Focke, Florens; Ruenzi, Stefan; Ungeheuer, Michael

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Advertising, Attention, and Financial Markets

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Abstract

We investigate the impact of product market advertising on investor attention and financial market outcomes. Using daily advertising data allows us to identify short-term effects of advertising. We measure daily investor attention based the company's number of Wikipedia page views. We show that TV and newspaper advertising positively impacts short-term investor attention. It also positively impacts turnover and liquidity, but the effects are not economically significant. Most importantly, asset prices are not influenced by advertising in the short run. These findings are different from studies using yearly advertising expenditures and suggest that attempts to temporarily inflate stock returns via short-term adjustments to advertising are ineffective.

Keywords: Advertising, Investor Attention, Wikipedia, Turnover, Liquidity, Returns

JEL Classification Numbers: G10, G12, G14, M37

1 Introduction

In this paper, we examine whether firms can create investor attention through marketing and challenge the widely held view that firms can influence short-term stock prices via product market advertising. Existing studies agree that product market advertising is positively linked to liquidity and contemporaneous returns on stock markets.[1] The documented patterns can be explained by advertising leading to increased investor recognition (see Merton (1987)) or short-term attention effects (see Barber and Odean (2008)). Understanding the impact of marketing on capital markets is important, as it might give rise to incentives for managers to use advertising in an opportunistic way. Consistent with this idea, Chemmanur and Yan (2009) and Lou (2014) find that managers increase advertising expenditures prior to initial or seasoned equity offerings of the firm and insider sales, respectively.

However, these studies typically rely on low-frequency balance-sheet data on advertising. Thus, it is difficult for them to establish a causal link from advertising to capital market outcomes. In contrast to the earlier literature, we use a unique dataset containing high frequency advertising expenditures on the daily level to examine the impact of product market advertising on investor attention and eventually financial market outcomes. We re-address the link between advertising and stock markets by first analyzing the impact of daily advertising expenditures in newspapers and on TV on investor attention. To measure investor attention, we introduce a new proxy based on page views of the company's Wikipedia page. We provide clear evidence that abnormal advertising leads to a short-term increase in investor attention.

The existence of a positive influence of advertising on attention is a necessary condition for advertising to also influence stock markets. Thus, we then investigate the impact of advertising on turnover, liquidity, and returns. Our analysis using daily data reveals a statistically significant and stable impact of advertising on turnover. Furthermore, there is some evidence of a statistically significant positive impact of advertising on liquidity measured based on the effective bid-ask spread, but not based on price impact. However, even when statistically significant, the effects are very small in terms of economic significance. Most importantly, we find no impact of advertising on short-term returns at all. Although this is a "non-result", we think this finding is important as it casts serious doubts on the conventionally held view that advertising is an efficient way to boost short-term stock market valuations.[2]

Thus, our results are in conflict with the arguments in Chemmanur and Yan (2011) and

[1] See, e.g., Grullon, Kanatas, and Weston (2004), Frieder and Subrahmanyam (2005), Chemmanur and Yan (2011), and Lou (2014))

[2] Another argument could be made based on the idea that advertising can serve as a signal for product quality for potential customers (see e.g. Kihlstrom and Riordan (1984) and Milgrom and Roberts (1986)). If capital market participants are also uninformed about the true quality of a company's products, advertising might also offer a valuable signal to them. It seems intuitive that good product quality c.p. should be desirable from an investor's point of view (as it leads to higher sales and predicts lower warranty costs in the future). However, given that we find no impact of advertising on returns to start with, this line of reasoning seems less relevant here, too.

Lou (2014), who find a positive relationship between changes in advertising and stock market returns in the same year. However, their studies are based on annual data and consequently could be subject to endogeneity problems. Particularly, it is quite possible that firms that do particularly well within a year also increase their advertising budgets for the rest of the year. In that situation, one would indeed find a positive relationship between advertising and contemporaneous stock market returns on a yearly frequency.

The main contribution of our paper is to provide evidence that advertising does indeed create attention among investors, but that managers are wrong in assuming that they can use advertising, e.g. around security issues or insider transactions, in order to artificially increase the stock price and eventually profits.

In our empirical analysis, we use two new databases. The first database contains the number of page views of a firm's Wikipedia page aggregated on a daily level. Wikipedia data is very reliable and available for a much larger number of firms than Google search volume, an alternative proxy for attention that is used in the literature. The second database provides information on daily advertising expenditures of virtually all firms that advertise in a large sample comprising of all national newspapers and a large number of local newspapers, as well as a sample of most important local and national TV channels. To the best of our knowledge, this is the most comprehensive sample of advertising expenditures of U.S. firms with detailed information on advertising used in the literature so far. For the years 2007 to 2012, for which the two databases overlap, we find a very strong impact of advertising on Wikipedia page views after controlling for time- and firm-fixed effects. The impact lasts for several days and results obtain for newspaper as well as for TV advertising.

Furthermore, they hold and are of virtually identical magnitude after controlling for the impact of important firm-related news like earnings announcements or coverage of the firm in newspapers, showing that our results are not driven by investor attention created by fundamental news. As advertising is typically pre-determined over longer horizons than a couple of days, our high frequency analysis of the link between advertising and attention should not be plagued by serious endogeneity concerns.

Additionally, we find that advertising on a per dollar basis has a stronger impact on Wikipedia page views for advertising in business and news channels as compared to entertainment channels and for advertising in national newspapers (particularly in the Wall Street Journal) as compared to local newspapers, confirming that our proxy for attention does actually capture investor attention. Consequently, advertising seems to be a good proxy for investor attention that is unlikely to be driven by fundamental news. We think this is a great advantage for studies trying to understand the impact of attention, as earlier proxies for attention are very closely linked or directly based on news about the firm.[3] Finally, we can also show that Wikipedia is a better

[3] For example, Barber and Odean (2008) use news coverage, trading volume, and extreme one-day returns as attention proxies.

proxy to capture attention than Google search volume (which is typically also only available for the very largest firms) and advocate to use the first in future research.

In the second main part of our analysis, we link our advertising data with financial markets data. Based on data from 1995 to 2010 and 2012, respectively, we find a highly significant positive impact of advertising on TV as well as in newspapers on turnover on the same and the following one to three days. These findings are consistent with the idea that attention creates trading (Barber and Odean (2008)). Looking at various advertising channels separately, we find no clear patterns, except that newspaper advertising in the Wall Street Journal has the strongest impact on turnover. However, irrespective of the specific channel, the effects are generally not very important in terms of economic magnitudes showing that the impact of non-news driven attention on stock markets is modest at best. Furthermore, we find only very limited (no) evidence of a positive influence of advertising on liquidity based on a firm's daily effective spread (price impact).

Most importantly, there is also no impact of advertising on contemporaneous and subsequent daily returns. Again, this result obtains independent of the specific advertising channel we look at. This finding also holds based on cross-sectional sample splits based on firm characteristics and for firms with high and low media coverage. In the last step, we analyze whether we find a stronger impact of advertising on capital market outcomes for firms where attention is more sensitive to changes in advertising. To do so, we first determine how sensitively Wikipedia page views react to advertising of a specific firm. Then, we sort firms according to this advertising sensitivity into subsamples. However, even among firms with above median sensitivity of attention to advertising, there is no significant impact of advertising on returns.

Our paper complements the literature on the link between investor attention and stock markets. Barber and Odean (2008) document a positive impact of investor attention on buy-sell imbalances, arguing that attention leads to retail investor buying pressure. Similarly, Gervais, Kaniel, and Mingelgrin (2001) show that increased turnover affects the subsequent price of a stock. Consistent with these results, Da, Engelberg, and Gao (2011) find inflated stock prices during periods of increased investor attention and a subsequent reversal. They use the Google search volume index to capture investor attention.[4] Furthermore, Fang and Peress (2009) find that high media coverage leads to lower subsequent returns. We contribute to this line of the literature by using high frequency abnormal advertising as a new proxy for (non news-driven) investor attention and by showing that it increases turnover, but has no sizable effects on liquidity or short-term returns. Our proxy has the advantage that it is available on a high-frequency and is thus unlikely to be driven by fundamental news. Hence, we are better able to separate the effect of changes in the news environment from pure attention effects.

Other studies that use advertising as a proxy for investor attention are Grullon, Kanatas,

[4] Other papers that use Google search volume include Drake, Roulstone, and Thornock (2012) and Fink and Johann (2014).

and Weston (2004) and Lou (2014).[5] However, these studies use low-frequency advertising expenditures. Our study is the first to use a broad sample of high-frequency advertising expenditure data on attention and capital market variables, allowing us to make a big step towards establishing causality in the relationship between advertising and attention.[6]

Our study also informs the literature on the strategic use of advertising in a financial context. Besides the study of Lou (2014) cited above, there are also papers that argue that firms use advertising strategically around IPOs and SEOs (Chemmanur and Yan (2009)), as well as M&A transactions (Hillert, Kunzmann, and Ruenzi (2014) and Fich, Starks, and Tran (2014)). Our results contribute to this literature by showing that managers might be wrong in believing that advertising helps to push-up short-term valuations.

2 Data and Methodology

In this section, we discuss the various data sources and variables used in this study. We first describe the financial markets data we use, including liquidity proxies based on high-frequency data and media coverage data (Section 2.1). We then introduce the Wikipedia page view data and define our measure for investor attention (Section 2.2). Finally, we introduce our advertising data set and the measures for (abnormal) advertising (Section 2.3). All variables are defined in detail in Appendix A.

2.1 Financial Markets Data

Our initial sample universe consists of all stocks in the NYSE/AMEX/NASDAQ (share code 10 or 11) Compustat/CRSP universe. Daily financial market data, specifically daily stock turnover, returns and market capitalization are taken from CRSP's daily stock file. Return on assets and advertising-to-sales ratios as well as other balance sheet data are based on Compustat. Summary statistics for the sample period used in the analysis of the impact of advertising on attention (i.e., from 2007—the year in which our Wikipedia data starts, see Section 2.2—to 2012) are presented in Panel A of Table 1. Summary statistics for the sample period used in the analysis of the impact of advertising on financial markets (i.e. from 1995 — the year in which our advertising data starts, see Section 2.3 — to 2012) are presented in Panel A of Table 6.

In our analysis of advertising's impact on liquidity in Section 4, we use Trade and Quote

[5] Frieder and Subrahmanyam (2005) show a negative relationship between brand recognition and the share of institutional investors in a firm.

[6] The only exception we are aware of is a contemporaneous paper that came to our attention after conducting our analysis: Madsen and Niessner (2014) document that Google searches are higher on days with print advertising of a company. However, our advertising measure is much more comprehensive by including print and TV advertising expenditures, with the latter clearly dominating overall advertising expenditures of firms. Furthermore, we use Wikipedia rather than Google ticker searches, which we later show is a much better proxy to capture attention.

(TAQ) data from 1996 to 2010. Specifically, we calculate effective spread and price impact.[7] The effective spread is calculated as the daily transaction-weighted average of transaction prices relative to prevailing quotes. Price impact is measured as daily transaction-weighted 5-minute price impact on quote midpoints.

Finally, we obtain earnings announcement dates from I/B/E/S. The national media coverage dummy (Wall Street Journal, New York Times, Washington Post, USA Today) is based on LexisNexis data.[8] In robustness checks for our analysis of advertising's impact on investor attention, we use daily GSV data for S&P 500 firms from 2005 to 2008 from Drake, Roulstone, and Thornock (2012). The authors report that daily data was largely unavailable for firms that are not part of the S&P 500 due to the truncation by Google. Summary statistics on the GSV data are presented in Appendix C, Table A4.

