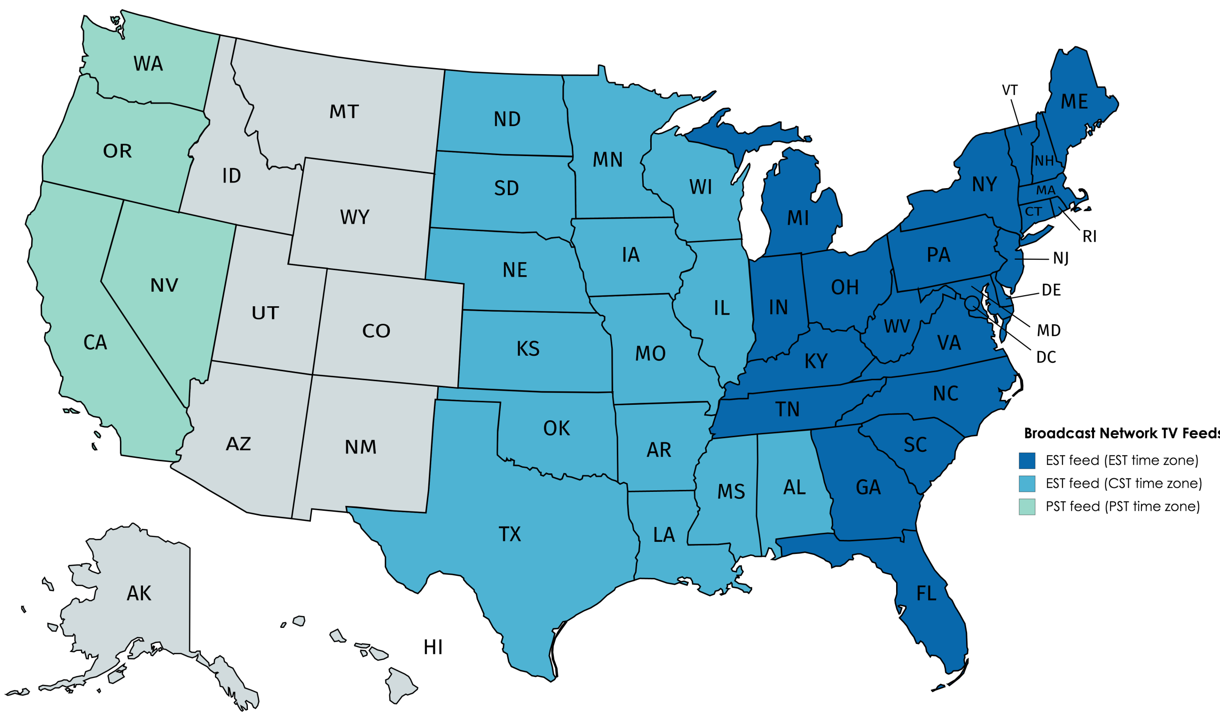
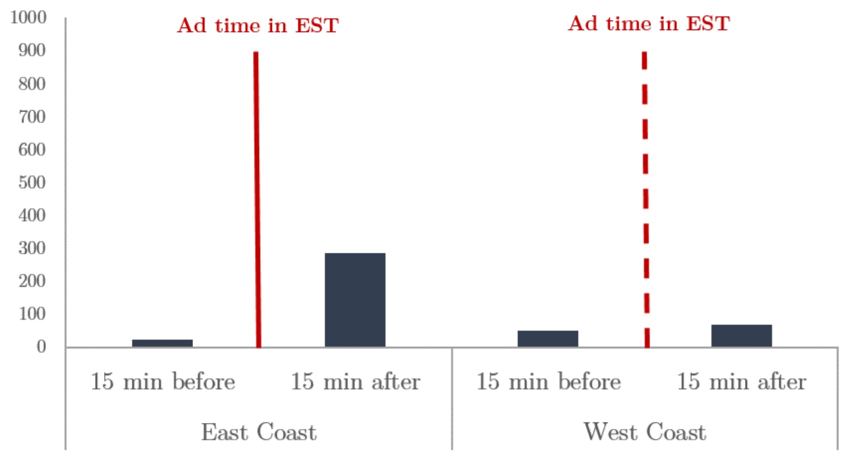


Figure 2: Identification Example: Citigroup Ad on March 3, 2017

This figure provides an example of variation in outcome variables that allows us to identify the treatment effect of an ad. We depict the number of queries (Y axis) for Citigroup Inc. financial information on SEC EDGAR coming from the IP addresses associated with EST versus PST time zones. Panel A compares the contemporaneous query activity in both time zones when the ad was aired in EST (and not yet aired in PST), whereas Panel B compares the corresponding contemporaneous queries when the ad was aired in PST 3 hours later.

(A) Ad shown in EST



(B) Ad shown in PST

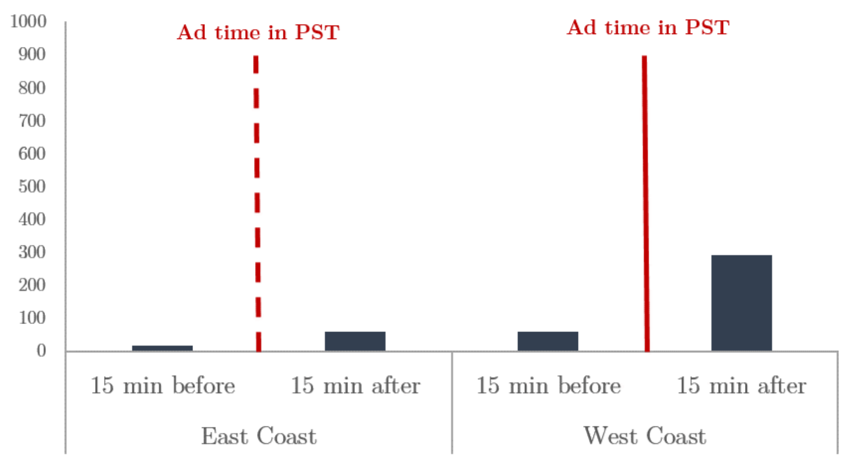
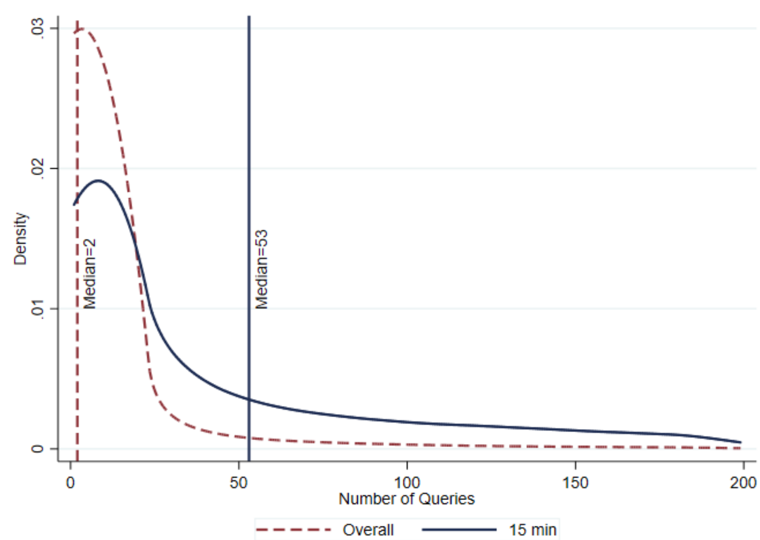


Figure 3: SEC EDGAR Usage Frequency

This figure summarizes the frequency of visits to SEC EDGAR for each unique IP address during our sample period. Panel A compares the kernel density distribution of frequency of visits for all of the unique IP addresses in our sample with those IP addresses that have conducted financial information searches on advertised companies within 15 minutes of an ad airing in the treated timezone. Vertical lines correspond to the medians within respective sub-samples. Panel B plots the number of unique users by the immediacy of visits: IP addresses that searched for advertised firm financial information within (i) the first interval of 5 minutes, (ii) the second interval of 5 minutes, and (iii) the third interval of 5 minutes of an ad airing, splitting them by their frequency of overall SEC EDGAR usage, i.e., (a) those who searched less then 10 times during the sample period, (b) those who searched 10-100 times, and (c) those who searched more than 100 times.

(A) Overall vs. 15 min



(B) Number of Users by SEC EDGAR Usage Frequency and Immediacy of Search

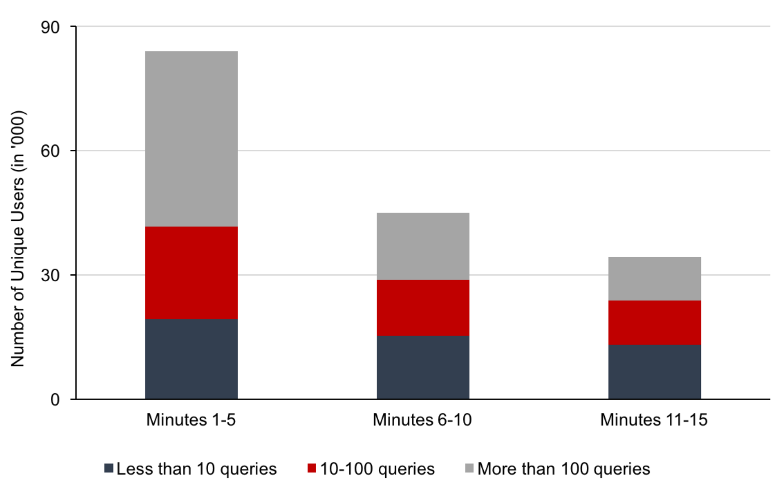
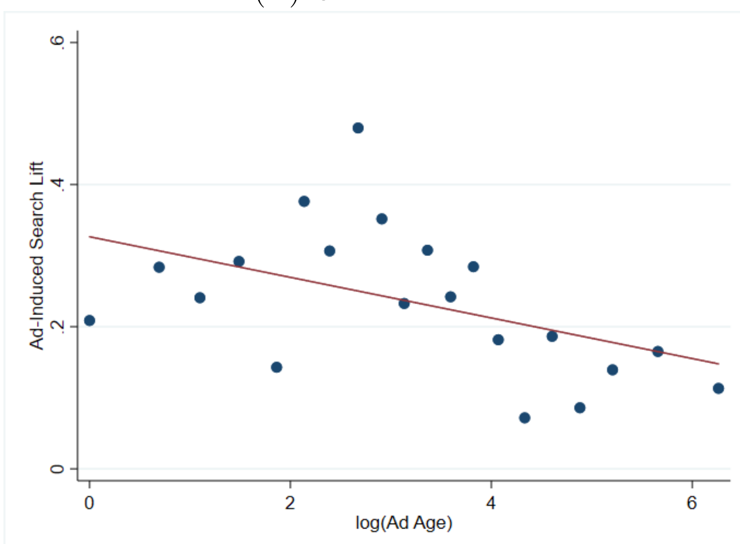


Figure 4: Ad-Induced Search Lifts by Ad Age

This figure plots the relationship between the log of length of time (in days) since a specific ad creative was aired for the first time (X axis) and net ad-induced search lifts (Y axis). The depicted scatterplots are conditional means of the Y variable for 20 equally sized bins of the X variable. The line depicts linear fit line using OLS and its slope is equivalent to the estimated OLS coefficient for the X variable. Panel A depicts the overall relationship between the ad age and ad-induced lift. Panel B depicts the above relationship separately for firms with headquarters (HQ) in the same timezone vs. firms with HQ in a different timezone as investors. Same timezone HQ are defined as: (i) HQ in EST & ad broadcast in EST, or (ii) HQ in PST & ad broadcast in PST.

(A) Overall Effect



(B) Ads by HQ location in same vs. different timezone as investors

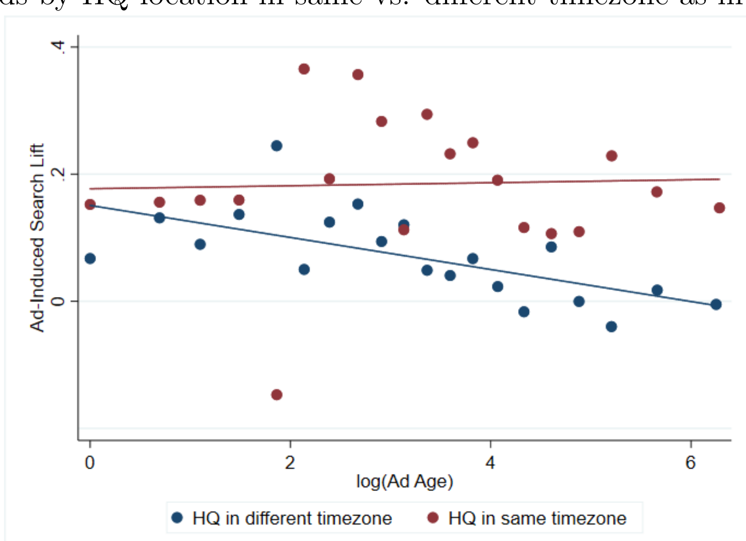


Table 1: Descriptive Statistics

This table shows descriptive statistics for 301 publicly traded firms that have placed ads during the time-shifted broadcast TV hours over 2015-2017 Q1. Panel A reports descriptive statistics of advertising data as reported by Kantar Media. Panel B splits this information across 11 GICS sectors. Panel C reports the financial data for the sample firms as reported in Compustat, CRSP, and Thomson Reuters 13f database. Panel D reports the total number of SEC EDGAR queries by time zone in our sample. Column (1) totals the queries that exclude IP addresses that have performed more than 500 daily queries, column (2) excludes IP addresses with more than 50 queries, column (3) reports total queries related to the firm's financial position and the annual reports (forms 10-K, 10-Q), column (4) reports the filings on material events (form 8-K), column (5) reports firm's insiders and beneficial ownership (forms 3, 4), and column (6) reports all other filings. Column (7) reports total queries that come from the IP addresses with more than 500 daily queries that we attribute to bot traffic.

(A) Kantar Advertising Data

	# of	Ad expenditures			
	ads	Mean	1%	99%	Total ($BN)
Total	326,745	$61,058	$3,400	$354,900	$20.00
ABC	87,973	$65,832	$5,600	$332,800	$5.79
CBS	91,461	$55,598	$3,100	$337,400	$5.09
CW	24,796	$20,972	$6,000	$73,800	$0.52
FOX	27,466	$86,447	$7,500	$549,300	$2.37
NBC	95,049	$65,015	$4,600	$551,700	$6.18
Primetime	181,266	$86,520	$7,300	$536,000	$15.68
2015	143,993	$58,813	$4,100	$322,000	$8.47
2016	146,168	$62,966	$3,200	$431,400	$9.25
2017 (Q1)	36,584	$62,270	$3,000	$339,500	$2.28

(B) Number of Firms and Advertising Data by GICS Sector

GICS	# of firms	# of ads	Avg. ad exp.	Total ad exp. (in $MM)
Energy	5	457	$157,588	$72
Materials	5	2,044	$44,300	$91
Industrials	23	2,146	$77,805	$167
Consumer Discretionary	115	125,211	$62,799	$7,863
Consumer Staples	43	81,926	$44,963	$3,684
Healthcare	31	63,237	$68,793	$4,350
Financials	30	16,617	$63,754	$1,059
Information Technology	38	17,513	$81,101	$1,420
Telecommunication Services	3	14,121	$71,899	$1,015
Utilities	1	1	$187,600	$0.188
Real Estate	3	558	$39,585	$22