2.2 Wikipedia Page Views

In order to measure investor attention, we use the daily number of page views of firms' Wikipedia pages (WIKI) for the time period from December 2007 (when Wikipedia data is first available) to December 2012. To our knowledge, we are the first to use WIKI data for a broad panel of firms.[9] On average, the Wikipedia pages of 2,019 distinct publicly listed companies are visited per day, generating 461,741 daily page views. The most similar alternative measure of investor attention is Google Search Volume (GSV), most prominently used by Da, Engelberg, and Gao (2011). WIKI—just as GSV—is a direct measure of attention, in contrast to financial market variables like trading volume or volatility, which are used in Barber and Odean (2008). This is an important feature of WIKI, since it enables us to disentangle the impact of advertising on investor attention from the subsequent impact on financial markets.

Additionally, WIKI has several advantages relative to GSV. First, it is available for a much broader set of firms on the daily level. GSV is only available above an unknown threshold (set by Google), which leads to many missing observations for sparsely searched, usually smaller firms.[10] Second, WIKI is a less noisy measure of investor attention. GSV data is usually collected for ticker symbols, because searches for company names (like 'Apple') are likely to be unrelated to investor attention. However, even spikes in Google searches for ticker symbols can be unrelated to investor attention: For example, ISIS Pharmaceuticals, Inc. has the ticker

[7] We would like to thank Olga Lebedeva and Stefan Obernberger for providing us with their data set. This data set has also been used in Lebedeva (2012) and Hillert, Maug, and Obernberger (2014).

[8] We would like to thank Alexander Hillert for providing us with the media coverage data. This data set has also been used in Hillert, Jacobs, and Mueller (2014).

[9] Moat, Curme, Avakian, Kenett, Stanley, and Preis (2013) use weekly page views for the 30 DJIA stocks. They aggregate firm-level page view counts for all 30 stocks each week to measure market-level investor attention and analyze a market timing strategy.

[10] We compare our WIKI data to the daily 2008 GSV data for S&P 500 firms provided by Drake, Roulstone, and Thornock (2012) and find that—even for these large firms—GSV is missing for 20.2% of firm-days. WIKI is never missing for these firms and non-zero for 95.4% of firm-days. This advantage should be even more important for the smaller, less visible non S&P 500 firms.

symbol 'ISIS', which we believe has since 2014 mostly been searched by Google users interested in the terror organization, not the pharmaceutical company. WIKI data is based on unambiguous identification of a firm's Wikipedia page, so that we don't need to identify and exclude firms with ambiguous tickers.[11] Furthermore, product pages (e.g., for the beverage 'Coca-Cola') can usually be separated from firm pages (e.g., for the 'The Coca-Cola Company') in cases where one can plausibly assume that users might often search for the product rather than the company. Third, WIKI is easier to interpret and comparable across firms and time, since it directly represents the number of page views for a firm's Wikipedia page. In contrast, GSV is scaled by the maximum search volume for each time window downloaded. Fourth, WIKI reliably returns the same number whenever it is downloaded, whereas GSV is calculated based on a randomly selected subset of search data, so that researchers downloading data at different points in time will work with different GSV measures. This problem is again particularly severe for smaller firms, that might or might not surpass the threshold mentioned above depending on the selected subset of search data.

Summary statistics in Table 1 confirm that WIKI data is available for a broad set of firms. 5,308 firms with common stocks (share code 10 or 11) listed on the NYSE, AMEX or NASDAQ have been included in the CRSP data set between December 2007 and December 2012. Out of these 5,308 firms, 3,058 have WIKI data (while GSV data is barely available for firms outside the S&P 500, see Drake, Roulstone, and Thornock (2012)). As might be expected, the average market capitalization of firms with WIKI data is higher than the average for the full NYSE/AMEX/NASDAQ universe ($4.7b relative to $2.8b), because many of the firms without a Wikipedia page are very small. However, summary statistics on the GSV data—presented in Appendix C, Table A4—confirm that firms with available daily GSV data are substantially larger than those with available daily Wikipedia data ($21.5b relative to the $4.7b from Table 1).

Figure 1 shows the average weekly number of page views per company. Wikipedia page views are relatively stable from December 2007 until the end of 2009.[12] Since then, they steadily increase, showing that Wikipedia gained popularity as an information source on companies.

In Figure 2 we plot the average number of WIKI page views for firms by weekdays. We observe that page views are substantially lower during weekends. Thus, we do not use the number of page views directly, but normalize ln(1+WIKI) by subtracting the median of ln(1+WIKI) on the same weekday during the last 8 weeks.[13] Abnormal WIKI for firm i on day t is thus defined

[11] We have manually checked — e.g. via headquarter location and ticker symbol — that each page we use refers to the same firm we link the page with in CRSP/Compustat. For details on the procedure we use to extract Wikipedia page view counts, see Appendix B.

[12] The spike between May 17, 2008 and July 4, 2008 seems to be caused by data errors following the inclusion of other Wikimedia projects (e.g., Wikibooks.org, Wiktionary.org, etc) in the page count system. The negative spike in September 2009 is due to server failures at Wikipedia over several days in that month. Our main results are not affected if we exclude these time periods.

[13] We use one plus the logarithm of the absolute number of page views to account for days with zero page

as:

$$AWIKI_{i,t} = \ln\left(\frac{1 + WIKI_{i,t}}{1 + median_{k\in\{7,14,...56\}}(WIKI_{i,t-k})}\right) \tag{1}$$

This normalization is analogous to the normalization of GSV in Drake, Roulstone, and Thornock (2012) and Da, Engelberg, and Gao (2011) and captures deviations from a firm- and weekday-specific benchmark.

2.3 Kantar advertising data

Our advertising dataset is from Kantar Media and is similar to the data used in Focke, Niessen-Ruenzi, and Ruenzi (2014). The dataset starts in 1995 and ends in 2012. Kantar tracks advertising of public and private firms. They provide estimates for firms' advertising expenditures in all important channels: TV (intradaily data), newspapers and magazines (daily), as well as internet, radio and outdoors / billboards (monthly). For TV and newspapers, these estimates are based on "rate cards" that indicate advertising prices depending, for example, on the length and timing of a TV spot or the size and day of the week of a newspaper advertisement. The high frequency of the TV and newspaper data enables us to cleanly identify effects of advertising. Advertising at lower frequencies (like Compustat's yearly advertising variable from financial statements) can be driven by the same latent factors that drive investor attention and financial market activity (omitted variable bias), or it can be directly caused by them (reverse causality). In the short-run—say within a couple of weeks—advertising is predetermined, which enables us to avoid these identification issues. We therefore focus on the TV and newspaper channels, which are available at the daily level.[14]

Kantar's newspaper advertising data covers a large proportion of newspaper advertising in the US. Kantar tracks all advertisements in 155 US newspapers, which include all four national as well as many important local newspapers. Total newspaper advertising expenditures tracked by Kantar from 1995 to 2012 are $328bn, whereas the Newspaper Association of America (NAA) estimates a total of $693bn for the entire newspaper industry from self-reported figures by newspaper publishing companies during this period. Thus, Kantar's tracking percentage for the whole period is nearly 50%. However, Kantar only began coverage of local newspapers in 1999. Thus, from 1999 to 2012, Kantar's tracking percentage is even higher at about 60%.

Kantar's TV advertising data covers 990 TV stations in 15 networks. In particular, it includes several news and business TV channels (CNN, CNBC, Fox News, MSNBC and CNN headline news).[15] The total of TV advertising expenditures tracked by Kantar from 1995 to 2012 is

views and for the strong skewness of the distribution of page views (see Table 1).

[14]We do not use data on magazine advertising, because magazines are published at lower frequencies (e.g., weekly or monthly) and are read throughout the time period in between issues. In contrast, TV spots are seen immediately and daily newspapers are mostly read on the same day. This allows us to attribute advertising to specific days more precisely.

[15]It does not include some other news channels like Fox Business News, NBC News or Bloomberg.

\$1,299bn.[16]

According to Kantar, TV (newspaper) advertising accounts for 59.25% (15.00%) of total advertising from 1995 to 2012. The development of advertising expenditures across the different media is shown in Figure 3. Throughout our sample period, TV is the dominant advertising channel.[17]

Figure 4 shows the development of weekly TV and newspaper advertising. The graph reveals strong seasonalities (e.g., the yearly SuperBowl spike in TV advertising). It also shows that TV advertising expenditures have increased steadily since 1995, whereas newspaper advertising has decreased.

For our analysis of advertising's impact on investor attention and financial markets in sections 3 and 4 we do not use advertising dollars directly. In order to avoid omitted variable bias through correlations between persistent latent factors (e.g. visibility of a company's products to consumer) and our dependent variable, we first normalize advertising. Due to large differences in the nature of TV and newspaper advertising, we normalize these two channels' advertising expenditures differently.

TV advertising is dominated by continuous campaigns. The average length of subsequent strictly positive expenditures for daily TV advertising by a firm in our data set is 12 days. We run an AR(7) model of current TV advertising on lagged TV advertising. Results (see Table A3 in Appendix C) show that TV advertising expenditures from $t-1$ are most relevant when predicting newspaper advertising in t. There is also a slightly increased coefficient estimate for TV advertising expenditures from $t-7$, but its magnitude of the impact of TV advertising in $t-1$ is four to five times as large. Furthermore, Figure 5 shows that there are no strong weekday effects for TV advertising. Thus, in order to prevent highly correlated regressors across the different lags, we use simple log-differences as our measure of abnormal TV advertising:

$$AA(TV)_{i,t} = \ln\left(\frac{1 + Adv_{i,t}}{1 + Adv_{i,t-1}}\right) \tag{2}$$

In contrast, newspaper advertising is dominated by campaigns in which a firm advertises on the same weekday each week, but not in between. We again run an AR(7) model of current newspaper advertising on lagged newspaper advertising. In this case, newspaper advertising expenditures of the same firm on the same day one week ago ($t-7$) is by far the most important predictor of current advertising (see columns 3 and 4 in Table A3 in Appendix C). Its impact is nearly four times as large as the impact of advertising on the previous day. Moreover, Figure 6 shows that newspaper advertising differs strongly by weekday. For instance, advertising on

[16] To the best of our knowledge, Kantar is the most comprehensive source of TV advertising data. Nielsen, MagnaGlobal and eMarketer, three other companies that offer advertising tracking data, only provide significantly smaller ad expenditure samples.

[17] This finding is confirmed by eMarketer, another ad tracking agency with a focus on digital marketing. According to their estimates, the percentage for TV (newspaper) advertising in 2012 was 39.1% (11.15%). See http://www.emarketer.com/Article/US-Total-Media-Ad-Spend-Inches-Up-Pushed-by-Digital/1010154

Sundays is more than four times larger than on Mondays. We thus normalize (similar as in our normalization of AWIKI) by subtracting the median of ln(1+advertising) on the same weekday during the last 8 weeks. Abnormal newspaper advertising for firm i on day t is defined as:

$$AA(NP)_{i,t} = \ln\left(\frac{1 + Adv_{i,t}}{1 + median_{k\in\{7,14,\ldots 56\}}(Adv_{i,t-k})}\right) \tag{3}$$

Summary statistics in Table 1, Panel C show that firms with advertising spending in Kantar are larger than firms with Wikipedia articles (\$7.4b relative to \$4.7b). These firms spend around \$80,000 (\$14,000) per day on TV (newspaper) advertising, confirming that TV is the dominant advertising channel.