(C) Firm Financial Information

	Mean	Median	St. dev.
Assets (in $MM)	83,709	10,769	283,468
Gross margin	0.472	0.444	0.222
Market to book value	4.490	3.620	2.935
R&D / Sales	0.057	0.017	0.084
Stock return volatility	0.018	0.015	0.009
Advertising expenses / Sales	0.056	0.037	0.061
Institutional ownership %	0.623	0.685	0.233

(D) Total SEC EDGAR Queries (in MM)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total queries	Queries<50	Financials	Events	Ownership	Other	Bot queries
Total	49.24	22.17	27.98	7.49	3.58	10.14	457
EST	39.50	17.40	22.80	6.05	2.59	8.03	262
PST	9.74	4.77	5.18	1.45	0.99	2.11	196

Table 2: Baseline Estimates

This table summarizes the results of advertising effect on SEC EDGAR queries. Panel A presents the mean difference-in-differences SEC EDGAR queries, where the first difference is taken between the average log of number of queries during 15 minutes when an ad was aired and when an ad was not aired in the time zone that was exposed to the ad (EST or PST) and the second difference is taken over the corresponding intervals in the other time zone that has not been exposed to the ad. Column (1) shows results for the entire sample, column (2) looks only at ads that had an estimated cost of at least $50,000, column (3) reports the results for ads shown only during the primetime hours (8PM-11PM) whereas columns (4) and (5) report difference-in-differences estimates based on 10 minute and 20 minute intervals, respectively. *** indicates significance level at 1% based on two sided t-tests. Panel B presents regression results where we control for *firm* × *time interval*, *firm* × *time zone*, and *time interval* × *time zone* fixed effects. Column (1) presents the baseline overall effect for all ads, column (2) looks only at ads that had an estimated cost of at least $50,000; column (3) presents the effect only for primetime ads, and column (4) reports the results of log of estimated ad expenditure. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

(A) Univariate Tests					
	(1) All Ads	(2) Ad>$50K	(3) Primetime	(4) 10 min	(5) 20 min
First Difference Only	0.450***	0.785***	0.540***	0.376***	0.492***
Diff-in-Diff	0.072***	0.147***	0.080***	0.073***	0.064***

(B) Regressions				
	(1) All ads	(2) Ad>$50K	(3) Primetime	(4) Ln(ad$)
TV Ad	0.025***	0.025***	0.032***	0.002***
	3.105	2.660	2.931	3.07
firm × time interval f.e.	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes
time interval × time zone f.e.	yes	yes	yes	yes
R-squared	0.374	0.374	0.374	0.374
N	47.2MM	47.2MM	47.2MM	47.2MM

Table 3: Robustness Tests

This table summarizes a number of robustness tests of advertising on EDGAR queries. In Panel A, column (1) excludes the IP addresses that have performed more than 50 queries during the day; column (2) only includes the IP addresses that have performed more than 500 queries during the day; column (3) only considers searches from the IP addresses that have not searched for this particular advertising firm since 2012; column (4) excludes CST; column (5) only considers California, Connecticut, and New York. In Panel B, column (1) estimates the effects on the next two time periods; column (2) reports results of a falsification test where a placebo ad is inserted at $t-1$; column (3) reports results where we move the interval formation by 5 minutes; column (4) reports the results if the sample is constructed in 10 minute rather than 15 minute intervals; column (5) reports the results if the sample is constructed in 20 minute interval. Column (6) excludes days with earnings announcements.

	(A) Robustness of Outcome Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
	<50 queries	Bots only	Virgins	No CST	CT&NY vs CA	Exclude EA
TV Ad	0.026***	0.004	0.009***	0.028***	0.029***	0.026***
	3.788	0.886	3.332	3.723	4.453	3.220
firm × time interval f.e.	yes	yes	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes	yes	yes
time interval × time zone f.e.	yes	yes	yes	yes	yes	yes
R-squared	0.319	0.401	0.173	0.332	0.241	0.370
N	47.2MM	47.2MM	47.2MM	47.2MM	47.2MM	46.7MM

	(B) Robustness with Respect to Time				
	(1)	(2)	(3)	(4)	(5)
	Carryover	Falsification	5 min shift	10 min intervals	20 min intervals
TV Ad	0.021***	0.009	0.024***	0.032***	0.013*
	3.306	1.532	3.009	3.968	1.657
TV Ad_{t-1}	0.011**				
	2.093				
TV Ad_{t-2}	0.007				
	1.394				
firm × time interval f.e.	yes	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes	yes
time interval × time zone f.e.	yes	yes	yes	yes	yes
R-squared	0.374	0.374	0.374	0.325	0.409
N	47.2MM	47.2MM	47.2MM	70.8MM	35.4MM

Table 4: Heterogeneity Tests

This table summarizes a number of heterogeneity tests of advertising on EDGAR queries. Panel A reports results on different EDGAR report types. Column (1) looks only at reports for firm's financial position and annual reports (forms 10-K and 10-Q); column (2) looks at filings on material events (form 8-K); column (3) looks at filings on firm's insiders and beneficial ownership (forms 3, 4); and column (4) looks at all other filings. Panel B summarizes the results of primetime advertising during the earnings announcement and M&A days. The first row indicates the overall primetime advertising effect and the second row indicates an effect of an interaction term between primetime advertising and a financial event. Column (1) presents interaction effect with earnings announcement day dummy, column (2) looks at interaction with the size of the earnings surprise, column (3) presents the interaction effect with M&A announcement day for a target firm, whereas column (4) reports interaction effect with M&A announcement day for an acquirer firm. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

(A) Effects by EDGAR Report Type				
	(1)	(2)	(3)	(4)
	Financials	Events	Ownership	Other
TV Ad	0.028***	0.022***	0.004**	0.032***
	3.108	3.529	2.423	5.289
firm×time interval f.e.	yes	yes	yes	yes
firm× time zone f.e.	yes	yes	yes	yes
time interval × time zone f.e.	yes	yes	yes	yes
R-squared	0.318	0.176	0.151	0.228
N	47.2MM	47.2MM	47.2MM	47.2MM

(B) Effects by Major Firm Events				
	(1)	(2)	(3)	(4)
	EA day	EA surprise	M&A (Target)	M&A (Acquirer)
Primetime Ad	0.031***	0.032***	0.031***	0.032***
	2.840	2.929	2.868	2.920
Primetime Ad×Event	0.077**	2.207	0.152**	0.057
	2.024	0.670	2.022	1.049
firm × time interval f.e.	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes
time interval × time zone f.e.	yes	yes	yes	yes
R-squared	0.374	0.374	0.374	0.374
N	47.2MM	47.2MM	47.2MM	47.2MM

Table 5: Financial Information Search on Google

This table reports the results of the effect of advertising on contemporaneous Google Search Volume Index (SVI) for all advertising firms in August 2016. Column (1) presents the baseline overall effect for all ads, column (2) looks only at ads that had an estimated cost of at least $50,000, column (3) presents the effect only for primetime ads, and column (4) reports the results of log of estimated ad expenditure. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) All ads	(2) Ad>$50K	(3) Primetime	(4) Ln(ad$)
TV Ad	0.078**	0.072*	0.091**	0.006**
	2.518	1.776	2.304	2.473
firm × time interval f.e.	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes
time interval × time zone f.e.	yes	yes	yes	yes
state f.e.	yes	yes	yes	yes
R-squared	0.645	0.645	0.645	0.645
N	5.75MM	5.75MM	5.75MM	5.75MM

Table 6: The Next-Day Effect on Stock Trading Volume

This table shows the results on the trading volume the day after the firm's ads are broadcast. The explanatory variable is the total lift in SEC EDGAR searches during the primetime hours in the prior day. In estimating this variable, we follow equation (1) and difference out γ_{it}, κ_{ik}, and θ_{tk} from total searches during the 15 minute time interval with an ad. We then aggregate these values across both timezones during primetime hours. In Panel A, the dependent variable is the log trading volume on a given day. In Panel B, the dependent variable is the log trading volume by retail investors as per Boehmer et al. (2017) on a given day. In both panels, column (1) reports baseline results where only ads during the primetime are considered, while column (2) totals ad-induced searches over the whole day instead of just primetime hours. Column (3) studies the intensive margin, i.e., the ad induced search lift magnitude. Column (4) studies the extensive margin, i.e., the fact whether an ad was aired or not (an ad dummy instead of a search lift magnitude). T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(A) Total Trading Volume			
	(1) Primetime	(2) All day	(3) Int. Margin	(4) Ext. Margin
Prior Day's Lift	0.000504***	0.000442***	0.000498***	
	3.806	3.401	3.629	
Prior Day Ad				-0.020669*
				-1.944
Prior Day's Overall Search	0.009861***	0.009870***	0.007725***	0.009831***
	3.734	3.736	2.871	3.679
Firm f.e.	yes	yes	yes	yes
Day f.e.	yes	yes	yes	yes
R-squared	0.912	0.912	0.906	0.912
N	0.161MM	0.161MM	0.048MM	0.161MM

	(B) Retail Trading Volume			
	(1) Primetime	(2) All day	(3) Int. Margin	(4) Ext. Margin
Prior Day's Lift	0.000712***	0.000605***	0.000664***	
	4.715	3.975	4.653	
Prior Day Ad				-0.015632
				-1.509
Prior Day's Overall Search	0.012828***	0.012825***	0.009533***	0.012784***
	3.876	3.869	3.052	3.809
Firm f.e.	yes	yes	yes	yes
Day f.e.	yes	yes	yes	yes
R-squared	0.887	0.887	0.892	0.887
N	0.151MM	0.151MM	0.045MM	0.151MM

Table 7: The Next-Day Effect on Stock Returns

This table shows the results on the stock returns the day after the firm's ads are broadcast. Column (1) reports the results where the dependent variable is the total daily returns (close-to-close). Column (2) reports the results where the dependent variable is the overnight returns (close-to-open), estimated as in Lou et al. (2018). Column (3) reports the results where the dependent variable is the intraday returns (open-to-close). The explanatory variable is the total lift in SEC EDGAR searches during the primetime hours in the prior day. In estimating this variable, we follow equation (1) and difference out γ_{it}, κ_{ik}, and θ_{tk} from total searches during the 15 minute time interval with an ad. We then aggregate and add these ad-induced searches across both timezones during primetime hours. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	Stock Returns		
	(1) Total Returns	(2) Overnight Returns	(3) Intraday Returns
Prior Day's Lift	0.00005	0.000009*	-0.000003*
	0.977	1.737	-1.962
Prior Day's Overall Search	0.000135*	0.000138*	-0.000003
	1.682	1.695	-0.375
Lagged Total Return	0.545561***	0.545610***	-0.000098
	6.371	6.381	-0.595
Day f.e.	yes	yes	yes
R-squared	0.318	0.320	0.188
N	0.16MM	0.16MM	0.16MM

Table 8: Product Market Information Spillovers

This table summarizes the results of advertising effect on SEC EDGAR queries of the advertising firm's closest product market rivals and suppliers. In Panel A, we look at the firm's rivals (219 unique rivals to advertising firms), defined according to the classification developed by Hoberg and Phillips (2010, 2016). For each advertising firm we pick the product market rival that is closest to the firm based on the firm-by-firm pairwise similarity scores, constructed by parsing the business descriptions of 10-K annual filings. We present the ad effects on the advertising firm as well as on the closest product market rival. In Panel B, we look at the firm's suppliers (715 unique suppliers to advertising firms). We gather firms suppliers that have advertising firm as the major customer from the Compustat Segment database, using the match developed by Cen et al. (2016). We present the ad effects on the advertising firm as well as on the firm's supplier. In both panels, column (1) presents the baseline overall effect for all ads, column (2) looks only at ads that had an estimated cost of at least $50,000, column (3) presents the effect only for primetime ads, and column (4) reports the results of log of estimated ad expenditure. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

(A) Rivals

	(1) All ads	(2) Ad>$50k	(3) Primetime	(4) Ln(ad$)
Rival TV Ad	0.022**	0.025*	0.031*	0.002**
	2.149	1.661	1.951	2.106
Own TV Ad	0.060***	0.076***	0.084***	0.005***
	4.530	5.793	5.001	4.771
firm × time f.e.	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes
time × time zone f.e.	yes	yes	yes	yes
R-squared	0.310	0.310	0.310	0.310
N	34.1MM	34.1MM	34.1MM	34.1MM

(B) Suppliers

	(1) All ads	(2) Ad>$50k	(3) Primetime	(4) Ln(ad$)
Customer TV Ad	0.004	0.008**	0.008*	0.000
	1.275	2.143	1.812	1.388
Own TV Ad	0.111***	0.143***	0.156***	0.009***
	9.229	10.205	10.531	9.412
firm × time f.e.	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes
time × time zone f.e.	yes	yes	yes	yes
R-squared	0.310	0.310	0.310	0.310
N	112.2MM	112.2MM	112.2MM	112.2MM

Table 9: The Next-Day Effect on Stock Trading Volume of Rivals and Suppliers

This table shows the results on the trading volume the day after the firm's rival and supplier ads are broadcast. The dependent variable is the log trading volume on a given day. The explanatory variable is the total lift in SEC EDGAR searches during the primetime hours in the prior day. In estimating this variable, we follow equation (1) and difference out γ_{it}, κ_{ik}, and θ_{tk} from total searches during the 15 minute time interval with an ad. We then aggregate these values across both timezones during primetime hours. Column (1) reports the results where the ad lift is estimated based on key rival ad broadcast while column (2) reports the results where the ad lift is estimated based on major customer ad broadcast. Rivals and suppliers are defined in Table 6. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
	Rivals	Suppliers
Prior Day's Lift	0.001206*	-0.000126
	1.776	-0.250
Prior Day's Overall Search	0.019069*	0.060048**
	1.938	2.148
Firm f.e.	yes	yes
Day f.e.	yes	yes
R-squared	0.823	0.815
N	0.147MM	0.185MM

Internet Appendix 1: Choice of 15 Minute Intervals

We need to make a methodological choice for how to define the start of the 15 minute intervals. Ideally, we want commercials to be distributed at a constant rate throughout the 15 minute interval. Alternatively, if they are not distributed at a constant rate, we would prefer to have them front-loaded at the start of the interval, so that we would capture the effect on search patterns in the same 15 minute interval, given that any increase in the information search attributable to an ad is likely to last several minutes. That is, if most commercials were shown at the end of the interval (e.g., during the 14th minute in the 15 minute interval), it is likely that the search behavior attributable to an ad would manifest itself in the subsequent 15 minute interval.

For example, one choice would be to start the intervals at the beginning of each hour, i.e., define them as (X:00-X:14; X:15-X:29; X:30-X:44; X:45-X:59, where X is a particular hour). However, ad insertions are indeed lowest during the beginning of each hour due to TV programming patterns.

We thus look at the distribution of ad insertions by minute if the 15 minute intervals are started at a particular minute. All of the possible interval definitions and the resulting distributions of ad insertions are reported in the Internet Appendix Figure IA1. Based on this inspection, we can see that commercials are not distributed at a constant rate across intervals and that starting the intervals at 3 to 7 minutes past the hour would provide us with most front-loading of commercials within the interval. As a result, we define our intervals starting at 5 minutes past each the hour. That is, our intervals are defined as X:05-X:19; X:20-X:34; X:35-X:49; X:50-X+1:04, where X is a particular hour. We perform robustness checks to this methodological choice in Section 4.3.

Internet Appendix 2: Heterogeneity by Firm

Our identification allows us to estimate the results at the firm level and study the heterogeneity of the effect. Due to computational constraints, we estimate the specification for each firm separately rather than a separate coefficient for each firm in our baseline specification.