The correlation between $AA(TV)$ and $AA(NP)$ is close to zero, suggesting that abnormal TV and newspaper advertising is not correlated on a high frequency and both advertising channels should be taken into account.

To arrive at our final dataset, we begin with all observations for which financial market data is available. We then merge this data with the control variables and information on advertising and WIKI (TAQ) in Section 3 (Section 4). In order to mitigate the impact of outliers on our results, we require that a firm has positive advertising on at least one day within the previous eight weeks. Summary statistics on the firm-day level as used in our regressions can be found in Appendix C, Table A1 for the investor attention regressions and Appendix C, Table A2 for the financial markets regressions.

3 Advertising and attention

3.1 Main results

The ultimate goal of our empirical analysis is to test whether advertising affects important capital market variables like short-term turnover, liquidity, and stock market returns. One necessary condition for such an effect is that advertising creates attention among potential investors. Thus, we start our empirical analysis in this section by investigating whether advertising has an impact on investor attention measured by the number of page views of a company's Wikipedia page. We focus on the Wikipedia page of the company itself rather than its products, which gives a cleaner proxy for potential investor attention (see Section 2).

Specifically, we regress daily abnormal Wikipedia page views for firm i on day t, $AWIKI_{i,t}$, on abnormal advertising of firm i on the same day, $AA_{i,t}$, as well as lags of abnormal advertising, controls lagged by seven days, and the seventh lag of the dependent variable. [18] Our regression

[18] Including the lagged dependent variable can lead to biased estimators in panel regressions (Nickell (1981)). However, this problem is only relevant in short panels. Our panel encompasses 1836 days and including the lagged dependent variable is thus unproblematic in our context. Not including the lagged dependent variable also leads to very similar results.

model is therefore:

$$AWIKI_{i,t} = \alpha + \beta_0 \cdot AA_{i,t} + \sum_{j=1}^{3} \beta_j \cdot AA_{i,t-j} + \gamma \cdot Controls_{t-7} + \delta \cdot AWIKI_{i,t-7} + \epsilon_{i,t}. \quad (4)$$

All regressions include firm fixed effects (to control for firm-specific increases in WIKI and advertising) and week fixed effects (to control for time trends in changes in WIKI and advertising). Furthermore, Wikipedia page views vary substantially depending on the day of the week (with much lower levels of page views on weekends; see Section 2.2). Although our normalization of WIKI should already partly control for this, we also include day-of-week fixed effects to purge any remaining weekday effects. We include the seventh lag of the dependent variable to account for a possible time-varying, firm-specific mean-reversion level that is not captured by control variables or time fixed effects. We use the seventh — instead of the first — lag of the dependent variable and the controls in order to avoid endogeneity with the lags of abnormal advertising: Lagged advertising may impact these variables directly and we want to capture direct *and* indirect effects of abnormal advertising on the contemporaneous dependent variable jointly. Standard errors are clustered by firm and all firm-day observations with positive advertising spending on any day within the previous eight weeks are included in the regression. Results using abnormal advertising on TV, $AA(TV)$, as dependent variable but not including any controls are shown in column (1) of Table 2.

[Insert Table 2 about here]

We find a highly significant positive impact of contemporaneous abnormal advertising on page views. The effect is statistically significant at the 1%-level. The effect of lagged advertising on days $t-1$ to $t-3$ is also positive and highly significant, with coefficient estimates being even higher than for contemporaneous abnormal advertising. A slightly lower coefficient of the contemporaneous impact of TV advertising makes sense, as some advertising might be aired only late on the day and viewers might often not have enough time to react on the same day by looking up the firm. The coefficient estimate is smaller for the impact of abnormal advertising on day $t-3$, but still substantial.[19] These findings show that the attention effect emanating from advertising lasts at least for a couple of days. That advertising can have an impact on behavior over several days is consistent with evidence from the marketing literature.[20]

In column (2) we run the same regression, but use contemporaneous and lagged abnormal advertising in newspapers, $AA(NP)$, as independent variables. Results show a very similar

[19] If we include further lags, estimates of the effect of one-day increases in advertising become smaller and eventually insignificant.

[20] For example, Aravindakshan and Naik (2010) find that the impact of product advertising on brand awareness can last for up to three weeks and Hill, Lo, Vavreck, and Zaller (2013) show that the impact of political advertising decays quickly but last for at least several days.

pattern as before. We again find a positive impact of abnormal advertising on page views and the effect is statistically significant at the 1%-level for contemporary as well as all lags of abnormal advertising. Now, the highest estimate is observed for contemporaneous advertising and decreases for lagged advertising. The fact that we now find the strongest impact of contemporaneous advertising also makes intuitive sense, as most newspapers appear in the morning and readers still have the full day to react.

The daily frequency of our data and the rich fixed effects that we include allows us to mitigate endogeneity concerns to a large extent. Earlier studies focusing on yearly advertising expenditures and their impact on contemporaneous attention or capital market outcomes face problems of reverse causality and are potentially plagued by omitted variables. As advertising is pre-determined at least in the short-term, it is very unlikely that advertising would be increased on a specific day because the firm observed that attention has increased. However, there is one remaining endogeneity concern: it is possible that firms strategically advertise more around corporate news events that they expect to trigger attention. Furthermore, Focke, Niessen-Ruenzi, and Ruenzi (2014) show that firms that advertise more are covered by newspapers more frequently. Thus, our results could be driven by news coverage that causes attention (and is positively correlated with advertising) rather than by advertising itself.

To address these concerns, we add dummy variables indicating whether there was an earnings announcement for firm i on day t, $EA_{i,t}$, and whether there was a newspaper article about firm i on day t, $News_{i,t}$. There might be other news events that create attention and that no newspaper writes about and that are not associated with earnings announcements. However, even if that is the case, our variables should capture at least the largest part of news-driven attention. Thus, if the effect we observe is really driven by strategic advertising around attention inducing news events, we should at least see a very substantial reduction in coefficient estimates. In columns (3) and (4) we repeat the same regressions as in columns (1) and (2) but include the two event dummies as well as further control variables to capture firm characteristics like previous turnover, previous return, and previous realized stock market volatility over the four week period ending one week prior to the day of the respective observation. We also include firm size on day $t - 7$ as an additional control.

As expected, we find a very strong positive impact of our two event dummies, EA and $News$, on $AWIKI$. Both coefficient estimates are positive and highly statistically significant at the 1%-level, showing that AWIKI is a very good proxy for news-induced attention by investors. However, the impact of our abnormal advertising variables on attention is not affected at all by the inclusion of the news event dummies. They all remain highly significant and the economic magnitude of the coefficient estimates is virtually identical. As our dummies likely capture the most important news events, not even observing a reduction in coefficient estimates for the impact of abnormal advertising strongly suggests that our results are not driven by high abnormal advertising around news events that create attention.

In column (5) we add both, $AA(TV)$ and $AA(NP)$, variables as well as the controls in the same regression.[21] Coefficient estimates for both sets of variables are virtually unchanged as compared to the results from column (3) and (4), respectively. This pattern shows that there is no strong correlation between abnormal advertising in newspapers and on TV, that is, not many firms seem to spend more advertising dollars at the same time for newspaper advertisements and for TV spots.[22]

The size of the coefficient estimate for the impact of the AA variables can also be interpreted economically. As they are measured as natural logarithm and $AWIKI$ is also a natural logarithm, we can directly interpret the coefficient estimate as an elasticity. Based on column (5), we find that increasing abnormal TV advertising by one standard deviation on a specific day leads to an increase in abnormal page views of $2.16 \cdot 0.086\% = 0.186\%$ on the same day. Similarly, increasing abnormal newspaper advertising by one standard deviation on a specific day leads to an increase in abnormal page views of $3.18 \cdot 0.128\% = 0.407\%$. To put these numbers into perspective, they can be compared to the impact of major news events like earnings announcements. The impact of EA in column (5) is 0.09738, i.e. page views on an earnings announcement day are 9.74% higher. Similarly, on a day with corporate news that a newspaper reports about, page views are 8.68% higher. While the impact of EA and $NEWS$ is clearly much larger than the impact of doubling advertising expenditures, one has to bear in mind that earnings announcements only happen four times per year and the average firm in our sample is covered on only 6.6 days per year in a newspaper article, while advertising occurs on a daily level and large percentage changes in advertising from one day to the next happen very frequently [23].

While the coefficient estimates for the impact of lagged abnormal advertising on TV and in newspapers are somewhat larger for TV but generally of comparable magnitude, one has to bear in mind that the amount of advertising dollars spent on TV is a magnitude larger than the amount spent on newspaper ads; while the firms in our sample spend on average 14,108 USD per day for newspaper advertising, this number is nearly six times as large at 79,846 USD for TV advertising (see Panel C in Table 1). Thus, on a per-dollar basis, newspaper advertising has a stronger impact than TV advertising.

Finally, in column (6) we look at an alternative proxy for attention that has been used in the finance literature before, namely Google search volume for a company ticker. To check whether this proxy is also suitable to capture (non-news driven) attention, we replace our dependent variable from the regression in column (5) by the abnormal Google search volume index, $ASVI_{i,t}$,

[21] The number of observations in this regression is somewhat larger than in columns (1) through (4). This increase is driven by the requirement that a firm needs to have positive advertising in the previous eight weeks *either* on TV *or* in newspapers, while in column (1) and (3) ((2) and (4)) we require positive advertising on TV (in newspapers).

[22] The correlation between $AA(TV)_{i,t}$ and $AA(NP)_{i,t}$ is 0.0022.

[23] For summary statistics on abnormal advertising, see appendix C, Table A1

from Drake, Roulstone, and Thornock (2012). We still observe a highly significant impact of EA and $News$, but the coefficient estimate is slightly (substantially) reduced for the impact of earnings announcements (newspaper articles) as compared to our previous results.[24] More importantly in our context, the impact of advertising on Google search volume is only significant for contemporaneous newspaper advertising and its first lag, while it is virtually always insignificant for the impact of TV advertising. This finding shows the advantage of using Wikipedia page views as a much more precise measure of attention than Google search volume as explained in more detail in Section 2.

3.2 Advertising Channels

So far, we show that advertising on TV as well as in newspapers has a strong impact on attention. We now examine different advertising channels in more detail. Specifically, with regard to TV advertising, we distinguish between advertising in news and business channels and other TV channels. With regard to newspaper advertising, we distinguish between advertising in local and national newspapers and specifically look at the Wall Street Journal, which is presumably the most important national newspaper for investors.

We start by splitting up TV advertising into advertising on CNN, CNBC, Fox News, MSNBC and CNN headline news and advertising on all other TV channels. The first channels are news or business channels, while the other channels mainly include pure entertainment channels. It is plausible that potential investors are more likely to watch news and business channels than other channels. Although the fraction of advertising dollars spend on spots in these channels is much lower (see Table 1), still finding an impact of advertising in $AWIKI$ here would reinforce our prior evidence that advertising also creates attention among potential investors. The results are presented in Table 3.

[Insert Table 3 about here]

In column (1) we present results from the same regression as in column (3) from Table 2, but calculate abnormal advertising only based on advertising dollars spent by the firm in one of the news or business channels, $AA(TVNWS)$. We still find a highly significant positive impact of current abnormal advertising and its lags on $AWIKI$. The coefficient estimates are even slightly larger than in Table 2. In column (2) we calculate abnormal advertising based on advertising in all other TV channels, $AA(TVNONWS)$. Results are again similar, but now coefficient estimates are slightly smaller than before. In column (3) we include both abnormal advertising variables, $AA(TVNWS)$ and $AA(TVNONWS)$, in one regression. The impact of all abnormal advertising variables is now slightly reduced in economic terms as compared to column (1) and (2), respectively. However, they are still all highly significant and the impact of $AA(TVNWS)$

[24] The economic magnitude of the impact of earnings announcement days and national newspaper articles on $ASVI_{i,t}$ is comparable to results from Drake, Roulstone, and Thornock (2012).

is still higher than that of $AA(TVNONWS)$, meaning that doubling advertising expenditures on news channels has a larger impact on the percentage increase in our attention proxy than doubling advertising expenditures on non-news channels. This pattern becomes much stronger, if we look at advertising on per dollar basis again. Firm spend on average 1,114 USD per day on advertising in news channels and 78,723 USD per day on advertising in all other channels (see Table 1). These patterns show that impact of an increase in abnormal advertising on a per dollar basis is more than 80 times as large for news channels than for other channels. On the one hand, this further supports the view that $AWIKI$ is a good proxy for investor attention. On the other hand, it shows that firms trying to attract investor attention should focus their advertising to news channels.

Looking at newspapers, we find a similar pattern. Here, we first split up newspapers into local and national newspapers, where the latter comprise of the New York Times, USA Today, the Washington Post, and the Wall Street Journal (WSJ). Results for the impact of abnormal advertising in local and national newspapers, $AA(NPLOC)$ and $AA(NPNAT)$, are presented in columns (1) and (2) of Table 4.

[Insert Table 4 about here]

In both cases, current and lagged abnormal advertising has a highly significant positive impact on $AWIKI$. Overall, the coefficient estimates are of similar size; while the impact of contemporaneous abnormal advertising and its second lag are stronger for national papers, the first and third lag of abnormal advertising is stronger in local newspapers. However, once we take into account that the average firm advertises nearly five times as much per day in local newspapers than in national newspapers (see Table 1), we can conclude that the impact of advertising is economically much stronger for national than for local newspapers on a per dollar basis. While it seems plausible that investors rely on national newspapers more than on local newspapers, we dig deeper into this issue by splitting up abnormal advertising in national newspapers into abnormal advertising in the Wall Street Journal, $AA(NPWSJ)$, and in the other three national newspapers, $AA(NP3NAT)$. Results are presented in column (3). Although $AA(NPWSJ)$ only captures advertising in one individual newspaper, we still find some significant effects. The impact of contemporaneous abnormal advertising and the second lag (first lag) are still statistically significant at the 1% (10%) level. Very similar results are obtained once we also include local newspaper advertising in the regression again in column (4). The impact of advertising in the other three newspapers is still highly significant for all lags and coefficient estimates are somewhat larger. However, they only indicate how much $AWIKI$ increases in percentage terms if, e.g., abnormal advertising doubles in all three other papers. Given that average daily advertising in by our sample firms in the Wall Street Journal amounts to 780 USD, while it amounts to 1,671 USD in the three other papers, the impact of advertising in the Wall Street Journal on a per dollar basis is significantly larger than the impact in the other three national newspapers.[25]

3.3 Stability tests

We now investigate the robustness of our hitherto findings by looking at cross-sectional sample splits, assessing the temporal stability of the relationships, and using alternative advertising definitions. All results are presented in Table 5.

[Insert Table 5 about here]

In Panel A we present results based on TV advertising. In the upper left part of the panel we split the sample into firms that belong to consumer industries and firms that belong to other industries and run the same regression as in column (5) of Table 2. We only show the impact of $AA(TV)_t$ and $AA(TV)_{t-1}$, but the other two lags as well as the same controls as before are included in the regression. We find highly significant coefficient estimates for both subsamples. As one might expect, the effect is somewhat stronger for firms from the consumer industry whose name might be more familiar to the viewers, but it is still substantial in non-consumer industries, too. In the following two columns, we split the sample according to the firms' media coverage. The low (high) media coverage sample contains all firms with a below (above) median number of national newspaper articles mentioning the firm over the previous 12 months. We now find a stronger effect among firms with low media coverage. In this case, the coefficient for contemporaneous as well as lagged abnormal advertising is positive and highly statistically significant, while it is insignificant for contemporaneous AA among firms with high media coverage. The coefficient estimates are also much larger in the first case. Thus, creating attention through advertising is particularly effective for firms that are not in the public limelight due to their low press coverage.

In the lower left part of the panel we split our sample period into the earlier years 2007 to 2009 and the later years 2010-2012. Despite the relatively short subample periods, we still find highly significant coefficients which are of similar magnitude as in the overall sample, confirming that our results are robust over time.

Finally, we replace our AA variables by more coarse and endogeneity-prone advertising measures. In the third column we define advertising as the natural logarithm of 1 plus the dollar amount spent on TV advertising by the respective firm, $Log(1 + Ad\$)$. In the last column, we replace AA by a dummy variable that takes on the value one, if the firm spent at least one USD on advertising on TV on the respective day, and zero otherwise, $\mathrm{I}_{Ad\$>0}$. In both cases, we still

[25] Based on column (4), we can calculate the impact of increasing advertising in the three other national newspapers by one standard deviation, i.e. increasing advertising by 10,911 USD, and compare the impact with the same USD advertising increase in the WSJ, which would mean a $10,911/780 = 1,399\%$ increase in WSJ advertising. This would lead to an increase of 0.81% (=0.124%·6.53) in the case of the three other papers and to an increase of 1.34%(=0.096%·13.99) in the case of the WSJ.

find positive coefficients of advertising on attention and the impact of contemporaneous as well lagged advertising is significant at the 1%-level.

Overall, the results from this section provide evidence that advertising does create attention. The stronger impact of advertising in the WSJ than in other papers and the stronger impact of news- and business channel advertising as compared to other channels clearly suggests that Wikipedia page views are a good way to capture attention not only in general, but among potential investors in particular.

4 Advertising and financial markets

4.1 Main results

The main purpose of our analysis is to identify the effect of product market advertising on financial markets. In Section 3 we measure a clear impact of advertising on investor attention, which is a necessary condition for short-term effects of advertising on financial market variables. We now analyze the most important equity market variables: turnover, liquidity and returns. Turnover is measured by the log of daily trading volume, scaled by shares outstanding. Our liquidity measures are the log of effective spread and the log of price impact, both based on TAQ-data (for more detailed variable descriptions, see Section 2 and the variable description in appendix A). Returns are measured in excess of that day's market return, constructed from the Fama-French model's market-return factor.[26] Similar to the analysis for investor attention, we regress each dependent variable for firm i on day t, $DV_{i,t}$, on contemporaneous abnormal advertising, $AA_{i,t}$, as well as lags of abnormal advertising, controls and the seventh lag of the dependent variable.[27]

$$DV_{i,t} = \alpha + \beta_0 \cdot AA_{i,t} + \sum_{j=1}^{3} \beta_j \cdot AA_{i,t-j} + \gamma \cdot Controls_{t-7} + \delta \cdot DV_{i,t-7} + \epsilon_{i,t}. \quad (5)$$

All regressions include firm fixed effects (e.g. to control for permanently higher turnover of firms with persistently increasing advertising expenditures) and week fixed effects (to control for market-wide time trends, e.g. business-cycle effects). Furthermore, we include day-of-week fixed effects (to control for weekly seasonality, e.g. turnover and liquidity tend to be lower on Mondays). We include the seventh lag of the dependent variable to account for a possible time-varying, firm-specific mean-reversion level that is not captured by control variables or time

[26] We use the daily factor portfolio returns and risk free rate provided on Kenneth French's web page to construct Fama-French market returns.

[27] Including the lagged dependent variable *and* firm fixed effects can lead to biased estimators in panel regressions, see Nickell (1981). However, this problem is only relevant in short panels. Our panel regressions use a minimum of 3777 trading days and including the lagged dependent variable is thus unproblematic in our context.

fixed effects. Control variables and the dependent variable are lagged by 7 days instead of 1 day in order to avoid endogeneity with the lags of abnormal advertising: Lagged advertising may impact these variables directly and we want to capture direct *and* indirect effects of abnormal advertising on the contemporaneous dependent variable jointly. Again, reverse causality or omitted variable bias should not be problems for our analysis since advertising is determined more than a week before it is broadcast. Standard-errors are clustered by firm and we require firms to have advertised at least once during the last eight weeks to be included in the regression. For the analysis of advertising's impact on returns, we additionally run the more common Fama-MacBeth regression in order to better control for cross-sectional correlation in errors.[28] Results for abnormal TV advertising, $AA(TV)$ are shown in Table 7.

[Insert Table 7 about here]

We find a positive impact of TV advertising on turnover (see column (1) in Table 7). The effect is statistically significant at the 5%-level. Lagged effects of TV advertising changes exist. An advertising campaign starting yesterday has a larger effect on today's turnover than on yesterday's turnover, probably because a lot of investors do not trade in response to an ad until after trading closes.[29] However, the effect seems to be short-lived, since a campaign starting two or three days ago has a smaller effect on today's turnover than campaigns starting today or yesterday. The standard deviation of $AA(TV)$ is 2.28, so that a one standard deviation change in TV advertising increases turnover by $2.28 \cdot 0.044\% = 0.10\%$ contemporaneously and $2.28 \cdot 0.051\% = 0.12\%$ tomorrow. For comparison: National newspaper coverage about a firm goes along with 15.95% more turnover on the same day and there is around 49.71% more trading on earnings announcement days. Of course advertising varies all the time, whereas national newspaper coverage (on average less than 14 days per year, standard deviation of 0.22, see Table A2 in the appendix) and earnings announcements (four per year, standard deviation of 0.12) happen infrequently. However, even the respective one standard deviation impacts of $0.22 \cdot 16\% = 3.51\%$ (newspaper coverage) and $0.12 \cdot 50\% = 5.97\%$ (earnings announcements) are large, relative to the impact of abnormal advertising.[30] Hence there is a statistically significant, but economically small positive effect of TV advertising on turnover.

The effect of TV advertising on illiquidity is consistently negative (see columns (2) and (3) in Table 7), but only statistically significant at lags two and three for the effective spread measure. This is consistent with an increase in noise trading due to product market advertising. Increased noise trading lowers adverse selection costs, so that liquidity improves. Grullon,

[28] We use Newey-West standard errors with 5 lags.

[29] For this analysis we measure TV advertising for day t from 4 pm on day $t-1$ to 4 pm on day t, so that evening TV ads on day t are counted towards advertising on day t+1.

[30] A qualifier: Advertising is determined a few weeks in advance, so that we can interpret the effect we measure for advertising as causal. Newspaper articles and earnings announcements of course come along with fundamental news, which might also cause trading. Hence we expect an upward bias in these coefficients, relative to the true causal effect. Therefore the comparison of economic significance is indicative only.

Kanatas, and Weston (2004) find that firms' advertising expenditures on the yearly level are contemporaneously positively correlated with liquidity, which is consistent with our results. However, relative to their results, the economic significance we measure is small. Contemporary effects are $2.28 \cdot (-0.047\%) = -0.11\%$ and $2.28 \cdot (-0.024\%) = -0.05\%$ for the effective spread and price impact, respectively.[31] As an illustration, the estimated effect on a stock with an effective spread of 100 basis points is an order of magnitude less than 1 basis point, whereas Grullon, Kanatas, and Weston (2004) estimate an effect of 4-8 basis points. Hence, consistent with a small increase in noise trading activity, liquidity improves slightly.