Given that our estimation is now performed at a 15 minute interval $\times$ time zone level for each firm separately and thus we cannot include a 15 minute interval $\times$ time zone fixed effect, which in the specification (1) was defined as θ_{tk}, we alter our specification to be:

$$Ln(EdgarIPSearches)_{tk} = \beta \times Ad_{tk} + \gamma_t + \kappa_k + \epsilon_{tk} \tag{6}$$

We report the distribution of the coefficients in Internet Appendix Figure IA3.[28] As we find, 124 firms have a statistically significant positive response to the TV advertising at a 5% level. The maximum effects are 205.54% lift for Energy Transfer Partners and 148.31% lift for Harley-Davidson Motor. We report the firms with top 30 largest coefficients in Internet Appendix Table IA3 together with the number of ads and expenditure on those ads from these firms over our sample period. As one can see, top seven firms with the largest lifts had very few TV commercials over the sample period and this is consistent with the novelty effect having a strong influence on the viewer attention.

In addition, we perform a similar exercise for Google searches. Given that we have fewer firms in August 2016 sample, for comparison reasons we limit our estimation of SEC EDGAR queries to the same set of firms. As expected, we find that Google searches have a larger economic effect and are statistically significant for more firms (relative to SEC EDGAR queries) as Google searches allow for a wider information environment. Specifically, as illustrated in Internet Appendix Figure IA4, we find that around half of the firms in the sample (71 out of 156) have a statistically significant Google search response to TV advertising at a 5% level versus 29 firms with a significant positive response for SEC EDGAR queries. The mean effect, however, calculated over the significant coefficients is similar: 0.46 for Google SVI and 0.40 for SEC EDGAR queries.[29] Internet Appendix Table IA4 lists all of the 29 firms for which the SEC EDGAR search effect was significant along with the corresponding estimated Google SVI search lift. These results highlight the fact that there is a significant overlap between the sets of firms for which the effect is significant for SEC EDGAR queries and the set of firms for which the effect is significant for Google searches.

[28]The average coefficient in this distribution does not correspond to our baseline estimate due to the fact that we estimate these firm-level regressions independently and thus we do not capture the correlation between firm responses in a particular time zone at a particular time, which was previously captured by θ_{tk}.

[29]As expected, the SEC EDGAR effect is larger in August 2016 sample relative to the effect in the full sample as due to 2016 Summer Olympics a significantly higher proportion of ads have a wider reach.

Figure IA1: Ad Insertions by Minute

This figure shows different distributions of ad insertions by minute if the 15 minute intervals are started at a particular minute. For instance, the top left figure shows the aggregated distribution of commercials if intervals are started at an hour. The next figure on the left shows the aggregated distribution of commercials if intervals are started at 1 minute past the hour.

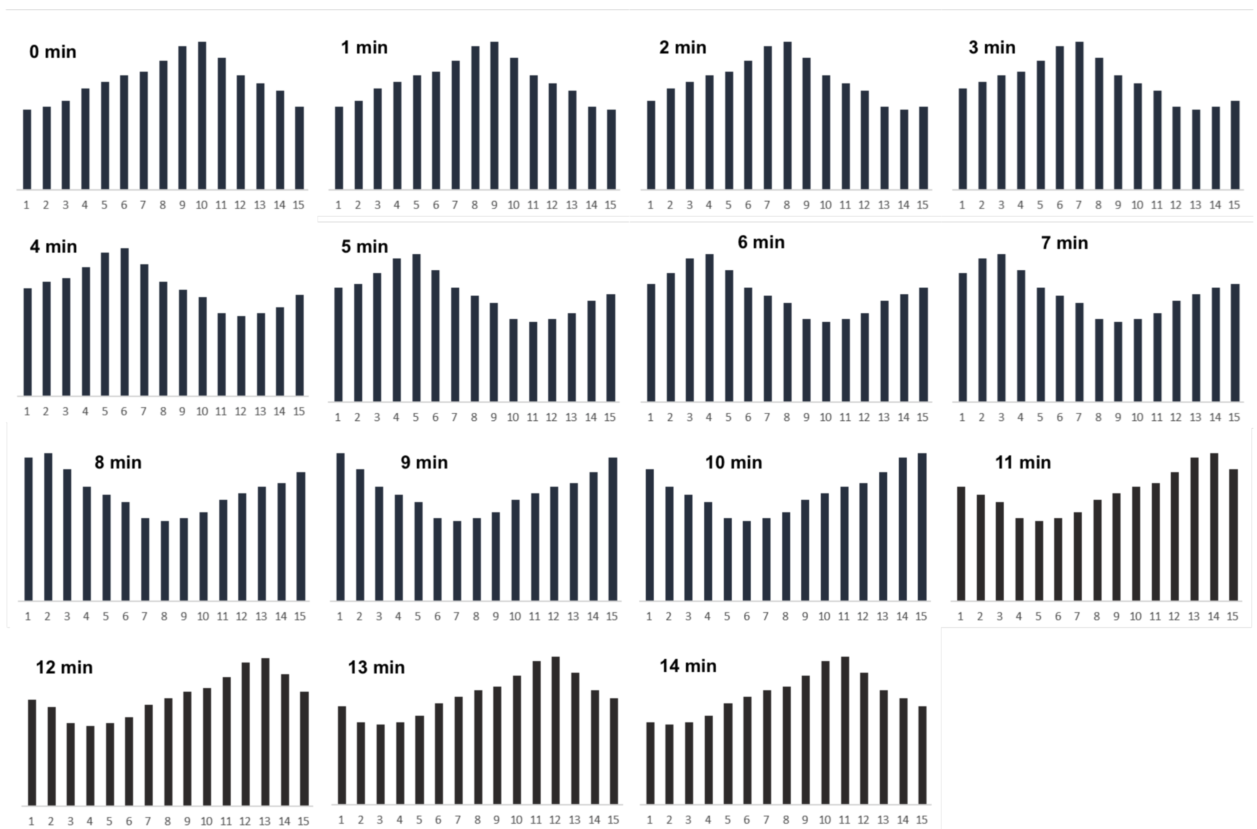


Figure IA2: Map of SEC EDGAR Queries

We create the bubble map for the total SEC EDGAR queries during our sample period by matching the IP addresses in the SEC EDGAR database to the MaxMind IP address data that contains information on the geographic coordinates - longitude and latitude. The IP addresses in SEC EDGAR data only contain the first three octets and the last part is anonymized using a static cypher (e.g., 66.208.17.efc). Since MaxMind reports locations for a range of IP addresses that are from the same location (e.g., 66.208.16.0 through 66.208.19.255 in Washington, DC), we can match the searches from the partially anonymized IP addresses in SEC EDGAR database to a specific county in the U.S. When the possible ranges of IP addresses from MaxMind map into multiple counties, we use the county that represents the majority of the IP addresses within the range. We remove the observations that are of unknown origin (MaxMind assigns U.S. IP addresses that are of unknown locations to the geographic center of the U.S., which is in the Reno County in Kansas. Approximately 4.7% of all searches in our SEC EDGAR sample database are assigned to this county).