One could expect an increase in prices due to attention-induced buying after TV ads, as proposed and tested for investor attention in general by Barber and Odean (2008). In fact Lou (2014) finds a strong contemporary positive correlation between advertising and returns on the yearly level, and interprets his findings as evidence for a *short-term* price impact of advertising. A short-term price impact of advertising should become even more visible at higher frequencies, since the price impact and reversal periods can be clearly separated. However, we find no economically significant impact of TV advertising on returns (see columns (4) and (5) in Table 7). If anything, Fama-MacBeth regressions suggest a negative impact.[32] The absence of a temporary price increase is consistent with our finding that liquidity improves after TV ads, even in the short run. A price increase as in the model by Barber and Odean (2008) should rather be accompanied by *decreases* in liquidity (due to increased inventory holding costs after attention-induced order imbalances).

Results for abnormal newspaper advertising, $AA(NP)$ are shown in Table 8. As for TV advertising, we find a statistically significant, positive impact of newspaper advertising on turnover, see column (1). The impact is significant at the 1%-level. Again, there are lagged reactions to advertising: Increased advertising yesterday and the day before have a stronger impact on today's turnover than contemporaneous newspaper advertising. The effect is short-lived, since it becomes insignificant at higher lags. The standard deviation of $AA(NP)$ is 3.01, so that a one standard deviation increase in abnormal newspaper advertising today leads to $3.01 \cdot 0.032\% = 0.10\%$ more contemporary turnover and $3.01 \cdot 0.050\% = 0.16\%$ more turnover two days from today. As for TV advertising, this economic effect is one to two orders of magnitude below the estimates for earnings announcements and national newspaper coverage. Thus we find a statistically significant, but economically small effect of newspaper advertising on turnover.

[Insert Table 8 about here]

The effect of newspaper advertising on illiquidity is mostly negative (see columns (2) and

[31] For comparison: Grullon, Kanatas, and Weston (2004) estimate an elasticity of relative spreads (price impact) w.r.t. Compustat's advertising of -4.7% (-8.0%) for the years 1993-1998.

[32] The one standard deviation impact of TV advertising on returns is $2.28 \cdot (-0.001\%) = -0.002\%$, which is less than a quarter of a basis point per day, i.e. less than $\frac{260}{400} = 0.65\%$ per year.

(3) in Table 8), but only statistically significant at the second lag for newspaper advertising's impact on effective spreads. The economic significance remains small: the largest impact is $3.01 \cdot (-0.039\%) = -0.12\%$, which implies a change in effective spread an order of magnitude below one basis point for a stock with an effective spread of 100 basis points. As for TV advertising and consistent with a small increase in noise trading activity, liquidity improves slightly.

The impact of newspaper advertising on returns (columns (4) and (5) of Table 8) is insignificant. Again, this is consistent with the relatively small increases in turnover and the improvement of liquidity due to advertising. None of the coefficients are statistically significant and economic significance is even lower than for TV advertising.

In summary: We find a significantly positive impact of product market advertising on turnover. The effect is economically small and additional trading seems to increase liquidity, rather than decreasing it. We do not find an economically significant price impact of advertising. The bottom line may be that markets react more efficiently to advertising-induced attention than could be expected based on previous studies that use yearly advertising data.

4.2 Advertising channels

Although we find that the impact of general product market advertising on financial markets is economically small, it may still be that advertising that is more visible to investors has a larger impact. To test this idea, we now turn to an analysis of subsets of our advertising channels as in Section 3.2. For TV, we distinguish news and business channels from all other channels. For newspapers, we consider the Wall Street Journal as well as other national and local newspapers separately.

While it seems plausible that advertising on news and business channels is more likely to reach investors, these channels only account for less than two percent of overall TV advertising spending (see Table 6). Hence, one needs to keep the different dollar values associated with the percentage changes given by the coefficients in mind. Specifically, an equally sized coefficient on the two measures would imply a 50 times larger per dollar impact of news and business TV advertising.

We begin our analysis by regressing our dependent variables on measures of abnormal news and business channel advertising, $AA(TVNWS)$, and abnormal advertising in all other channels, $AA(TVNONWS)$. The set of control variables and fixed effects is the same as in Section 4.1. Table 9 presents the results.

[Insert Table 9 about here]

Column (1) shows that the effect of advertising on turnover is consistently positive across the two measures. However, only the contemporaneous effect of $AA(TVNONWS)$ is significant.

When we consider the dollar impact associated with the coefficient estimates, the effect of contemporaneous advertising on turnover is of similar magnitude for both types of channels, while the effects associated with lags of advertising are substantially larger for $AA(TVNWS)$ than for $AA(TVNONWS)$. Therefore, it is possible that the insignificant results on $AA(TVNWS)$ are caused by insufficient power to measure such a small effect or noise in the variable due to the low overall dollar level.

For our measures of illiquidity, we find a substantially stronger effect both in statistical and economic terms for $AA(TVNWS)$ than for $AA(TVNONWS)$. As can be seen in column (2), the coefficients on lags one to three of $AA(TVNWS)$ are significant at least at the 5% level for $EffSpr_t$. Except for lag two, which is significant at the 10% level, $AA(TVNONWS)$ is insignificant. Column (3) reveals a similar pattern for $PrcImp$ in that lags one and two are significant at the 5% and 10% level, respectively, for $AA(TVNWS)$ and all coefficients are insignificant for $AA(TVNONWS)$. The economic significance of all coefficients on $AA(TVNWS)$ is substantially higher in absolute terms than for $AA(TVNONWS)$. For instance, the coefficients on the first lag in column (2) imply that a campaign starting on day t-1 and doubling the amount of advertising spent in news and business (other) TV channels is associated with a decrease in $EffSpr_t$ by 0.24% (0.06%). Given that advertising spending on news and business TV is 50 times smaller than on all other channels, this suggests a substantially stronger effect of news and business TV advertising on illiquidity.

When we investigate the effect on returns, we find no effect of either $AA(TVNWS)$ or $AA(TVNONWS)$ (see columns (4) and (5)), consistent with our earlier result that return effects are negligible. Overall, the results suggest that news and business TV advertising does not have a stronger effect on turnover or returns, but it does have a stronger (i.e. more negative) effect on illiquidity than advertising in other TV channels.

Next, we study the effect of advertising in specific newspapers by computing abnormal advertising separately for the Wall Street Journal, $AA(NPWSJ)$, the other three national newspapers (New York Times, USA Today, Washington Post), $AA(NP3NAT)$, and for all local newspapers $AA(NPLOC)$. Advertising in the Wall Street Journal (the other three national newspapers) is about 5 (4) times smaller than aggregate advertising in the 151 local newspapers, so that the coefficients need to be interpreted accordingly in dollar terms. Results are presented in Table 10

[Insert Table 10 about here]

Column (1) shows that the effect on turnover is strongest for $AA(NPWSJ)$. For lags one to three, the coefficient on $AA(NPWSJ)$ is significant at least at the 5% level, whereas it is insignificant for the other three national newspapers and significant to a similar extent for the local newspapers. Except for the contemporaneous effect, the coefficients on all lags of advertising are largest for $AA(NPWSJ)$. For instance, the coefficients on the first lag imply that doubling the amount of advertising spent in the Wall Street Journal (local) newspapers is associated with an increase in turnover by 0.07% (0.03%). Since five times less advertising dollars are spent in the Wall Street Journal alone compared to all local newspapers, this suggests that the economic impact on turnover is strongest for $AA(NPWSJ)$.

We find no significant impact of $AA(NP3NAT)$ or $AA(NPLOC)$ on our measures of illiquidity (see columns (2) and (3)). For $AA(NPWSJ)$, the coefficients are negative, but not significant, for the contemporaneous effect and the first two lags. In the third lag, we observe a positive coefficient that is significant at the 1% level. This suggests that illiquidity increases following an increase in advertising in t-3. Given that the other coefficients are consistently negative, we conclude that there is also no strong effect of $AA(NPWSJ)$ on illiquidity. On returns, we also find hardly any effects, especially in the Fama-MacBeth regression (see columns (4) and (5)).

The above results suggest a larger impact of news and business media advertising on illiquidity (for TV) and turnover (for newspapers). There is no strong difference between the different advertising channels for returns (for both media), turnover (for TV) and illiquidity (for newspapers). Importantly, our results show that even for news and business media advertising, which is more likely to reach investors, the size of the effect on financial market outcomes is small.

4.3 Advertising sensitivity

Having studied the impact of different advertising channels, we now turn to cross-sectional differences between firms. It may well be that the effects of advertising differ by firm. For example, some firms might be relatively unknown to investors ex-ante or might have particularly effective marketing plans so that advertising is more effective in attracting investor attention for them. We study some of these determinants by cross-sectional sample splits based on observable firm characteristics in Section 4.4. In this section, we take a more general approach by *estimating* the advertising sensitivity of each firm's investor attention directly and then splitting the sample based on this sensitivity. This approach offers the advantage that we do not require the identification of observable characteristics that determine the sensitivity of the firm's investor attention to advertising. To estimate firms' advertising sensitivity, we repeat the regressions from Section 3 separately for each firm. Hence, we regress $AWIKI$ on contemporaneous advertising as well as its first three lags and use the full set of control variables, $AWIKI_{t-7}$ and day-of-week fixed effects. These regressions are computed for TV and newspaper advertising separately to allow advertising sensitivity to differ by medium. To reduce the noisiness of our results, we require that there be at least 50 observations on each firm and that all advertising coefficients can be estimated. This results in valid estimates for 998 (1098) firms in the TV (newspaper) regressions. The lower number of estimates for TV is due to some firms not advertising on TV. The advertising sensitivity for each firm is the sum of the four advertising coefficients. We then split the sample at the median of the estimated sensitivity and run the same regressions as in 4.1. We expect the effect of advertising to be stronger in the high advertising sensitivity group. In Table 11, we present results from this sample split for TV advertising.

[Insert Table 11 about here]

Panel A shows that the only significant coefficient in the low sensitivity group is a negative contemporaneous effect on returns in the Fama-MacBeth regression in column (5). However, the other lags in column (5) are positive and all other advertising coefficients across columns (1) to (4) are insignificant. Hence, we conclude that we find no significant effect of advertising on financial markets in the low advertising sensitivity group.

Panel B presents the results for the high sensitivity group. For turnover, column (1) shows that the coefficients are slightly larger than for low sensitivity firms for lags two and three and significant at the 5% level for lag 2. For our measures of illiquidity, columns (2) and (3) show that the coefficients on advertising are always larger, in absolute terms, in the high sensitivity group. For lags one to three, they are also significant at least at the 10% level for $EffSpr$, although the coefficients are insignificant for $PrcImp$. For turnover and illiquidity, our results therefore appear somewhat stronger for high advertising sensitivity firms compared to low sensitivity firms. However, the confidence intervals are quite wide and often overlapping. For instance, the 10% confidence interval for the first lag of $AA(TV)$ on $EffSpr$, where the difference is strongest, is [-0.00122, 0.00081] in the low sensitivity sample (see Table 11, panel A, column (2)) and [-0.00267, -0.00013] in the high sensitivity sample (see Table 11, panel B, column (2)). Moreover, even the largest effects accommodated by our results are still economically small. The lower bound of the interval in the high sensitivity sample, -0.0027, implies that a campaign starting yesterday with a one standard deviation increase in $AA(TV)$ is associated with a decrease in $EffSpr$ by 2.28*(-0.27%)=-0.61%. For returns, we only find the coefficient on the second lag to be positive and significant in the panel regression, but not in Fama-MacBeth (see columns (4) and (5)). We therefore conclude that the advertising effect appears to be somewhat stronger for high sensitivity firms, but even in the high sensitivity group, where we would expect the strongest effect, the impact of advertising on financial market outcomes remains small.