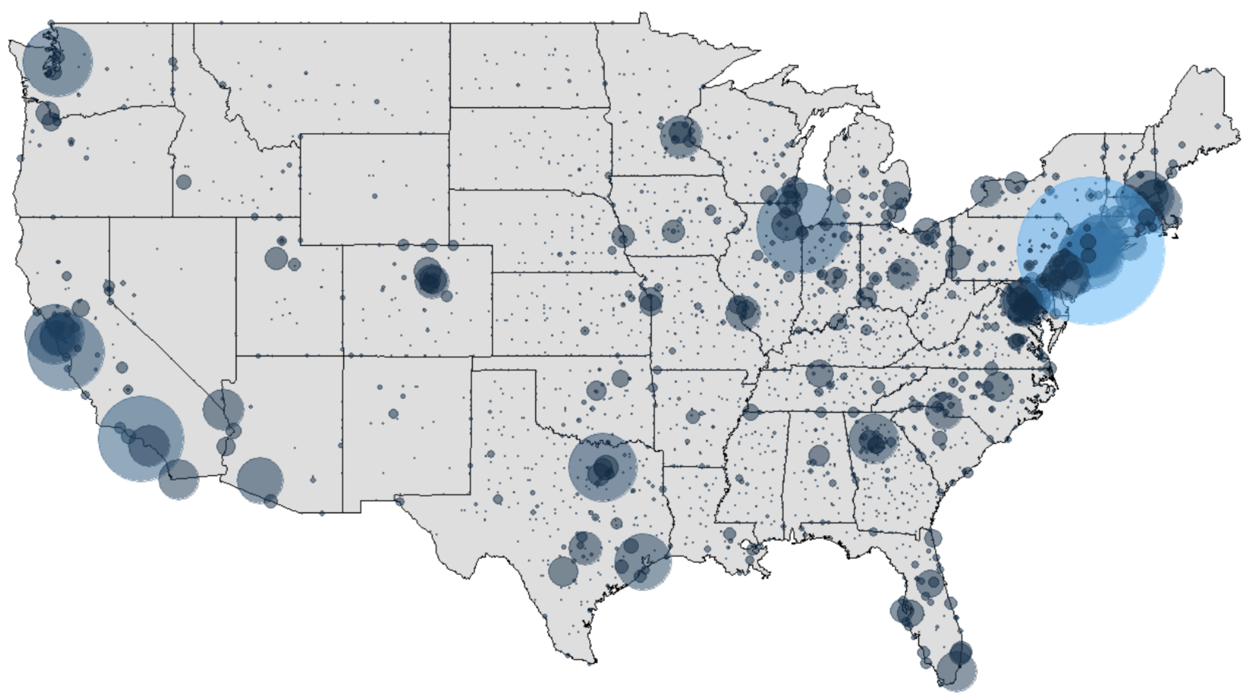
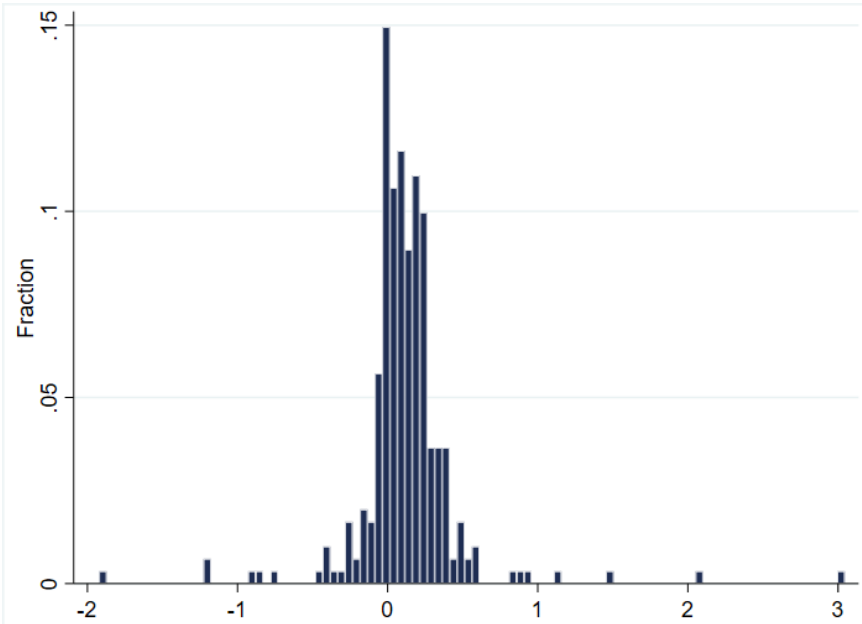


Figure IA3: Firm-Level Coefficient Estimates: SEC EDGAR

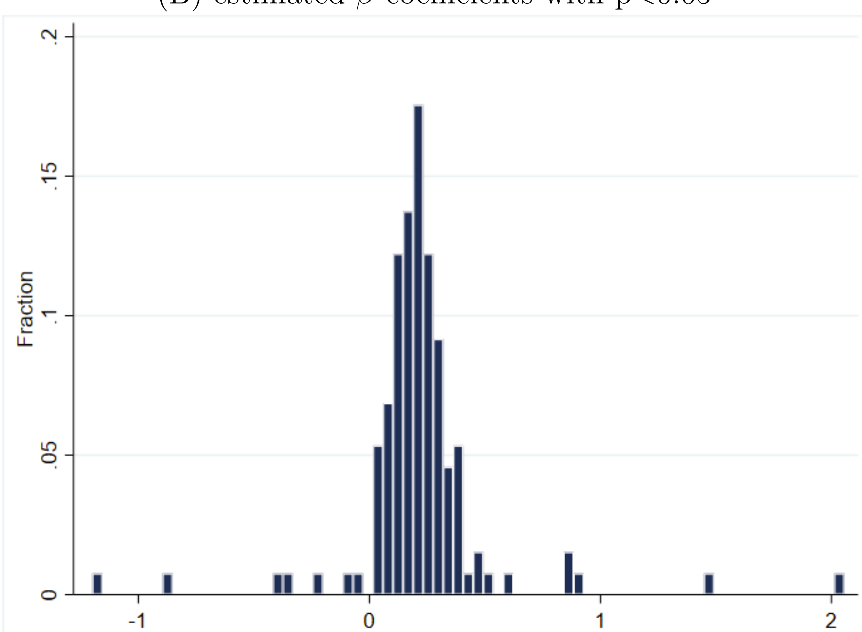
This figure plots the firm-level β coefficients estimated from the specification (6) for 301 firms in our full sample. Panel A plots all of the estimated coefficients, while panel B only plots coefficients that were estimated to be statistically significant at p<0.05 level.

(A) All estimated β coefficients



N=301

(B) estimated β coefficients with p<0.05



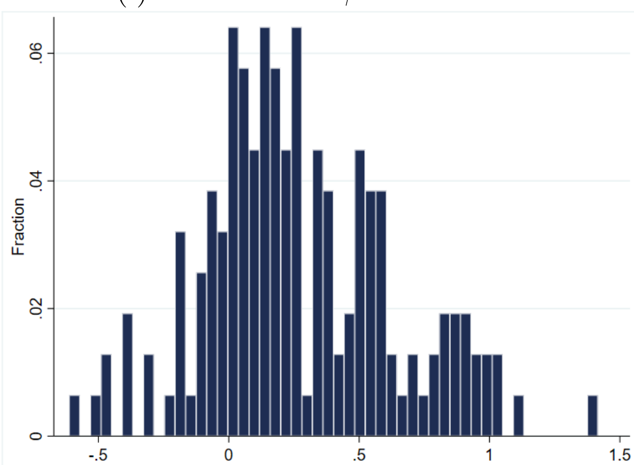
N=131

Figure IA4: Firm-Level Coefficient Estimates: SEC EDGAR and Google

This figure plots the firm-level β coefficients estimated from the specification (6) for 156 firms in our August 2016 sample. Panel A plots the estimated coefficients for Google search volume index, while panel B plots coefficients for SEC EDGAR searches restricted only to August 2016 sample. In both of the panels, the left graph (i) depicts all of the estimated coefficients, whereas the right graph (ii) plots only those coefficients that were estimated to be statistically significant at p<0.05 level.

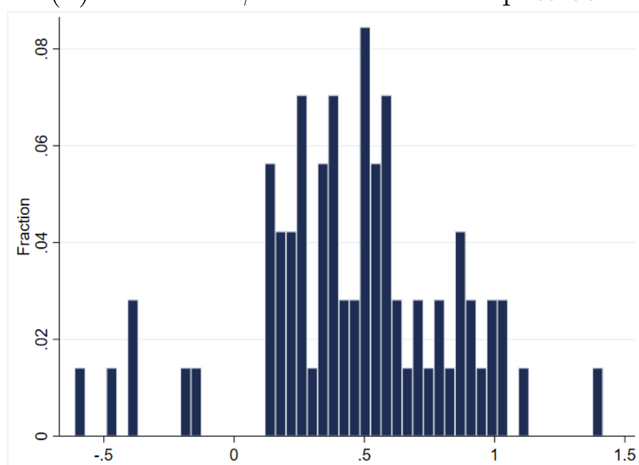
(A) Google Search Volume Index

(i) all estimated β coefficients



N=156

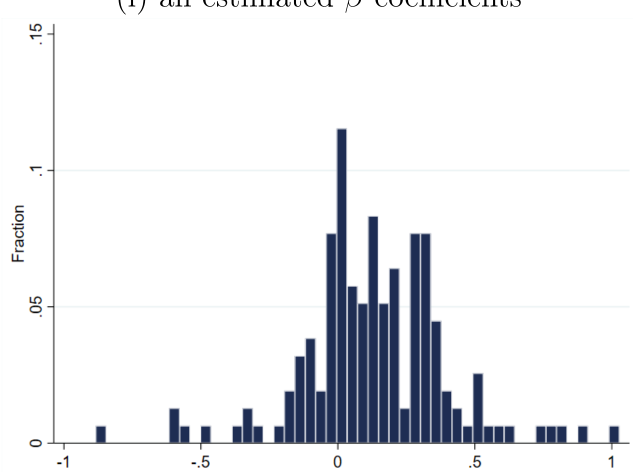
(ii) estimated β coefficients with p<0.05



N=71

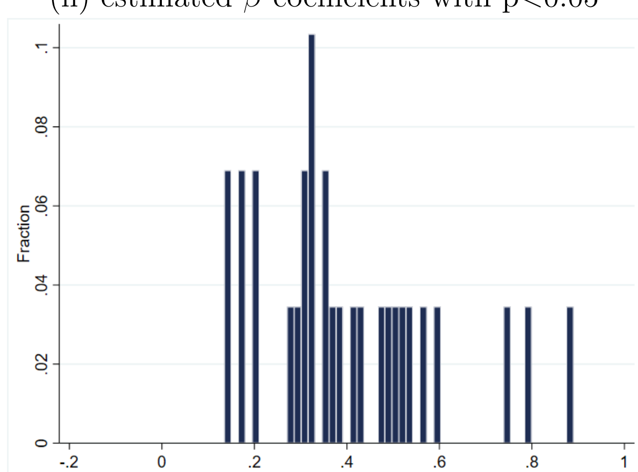
(B) SEC EDGAR Searches (August 2016 Sample)

(i) all estimated β coefficients



N=156

(ii) estimated β coefficients with p<0.05



N=29

Table IA1: Heterogeneity Tests: SEC EDGAR Search Results by Ad Creative Characteristics

This table reports results of the effect of advertising on SEC EDGAR searches by ad video creative characteristics. The explanatory variable is the net total lift in SEC EDGAR searches due to a specific ad creative. In calculating this variable, we follow equation (1) and difference out γ_{it}, κ_{ik}, and θ_{tk} from total searches during the 15 minute time interval with an ad. We then add these values across both timezones to reflect the total search lift attributable to a specific ad creative. Column (1) presents the results for a dummy variable that take a value of one if an ad was for a brand whose name sounded similar to the name of the parent company. Column (2) presents results for a dummy for the first ad in any given ad break. Column (3) presents the effect as a function of the ad length in seconds. T-stats based on the standard errors clustered at the ad creative level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Brand Like Parent	0.195***		
	5.97		
First Ad in Break		0.095**	
		2.09	
Ad Length			0.0051***
			4.53
firm x time interval f.e.	yes	yes	yes
firm x time zone f.e.	yes	yes	yes
time interval x time zone f.e.	yes	yes	yes
N	326,740	326,740	323,849

Table IA2: Heterogeneity Tests: SEC EDGAR Search Results by Industry Sector

This table reports results of the effect of advertising on SEC EDGAR searches by GICS sectors. Column (1) presents the baseline overall effect for all ads, column (2) looks only at ads that had an estimated cost of at least $50,000, column (3) presents the effect only for primetime ads, and column (4) reports the results of log of estimated ad expenditure. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) All ads	(2) Ad>$50K	(3) Primetime	(4) Ln(ad$)
Industrials	-0.001	0.001	-0.021	-0.000
	-0.062	0.053	-0.553	-0.124
Consumer Discretionary	0.017	0.022	0.027	0.001
	1.286	1.210	1.613	1.330
Consumer Staples	0.029**	0.023	0.033*	0.002*
	2.003	1.003	1.662	1.957
Pharmaceuticals	0.036**	0.041**	0.042	0.003**
	2.215	2.019	1.476	2.257
Financials and Real Estate	0.057***	0.109***	0.109***	0.005***
	2.870	3.947	2.955	2.969
Information Tech and Telecom Services	0.003	0.003	0.007	0.000
	0.073	0.057	0.137	0.083
Other (Utilities, Energy, Materials)	-0.024	-0.049	-0.068	-0.002
	0.381	0.381	-0.918	0.381
firm $\times$ time interval f.e.	yes	yes	yes	yes
firm $\times$ time zone f.e.	yes	yes	yes	yes
time interval $\times$ time zone f.e.	yes	yes	yes	yes
R-squared	0.381	0.381	0.381	0.381
N	47.1MM	47.1MM	47.1MM	47.1MM

Table IA3: Top 30 Ad-Induced SEC EDGAR Query Lifts by Firm

This table reports top 30 firms by estimated coefficient in firm-level regressions of ad effect on the SEC EDGAR queries. We report the firm name, ticker, the economic effect, T-stats based on the standard errors clustered at the industry level, and the number of ads during our sample period.

No	Parent Company	Ticker	% lift	T-stat	# of ads	Ad Exp (in $MM)
1	Energy transfer partners LP	ETP	205.54%	1.96	1	$0.02
2	Harley-Davidson motor co	HOG	148.31%	2.30	4	$0.15
3	Paypal holdings Inc	PYPL	92.26%	1.96	13	$1.27
4	Mylan Inc	MYL	87.25%	3.51	35	$1.25
5	National amusements/TW	TWX	85.89%	3.49	92	$1.28
6	Hasbro Inc	HAS	58.92%	2.02	19	$1.67
7	Dicks sporting goods Inc	DKS	52.90%	3.67	79	$36.49
8	Conagra brands Inc	CAG	48.51%	9.57	788	$44.80
9	Wyndham worldwide corp	WYN	47.82%	3.14	69	$4.22
10	Dell technologies Inc	DELL	42.54%	5.83	336	$25.82
11	Marriott intl Inc	MAR	40.34%	5.34	380	$28.64
12	AT&T Inc	T	38.99%	18.09	9,951	$632.09
13	Whirlpool corp	WHR	37.90%	3.30	129	$20.63
14	Wendys co	WEN	37.44%	7.73	934	$46.66
15	Wells fargo & co	WFC	37.24%	5.22	553	$49.61
16	Darden restaurants Inc	DRI	36.73%	12.58	2,908	$108.93
17	Yum brands Inc	YUM	36.57%	12.88	3,116	$192.56
18	Ameriprise financial Inc	AMP	36.09%	3.68	177	$17.31
19	3M co	MMM	34.82%	1.98	75	$5.02
20	Unitedhealth group Inc	UNH	33.83%	7.40	1,138	$81.99
21	Time warner Inc	TWX	33.09%	17.33	8,490	$599.05
22	Verizon communications Inc	VZ	33.02%	11.60	4,168	$382.57
23	Dunkin brands Inc	DNKN	32.45%	4.69	438	$32.73
24	L brands Inc	LB	31.71%	7.73	1,465	$84.86
25	Best buy co Inc	BBY	31.65%	5.14	816	$54.80
26	Citigroup Inc	C	31.55%	7.99	1,684	$142.56
27	Bloomin brands Inc	BLMN	30.68%	8.70	1,023	$50.81
28	Valeant pharmaceuticals intl	VRX	30.17%	6.23	1,198	$122.56
29	JP morgan chase & co	JPM	29.95%	4.93	506	$48.02
30	General motors corp	GM	29.62%	11.57	4,721	$494.37

Table IA4: Top Ad-Induced SEC EDGAR Queries and Corresponding Google Search Lifts by Firm

This table reports firms ordered by estimated significant coefficient in firm-level regressions of ad effect on the SEC EDGAR queries in August, 2016. We report the firm name, ticker, the economic effect on SEC EDGAR queries, and the economic effect on Google searches for the same firm. n.s. indicates estimate with p>0.1 that we consider not to be statistically significant.