Next, we conduct the same sample split for newspaper advertising. The results are presented in Table 12.

[Insert Table 12 about here]

Panel A shows that we find hardly any effect of advertising on our dependent variables in the low sensitivity group. The only significant coefficient is now the second lag of $AA(NP)$ on turnover, which is significant at the 10% level (see column (1)).

In the high sensitivity sample (panel B), we find strong effects for contemporaneous advertising as well as for the first and second lag on turnover (see column (1)). All four advertising coefficient estimates are larger than in the low sensitivity sample. Comparing the 10% confidence intervals in Panel A and B, we find that they are not overlapping for the contemporaneous effect, but again overlapping for the lags. Importantly, the highest contemporaneous effect of advertising on turnover in the confidence interval implies an increase by 3.01*0.09% = 0.29% for a one standard deviation change in $AA(NP)$. Columns (2) and (3) show that we do not find larger effects on illiquidity for high advertising sensitivity firms. For returns, there are two marginally significant coefficients in the Fama-MacBeth regression (column (5)). However, these have opposing signs so that we conclude that there is no strong effect of advertising on returns.

Focusing on those firms with high advertising sensitivity, we therefore find stronger effects for liquidity (for TV) and turnover (for newspapers), and no differential effect for our other dependent variables. This result is consistent with Section 4.2, where we find a stronger effect of news compared to non-news TV channels on liquidity and of the Wall Street Journal compared to other newspapers on turnover. However, even the strongest effects we estimate for the high advertising sensitivity subgroup of firms are still economically small.

4.4 Stability tests

We now perform stability tests by splitting the sample based on observable firm characteristics. We also test the robustness of our results when TV and newspaper advertising are jointly included in the regression, with respect to temporal splits, splits by trading venues and the usage of other measures of advertising. The regression specifications remain the same as in Section 4.1, but in order to keep the presentation of results simple, we only report the contemporaneous and first-lag effects of advertising.

[Insert Table 13 about here]

We report results for TV advertising and splits by observable firm characteristics in Table 13. In the first stability check we split the TV advertising sample at the median of analyst coverage. One could expect low analyst coverage firms to be less visible to investors, so that advertising should have a particularly large effect on these firms. Indeed, the impact of TV advertising on turnover is larger for low coverage firms. It is statistically significant at the 5% (1%) level contemporaneously (at the first lag). Economic significance remains small. Again, the impact of TV advertising on liquidity is consistently positive, but there are no clear differences between low and high coverage firms. For returns, there is a statistically significant negative contemporaneous impact for the low coverage group. However, the economic significance of this impact is still miniscule: A doubling of TV advertising decreases daily returns by merely one fifth of a basis point.

In the second split, we analyze low and high media coverage firms separately.[33] One could expect low media coverage firms to be less visible to investors and thus more susceptible to the impact of advertising. Turnover in fact seems to react more strongly to TV advertising for low coverage firms. Liquidity and (in the Fama-MacBeth regressions) returns however are impacted more for high coverage firms. In any case, effects remain economically small.

In a third split by observable firm characteristics, we separately examine consumer industry firms and other firms. Consumer industry firms should be known to more retail investors, so that stronger effects of advertising could be expected for the remaining, less-known firms. Although the only statistically significant coefficients are indeed in the non-consumer industry subgroup, coefficient sizes do not systematically vary over the two groups. Signs are consistent with our previous results, i.e. TV advertising positively impacts turnover and liquidity. More importantly, the economic significance of coefficients is small for both subsamples.

[Insert Table 14 about here]

In Table 14, we further analyze the stability of our results. In the first test, we jointly estimate the effects of TV and newspaper[34] advertising.[35] If firms increase advertising across different channels (TV and newspapers) simultaneously, any effect measured for TV advertising might actually be due to the impact of newspaper advertising and vice versa. Correlations between $AA(TV)$ and $AA(NP)$ are close to zero (0.0012), so that we do not expect results to be significantly affected by this potential omitted variable bias. This is confirmed in the first stability check of Table 14 since coefficients remain similar to Table 7. TV advertising still has a positive effect on turnover, significant at the 1% level. TV ads seem to increase liquidity (statistically insignificant). Again, we observe a negative but small impact on contemporaneous returns. All effects remain economically small.

In order to analyze the temporal stability of results, we then split our sample into the 9-year subperiods of 1995-2003 and 2004-2012. The coefficient of TV advertising on turnover is higher for the pre-2003 period. This could be because during the later period algorithmic trading and the associated increase in activity may mask the relatively small impact of advertising on turnover. Liquidity on the other hand seems to be more strongly impacted by TV advertising during the post-2003 period. Possibly, high frequency trading strengthens the effect through a quicker, more efficient detection of uninformed trading due to advertising. In both periods prices tend to decrease in response to TV advertising. Although the effect is somewhat stronger in the later period, even this stronger effect remains economically small: doubling the level of TV advertising leads to a decrease in daily return by around one fifth of a basis point.

[33] We use the number of national newspaper articles during the last 12 months in order to measure media coverage. We split at the cross-sectional median.

[34] Results for newspaper ads are reported in Table 16 and discussed later in this section.

[35] For inclusion in this panel we require a firm to have advertised at least once *on either channel* during the last 8 weeks.

Next, we split the sample by trading venue. NYSE/AMEX are limit order markets, whereas NASDAQ is a dealer market. This leads to differences in trading volumes,[36] and possibly in the response of financial markets to advertising-induced trading. On both types of exchanges, TV advertising impacts turnover and liquidity positively. The positive effect on liquidity seems to be stronger on NASDAQ (maybe because NASDAQ-firms tend to be less well-known), while the negative effect on stock returns is stronger on NYSE/AMEX. For both types of exchanges, the economic magnitude of effects remains low.

In a last robustness check we change our advertising measure. We believe that analyzing *abnormal* advertising-dollars is important for a clean identification: it alleviates the problem that persistent firm-specific advertising might drive our estimates. However, we find similar results when we use the log of TV advertising dollars or a dummy that indicates whether TV ads were broadcast on that day. TV advertising significantly increases turnover contemporaneously. The economic impact implied by the coefficients is comparable to our earlier results: For $ln(advertising)$ the coefficients can be directly compared (and interpreted as elasticities), while for dummies the 0.30% increase in turnover on days with TV ads is similar in magnitude to a two to three standard deviation impact for our results based on abnormal advertising from Section 4.1. The effect of the alternative measures of advertising on liquidity is mostly positive and statistically insignificant, while the contemporaneous effect on returns tends to be negative and insignificant. Hence, the normalization of advertising does not drive our results.

[Insert Table 15 about here]

Table 15 and 16 describe the results of analogous stability checks for *newspaper* advertising. First, we split by firm characteristics. In contrast to our results for TV advertising, we do not find that low coverage firms are more strongly impacted by newspaper advertising. For turnover, the coefficient of newspaper advertising is actually statistically significant only in the high coverage sub group. However, overall, coefficient sizes are not systematically larger for the high coverage subgroup, particularly for liquidity and returns. Importantly, economic significance does not change markedly.

Results for the impact of newspaper advertising in media coverage subgroups are likewise mixed. It seems that turnover for the low media coverage group reacts more strongly contemporaneously, but more weakly a day after the ad. The coefficients for liquidity measures indicate a higher (more positive) impact of newspaper advertising on liquidity of low media coverage firms, relative to high media coverage firms. However, coefficient sizes are economically near zero and mostly statistically insignificant. Return effects are zero, except for a small positive, statistically significant (5% level) lagged effect in the low media coverage group.

[36] Interdealer trades on NASDAQ increase trading volumes by a factor that varies over stocks and over time, see Atkins and Dyl (1997) and Anderson and Dyl (2007).

In the consumer industry split, we find that turnover effects are similar in both subgroups. Liquidity however increases in the non-consumer industry subgroup and *decreases* in the consumer industry subgroup. Note that, except for the first lag in the price impact regression, these coefficients are insignificantly different from zero. For returns we find barely significant positive coefficients for the non-consumer industry subgroup. In any case, confidence intervals are very close to zero or include zero, i.e. effects remain economically small.

[Insert Table 16 about here]

In Table 16, we report remaining stability checks. Again, jointly estimating the impact of advertising on turnover for TV and newspaper advertising does not change our results compared to Section 8.[37] If anything, the positive effect of newspaper advertising on turnover becomes a bit stronger when we control for TV advertising. However, it still remains economically insignificant. A doubling of newspaper advertising increases tomorrow's turnover by less than 0.1%. Liquidity and returns are not significantly impacted by newspaper advertising.

Splitting our sample into the subperiods 1995-2003 and 2004-2012, we again find a stronger impact of advertising on turnover for the earlier subperiod. As discussed, this might be caused by the increased fraction of algorithmic trading in the later subperiod. The insignificance of newspaper advertising's effect on liquidity and returns is temporally stable.

In the trading venue split, we find that newspaper advertising has a slightly stronger impact on NYSE/AMEX firms' turnover. Although the statistical significance is stronger for this sub group, coefficient sizes are similar, i.e. standard errors are larger for NASDAQ-coefficients. Effects on liquidity on the other hand are stronger for the NASDAQ subgroup. Particularly the positive reaction of liquidity to newspaper advertising *yesterday* is strong and significant only for NASDAQ firms. Return effects are mostly insignificant, particularly for the Fama-MacBeth regressions, which are more robust to cross-sectional correlations.

In a last robustness check we use alternative measures of advertising. Instead of subtracting out the persistent level of newspaper advertising first, we directly use the log of advertising and a dummy that indicates whether the firm had a newspaper ad on that day. For $log(advertising)$ we find insignificant coefficients throughout. Signs indicate a negative impact for liquidity. Importantly, confidence intervals do not include economically significant values. For the dummy specification, the effect of an ad today on tomorrow's turnover is statistically significant (10% level) and positive at +0.25%, which is in the range of the 1-2 standard deviations effect for our default abnormal advertising specification in Table 8. Other effects are insignificantly different from zero.

In summary, our stability checks show that our main result is robust: Product market advertising does not have an economically significant impact on turnover, liquidity and returns.

[37] For inclusion in this panel we require a firm to have advertised at least once *on either channel* during the last 8 weeks.

The effect of advertising on turnover and liquidity tends to be positive, while the return effect tends to be negative, but magnitudes are always small relative to what has been found based on yearly advertising data. Even if we specifically look for advertising channels or firms for which financial markets might be more advertising-sensitive, effects remain economically small. These findings are stable over time and trading venues. They are not driven by our measure for abnormal advertising.

5 Conclusion

Using advertising to create investor attention and artificially inflate stock prices seems like a tempting opportunity for corporations and their managers. However, the findings in this paper challenge the view that stock prices can be easily manipulated by advertising. Thus, some patterns of managerial behavior like increasing advertising expenditures prior to security issuances, M&A transactions, or insider sales that are documented in the literature might have other explanations or are driven by managers wrongly believing that advertising has an impact on asset prices.

The findings in our study clearly show that advertising leads to increased investor attention as measured by the page views of the respective firm's Wikipedia page. The effect is highly significant and not driven by earnings announcements or other news events. This finding supports the idea that advertising can create investor attention and shows that advertising is a suitable proxy for non-news driven investor attention.

However, advertising creating investor attention is only a necessary condition for advertising to also affect capital market outcomes. Our further evidence shows that advertising has some impact on turnover, but the evidence for an impact on liquidity is mixed. In both cases, the economic significance of the effects is rather small.

Most importantly, we find no impact of abnormal advertising whatsoever on short-term stock market returns. This result is obtained after controlling for news events like earnings announcements and newspaper articles. As our empirical setting using high frequency advertising data and firm fixed effects alleviates endogeneity concerns—at least as long as advertising is predetermined at least on a short-term level, which is likely to be the case—we think that the contrasting findings from existing studies that find a positive relationship between yearly advertising and contemporaneous returns might be driven by the low data frequency and the resulting potential endogeneity problems.

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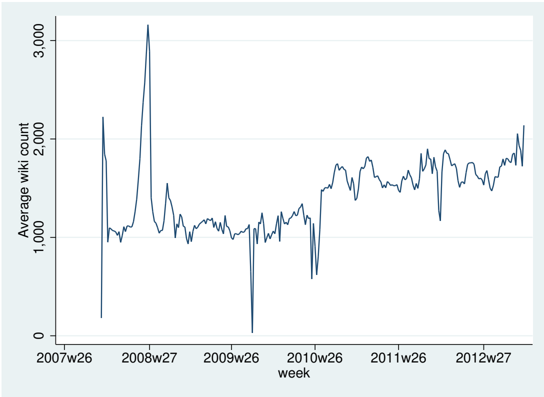
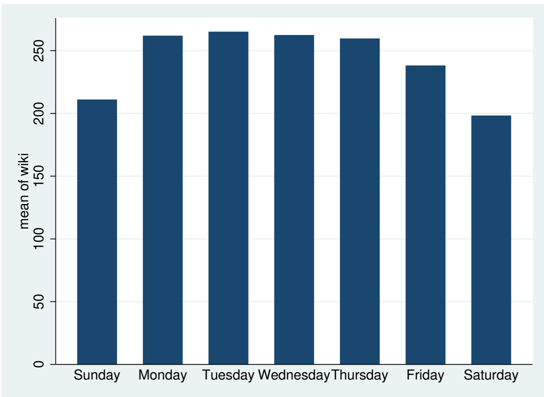
Figure 1: Average Wikipedia Page Views from 2007 to 2012



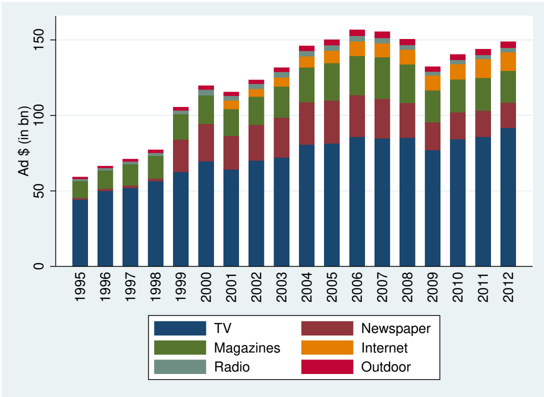
This figure displays the evolution of average Wikipedia page views per company from December 2007 - 2012. Weekly data is used to provide better readability. The increase in page views between May 17, 2008 and July 4, 2008 seems to be caused by data errors following the inclusion of other Wikimedia projects (e.g., Wikibooks.org, Wiktionary.org, etc) in the page count system. Our main results are not affected if we exclude this time period. The drop in September 2009 is due to server failures at Wikipedia over several days.

Figure 2: Wikipedia Page Views by Day-of-the-Week



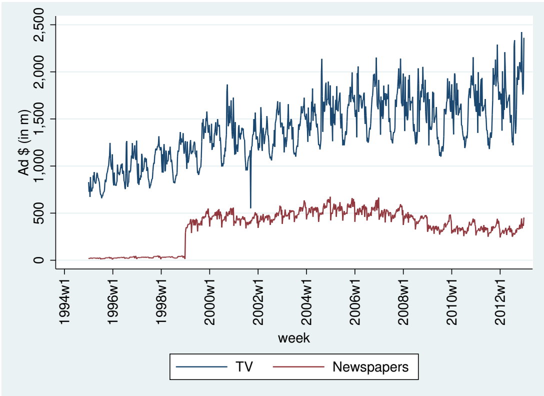
This figure displays average Wikipedia page views by day-of-the-week. The sample period is from 2007 - 2012.

Figure 3: Advertising Expenditures from 1995 to 2012 across Different Media



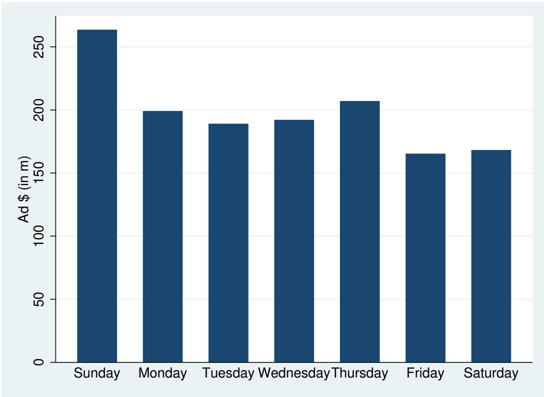
This figure displays the evolution of aggregate advertising spending from 1995 - 2012. It includes all media channels for which we have data. We have daily data on TV and newspapers and monthly data on magazines, internet, radio and outdoor. The increase in newspaper advertising in 1999 is due to the start of availability for local newspaper advertising data.

Figure 4: Advertising Expenditures from 1995 to 2012 in TV and Newspapers



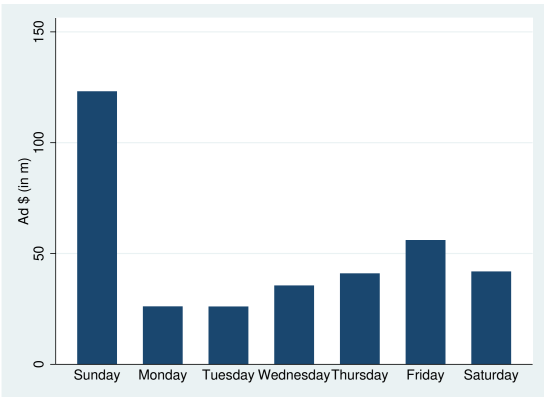
This figure displays the evolution of aggregate advertising spending in TV and newspapers from 1995 - 2012. Weekly data is used to provide better readability. The increase in newspaper advertising in 1999 is due to the start of availability for local newspaper advertising data. The drop in TV advertising at the end of 2001 is due to the decrease in advertising on Sept 11, 2011 and the days thereafter.

Figure 5: TV Advertising Expenditure by Day-of-the-Week



This figure displays average TV advertising dollars by day-of-the-week. The sample period is from 1995 - 2012.

Figure 6: Newspaper Advertising Expenditure by Day-of-the-Week



This figure displays average Newspaper advertising dollars by day-of-the-week. The sample period is from 1995 - 2012.

Table 1: Summary Statistics - Advertising and Investor Attention

This table gives summary statistics on financial market data, Wikipedia page views and Kantar advertising expenditures. The sample goes from 2007 until 2012. Wiki page views and the advertising variables are per day. MarketCap is the firm's market capitalization. Return on assets and advertising-to-sales ratios are based on Compustat data. $\text{Turnover}_{t-7,t-36}$ is the trading volume over the 4 weeks up to t-7, divided by average shares outstanding. $\text{Return}_{t-7,t-36}$ is the holding period return over the 4 weeks up to t-7. $\text{ReaVola}_{t-7,t-36}$ is realized volatility, defined as average absolute return during the 4 weeks up to t-7. News is a national newspaper article dummy. Panel A to C report cross-sectional summary statistics that are based on within-firm time series averages.

	Mean	Median	SD	10%ile	90%ile	N
Panel A: All public firms						
Market Cap (Million $)	2,823.46	281.87	13,542.11	27.23	4,422.01	5,308
Firm age	16.63	12.93	15.41	2.32	38.20	5,308
Return on assets (%)	3.73	7.79	22.62	-18.47	22.73	5,021
Advertising-to-sales (%)	5.58	0.98	19.75	0.02	8.37	3,385
$\text{Turnover}_{t-7,t-36}$ (%)	205.62	162.69	177.32	32.16	431.95	5,299
$\text{ReaVola}_{t-7,t-36}$ (%)	61.84	55.22	31.18	30.79	101.48	5,299
$\text{Return}_{t-7,t-36}$ (%)	-0.45	0.33	4.97	-5.04	3.19	5,299
News_t (%)	0.63	0.00	4.03	0.00	0.60	5,308
Panel B: Public firms with Wikipedia articles						
Market Cap (Million $)	4,720.18	789.44	17,598.72	68.55	8,912.83	3,058
Firm age	19.08	14.52	17.40	2.80	40.95	3,058
Return on assets (%)	7.46	10.50	19.79	-8.55	24.27	2,935
Advertising-to-sales (%)	5.16	1.00	18.23	0.01	8.40	2,093
$\text{Turnover}_{t-7,t-36}$ (%)	261.90	220.80	188.44	64.15	506.48	3,054
$\text{ReaVola}_{t-7,t-36}$ (%)	55.55	50.91	25.23	29.37	85.64	3,054
$\text{Return}_{t-7,t-36}$ (%)	0.16	0.64	4.13	-3.22	3.19	3,054
News_t (%)	1.08	0.00	5.27	0.00	1.62	3,058
Wiki page count	205.06	25.30	1,850.88	0.22	313.84	3,058
Panel C: Public firms with Wikipedia articles and Kantar ads						
Market Cap (Million $)	7,491.42	1,557.88	22,746.40	142.65	16,746.38	1,730
Firm age	22.81	16.86	19.56	3.61	48.62	1,730
Return on assets (%)	11.84	11.95	13.13	1.14	24.84	1,684
Advertising-to-sales (%)	3.49	1.11	11.88	0.01	6.91	1,290
$\text{Turnover}_{t-7,t-36}$ (%)	289.67	252.13	192.25	89.20	535.07	1,729
$\text{ReaVola}_{t-7,t-36}$ (%)	49.84	45.96	21.63	27.10	76.46	1,729
$\text{Return}_{t-7,t-36}$ (%)	0.40	0.72	3.00	-1.92	2.91	1,729
News_t (%)	1.81	0.09	6.89	0.00	3.60	1,730
Wiki page count	326.80	45.98	2,450.97	1.74	554.59	1,730
TV Ad (daily $)	79,846.13	56.97	405,088.47	0.00	94,766.99	1,730
News TV Ad (daily $)	1,114.07	0.00	5,718.18	0.00	1,363.76	1,730
Newspaper (daily $)	14,108.04	81.81	106,206.52	0.29	11,473.72	1,730
WSJ Ad (daily $)	780.10	0.00	6,698.93	0.00	507.23	1,730
3 National newspaper Ad (daily $)	1,671.44	0.00	10,910.57	0.00	1,180.74	1,730
Local Newspaper Ad (daily $)	11,656.50	43.12	93,485.94	0.00	6,977.19	1,730