No	Parent Company	Ticker	SEC EDGAR % lift	Google SVI % lift
1	Best Buy co Inc	BBY	88.99%	83.57%
2	Unitedhealth group Inc	UNH	79.82%	100.28%
3	Priceline.com Inc	PCLN	74.13%	25.74%
4	Dell technologies Inc	DELL	60.03%	33.81%
5	Yum brands Inc	YUM	56.81%	33.59%
6	Amgen Inc	AMGN	52.99%	n.s.
7	Brinker intl Inc	EAT	52.72%	n.s.
8	AT&T Inc	T	50.86%	13.43%
9	Allergan plc	AGN	49.56%	n.s.
10	Pepsico Inc	PEP	47.26%	48.31%
11	Clorox co	CLX	42.58%	n.s.
12	Skechers usa Inc	SKX	41.53%	n.s.
13	Campbell soup co	CPB	38.15%	n.s.
14	Progressive corp	PGR	37.32%	n.s.
15	General mills Inc	GIS	35.17%	110.17%
16	Fiat Chrysler automobiles nv	FCAU	34.83%	n.s.
17	Time warner Inc	TWX	33.04%	20.15%
18	Darden restaurants Inc	DRI	31.99%	78.17%
19	L brands Inc	LB	31.93%	10.49%
20	Abbvie Inc	ABBV	30.83%	n.s.
21	General motors corp	GM	30.71%	37.20%
22	Honda motor co ltd	HMC	29.20%	n.s.
23	Target corp	TGT	27.37%	62.64%
24	Costar group Inc	CSGP	21.01%	n.s.
25	Pfizer Inc	PFE	20.28%	21.84%
26	Procter & Gamble co	PG	17.53%	75.62%
27	Toyota motor corp	TM	17.15%	54.24%
28	Unilever	UL	14.00%	60.00%
29	Glaxosmithkline plc	GSK	13.48%	24.84%

Table IA5: Robustness of Financial Information Search on Google

This table reports results of the effect of advertising on contemporaneous Google Search Volume Index (SVI) for all advertising firms in August 2016. Column (1) presents the baseline overall effect for all ads, column (2) looks only at ads that had an estimated cost of at least $50,000; column (3) presents the effect only for primetime ads, and column (4) reports the results of log of estimated ad expenditure. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1) All ads	(2) Ad>$50K	(3) Primetime	(4) Ln(ad$)
TV Ad	0.078**	0.072*	0.091**	0.006**
	2.511	1.771	2.298	2.467
firm × time interval f.e.	yes	yes	yes	yes
firm × state f.e.	yes	yes	yes	yes
time interval × state f.e.	yes	yes	yes	yes
R-squared	0.678	0.678	0.678	0.678
N	5.75MM	5.75MM	5.75MM	5.75MM

Table IA6: Robustness Tests for the Next-Day Effect on Stock Trading Volume

This table shows the robustness results that complement the results presented in Table 6. The explanatory variable is the total lift in SEC EDGAR searches during the primetime hours in the prior day. In estimating this variable, we follow equation (1) and difference out γ_{it}, κ_{ik}, and θ_{tk} from total searches during the 15 minute time interval with an ad. We then aggregate these values across both timezones during primetime hours. In Panel A, the dependent variable is the log trading volume on a given day. In Panel B, the dependent variable is the log trading volume by retail investors as per Boehmer et al. (2017) on a given day. In both panels, column (1) considers ad effect over 10 minute interval only. Column (2) reports the results when earnings announcement days are excluded from the sample, while column (3) excludes merger announcement days. Column (4) estimates the specification with one-day lagged volume, instead of firm fixed effects. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

(A) Total Trading Volume Robustness				
	(1)	(2)	(3)	(4)
	10 min	Exclude EA	Exclude M&A	Lagged Volume
Prior Day's Lift	0.000594***	0.000535***	0.000513***	0.000187**
	2.979	4.373	3.994	2.544
Prior Day's Overall Search	0.009861***	0.010002***	0.009803***	0.003044***
	3.736	3.731	3.727	5.021
Lagged Volume				0.958267***
				351.079
Firm f.e.	yes	yes	yes	no
Day f.e.	yes	yes	yes	yes
R-squared	0.912	0.916	0.922	0.926
N	0.161MM	0.158MM	0.148MM	0.159MM

(B) Retail Trading Volume Robustness				
	(1)	(2)	(3)	(4)
	10 min	Exclude EA	Exclude M&A	Lagged Volume
Prior Day's Lift	0.000865***	0.000756***	0.000733***	0.000535***
	3.441	5.363	5.060	5.052
Prior Day's Overall Search	0.012842***	0.012953***	0.012796***	0.007451***
	3.880	3.862	3.878	5.372
Lagged Volume				0.936990***
				227.334
Firm f.e.	yes	yes	yes	no
Day f.e.	yes	yes	yes	yes
R-squared	0.887	0.892	0.887	0.895
N	0.151MM	0.149MM	0.150MM	0.151MM

Table IA7: Product Market Spillovers Based on Factset

This table summarizes the results of advertising effect on SEC EDGAR queries of the advertising firm's closest product market rivals and suppliers, based on the data from Factset, information service provider. In Panel A, we look at all rivals of the advertising firm. We present the ad effects on the advertising firm as well as on the closest product market rival. In Panel B, we look at all suppliers of the advertising firm. We present the ad effects on the advertising firm as well as on the firm's supplier. In both panels, column (1) presents the baseline overall effect for all ads, column (2) looks only at ads that had an estimated cost of at least $50,000, column (3) presents the effect only for primetime ads, and column (4) reports the results of log of estimated ad expenditure. T-stats based on the standard errors clustered at the firm level are displayed below. *, ** and *** indicate significance levels of 10%, 5%, and 1%, respectively.

(A) Rivals				
	(1)	(2)	(3)	(4)
	All ads	Ad>$50k	Primetime	Ln(ad$)
Rival TV Ad	0.013	0.028**	0.029*	0.001
	1.182	2.053	1.954	1.289
Own TV Ad	0.058***	0.055**	0.075***	0.004**
	2.643	2.21	2.778	2.481
firm × time f.e.	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes
time × time zone f.e.	yes	yes	yes	yes
R-squared	0.333	0.333	0.333	0.333
N	31.1MM	31.1MM	31.1MM	31.1MM

(B) Suppliers				
	(1)	(2)	(3)	(4)
	All ads	Ad>$50k	Primetime	Ln(ad$)
Customer TV Ad	0.003	0.009	0.005	0.000
	0.492	1.304	0.598	0.646
Own TV Ad	0.061***	0.051**	0.081***	0.004***
	2.681	2.046	2.937	2.549
firm × time f.e.	yes	yes	yes	yes
firm × time zone f.e.	yes	yes	yes	yes
time × time zone f.e.	yes	yes	yes	yes
R-squared	0.333	0.333	0.333	0.333
N	31.1MM	31.1MM	31.1MM	31.1MM