Table 2: Advertising and Investor Attention - Main Results

This table shows regressions of abnormal Wikipedia page visits (AWIKI) or abnormal Google search volume on abnormal advertising (AA). The sample covers all publicly listed companies with Wikipedia page visits and positive advertising in the previous 8 weeks from 2007 to 2012. AWIKI is abnormal Wikipedia page views. ASVI is abnormal Google search volume. $AA(NP)_t$ and $AA(TV)_t$ are abnormal advertising. EA is an earnings announcement dummy. News is a national newspaper article dummy. $Turnover_{t\text{-}7,t\text{-}36}$ is the trading volume over the 4 weeks up to t-7, divided by average shares outstanding. $Return_{t\text{-}7,t\text{-}36}$ is the holding period return over the 4 weeks up to t-7. $ReaVola_{t\text{-}7,t\text{-}36}$ is realized volatility, defined as average absolute return during the 4 weeks up to t-7. MarketCap is the firm's market capitalization. Standard-errors are clustered by firm and shown in parentheses. 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) AWIKI	(2) AWIKI	(3) AWIKI	(4) AWIKI	(5) AWIKI	(6) ASVI
$AA(TV)_t$	0.00083***		0.00085***		0.00086***	-0.00013
	(0.00017)		(0.00017)		(0.00017)	(0.00012)
$AA(TV)_{t\text{-}1}$	0.00146***		0.00148***		0.00146***	-0.00002
	(0.00021)		(0.00021)		(0.00021)	(0.00015)
$AA(TV)_{t\text{-}2}$	0.00150***		0.00152***		0.00149***	0.00025*
	(0.00021)		(0.00021)		(0.00021)	(0.00015)
$AA(TV)_{t\text{-}3}$	0.00117***		0.00119***		0.00116***	0.00009
	(0.00019)		(0.00019)		(0.00019)	(0.00013)
$AA(NP)_t$		0.00125***		0.00126***	0.00128***	0.00024***
		(0.00013)		(0.00013)	(0.00013)	(0.00008)
$AA(NP)_{t\text{-}1}$		0.00115***		0.00114***	0.00115***	0.00027***
		(0.00012)		(0.00012)	(0.00012)	(0.00008)
$AA(NP)_{t\text{-}2}$		0.00098***		0.00098***	0.00099***	0.00011
		(0.00012)		(0.00012)	(0.00012)	(0.00008)
$AA(NP)_{t\text{-}3}$		0.00085***		0.00085***	0.00087***	-0.00002
		(0.00012)		(0.00012)	(0.00012)	(0.00008)
EA_t			0.10059***	0.10183***	0.09738***	0.06419***
			(0.00482)	(0.00498)	(0.00448)	(0.00837)
$News_t$			0.08613***	0.08031***	0.08684***	0.02534***
			(0.00563)	(0.00502)	(0.00525)	(0.00369)
$\ln(Turnover_{t\text{-}7,t\text{-}36})$			-0.01148***	-0.00881***	-0.00969***	-0.00633***
			(0.00204)	(0.00198)	(0.00173)	(0.00221)
$Return_{t\text{-}7,t\text{-}36}$			-0.00036	-0.00706	-0.00395	-0.01574*
			(0.00778)	(0.00702)	(0.00644)	(0.00808)
$\ln(ReaVola_{t\text{-}7,t\text{-}36})$			-0.00437	-0.00278	-0.00247	-0.00063
			(0.00275)	(0.00274)	(0.00240)	(0.00262)
$\ln(MarketCap_{t\text{-}7})$			0.00172	0.00132	0.00215	-0.00345
			(0.00241)	(0.00197)	(0.00202)	(0.00231)
$AWIKI_{t\text{-}7}$	0.21113***	0.20697***	0.21023***	0.20587***	0.19933***	
	(0.00735)	(0.00695)	(0.00730)	(0.00690)	(0.00609)	
$ASVI_{t\text{-}7}$						0.33646***
						(0.02743)
Firm FEs	YES	YES	YES	YES	YES	YES
Week FEs	YES	YES	YES	YES	YES	YES
Day-of-week FEs	YES	YES	YES	YES	YES	YES
R^2	0.185	0.187	0.188	0.189	0.177	0.153
No. obs.	947,982	930,230	945,457	927,759	1,209,864	355,074

Table 3: Advertising and Investor Attention – TV Channel Subsets

This table shows regressions of abnormal Wikipedia page visits (AWIKI) on abnormal advertising (AA). The sample covers all publicly listed companies with Wikipedia page visits and positive advertising in the previous 8 weeks from 2007 to 2012. AWIKI is abnormal Wikipedia page visits. $AA(i)_t$ is abnormal advertising, with i={TVNWS,TVNONWS}. TVNWS to news channels (CNN, CNBC, Fox News, MSNBC, CNN headline news), TVNONWS to all non-news TV channels All regressions include the same set of controls as in Table 2, column 5. Hence, they include $Turnover_{t-7,t-36}$, $Return_{t-7,t-36}$, $ReaVola_{t-7,t-36}$, $MarketCap_{t-7}$, $AWIKI_{t-7}$. Standard-errors are clustered by firm and shown in parentheses. 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) AWIKI News TV	(2) AWIKI No News TV	(3) AWIKI All
$AA(TVNWS)_t$	0.00133***		0.00120***
	(0.00031)		(0.00029)
$AA(TVNWS)_{t-1}$	0.00176***		0.00151***
	(0.00040)		(0.00038)
$AA(TVNWS)_{t-2}$	0.00173***		0.00148***
	(0.00043)		(0.00040)
$AA(TVNWS)_{t-3}$	0.00164***		0.00148***
	(0.00037)		(0.00035)
$AA(TVNONWS)_t$		0.00067***	0.00059***
		(0.00017)	(0.00016)
$AA(TVNONWS)_{t-1}$		0.00133***	0.00122***
		(0.00021)	(0.00020)
$AA(TVNONWS)_{t-2}$		0.00144***	0.00133***
		(0.00021)	(0.00020)
$AA(TVNONWS)_{t-3}$		0.00114***	0.00105***
		(0.00019)	(0.00018)
Firm FEs	YES	YES	YES
Week FEs	YES	YES	YES
Day-of-week FEs	YES	YES	YES
Controls	YES	YES	YES
R^2	0.263	0.188	0.188
No. obs.	256,649	938,261	945,457

Table 4: Advertising and Investor Attention – Newspaper Subsets

This table shows regressions of abnormal Wikipedia page visits (AWIKI) on abnormal advertising (AA). The sample covers all publicly listed companies with Wikipedia page visits and positive advertising in the previous 8 weeks from 2007 to 2012. AWIKI is abnormal Wikipedia page visits. $AA(i)_t$ is abnormal newspaper advertising, i = {NPLOC, NPNAT, NPWSJ, NP3NAT}. NPLOC refers to local newspapers, NPNAT to national newspapers (Wall Street Journal, New York Times, USA Today and Washington Post), NPWSJ to the Wall Street Journal and NP3NAT to the other three national newspapers. All regressions include the same set of controls as in Table 2, Column 5. Standard-errors are clustered by firm and shown in parentheses. 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) AWIKI Local papers	(2) AWIKI National papers	(3) AWIKI WSJ and other national	(4) AWIKI All
$AA(NPLOC)_t$	0.00111***			0.00098***
	(0.00014)			(0.00014)
$AA(NPLOC)_{t-1}$	0.00116***			0.00104***
	(0.00013)			(0.00013)
$AA(NPLOC)_{t-2}$	0.00094***			0.00084***
	(0.00013)			(0.00013)
$AA(NPLOC)_{t-3}$	0.00086***			0.00076***
	(0.00013)			(0.00013)
$AA(NPNAT)_t$		0.00141***		
		(0.00019)		
$AA(NPNAT)_{t-1}$		0.00109***		
		(0.00019)		
$AA(NPNAT)_{t-2}$		0.00103***		
		(0.00018)		
$AA(NPNAT)_{t-3}$		0.00080***		
		(0.00019)		
$AA(NPWSJ)_t$			0.00089***	0.00096***
			(0.00024)	(0.00025)
$AA(NPWSJ)_{t-1}$			0.00046*	0.00048*
			(0.00024)	(0.00025)
$AA(NPWSJ)_{t-2}$			0.00065***	0.00068***
			(0.00024)	(0.00025)
$AA(NPWSJ)_{t-3}$			0.00021	0.00029
			(0.00027)	(0.00029)
$AA(NP3NAT)_t$			0.00134***	0.00124***
			(0.00022)	(0.00022)
$AA(NP3NAT)_{t-1}$			0.00121***	0.00100***
			(0.00022)	(0.00022)
$AA(NP3NAT)_{t-2}$			0.00103***	0.00088***
			(0.00020)	(0.00020)
$AA(NP3NAT)_{t-3}$			0.00090***	0.00080***
			(0.00021)	(0.00022)
Firm FEs	YES	YES	YES	YES
Week FEs	YES	YES	YES	YES
Day-of-week FEs	YES	YES	YES	YES
Controls	YES	YES	YES	YES
R^2	0.188	0.256	0.256	0.189
No. obs.	871,231	363,816	363,816	927,759

Table 5: Advertising and Investor Attention – Stability

This table shows regressions of abnormal Wikipedia page visits (AWIKI) on abnormal advertising (AA). The sample covers all publicly listed companies with Wikipedia page visits and positive advertising in the previous 8 weeks from 2007 to 2012. AWIKI is abnormal Wikipedia page visits. $AA(TV)_t$ and $AA_{news,t}$ are abnormal advertising. All regressions include the same set of fixed effects and controls as in Table 2, Column 5. Splits are done at the cross-sectional median except for the consumer industry split. Consumer industry is defined according to the Fama French five industry classification as in Lou (2014). Media coverage is the number of national newspaper articles on the firm in the previous 12 months. Panel A (B) displays results using television (newspaper) advertising. Standard-errors are clustered by firm and shown in parentheses. 1/2/3 stars denote significance at the 10/5/1%-level.

Panel A: Television

Industry and news coverage

	Consumer Industry		Media coverage	
	Yes	No	Low	High
$AA(TV)_t$	0.00135***	0.00065***	0.00114***	0.00029
	(0.00034)	(0.00019)	(0.00022)	(0.00026)
$AA(TV)_{t-1}$	0.00239***	0.00108***	0.00175***	0.00097***
	(0.00044)	(0.00023)	(0.00027)	(0.00029)
FEs and Controls	YES	YES	YES	YES
R^2	0.217	0.180	0.172	0.279
No. obs.	315,947	629,494	618,948	326,509

Temporal stability and ad channels

	Temporal stability		Ad definitions	
	2007-2009	2010-2012	Log(1+Ad $)	$I_{Ad\ \$>0}$
$AA(TV)_t$	0.00077***	0.00086***	0.00193***	0.00974***
	(0.00027)	(0.00019)	(0.00021)	(0.00143)
$AA(TV)_{t-1}$	0.00157***	0.00136***	0.00117***	0.00646***
	(0.00032)	(0.00025)	(0.00017)	(0.00120)
FEs and Controls	YES	YES	YES	YES
R^2	0.189	0.195	0.189	0.189
No. obs.	345,878	599,579	945,457	945,457

Panel B: Newspaper				
Industry and news coverage				
	Consumer Industry		Media coverage	
	Yes	No	Low	High
$AA(NP)_t$	0.00129***	0.00111***	0.00157***	0.00077***
	(0.00021)	(0.00015)	(0.00017)	(0.00016)
$AA(NP)_{t-1}$	0.00124***	0.00094***	0.00155***	0.00062***
	(0.00019)	(0.00014)	(0.00018)	(0.00013)
FEs and Controls	YES	YES	YES	YES
R^2	0.227	0.179	0.174	0.276
No. obs.	306,015	621,741	600,437	327,322
Temporal stability and alternative ad definitions				
	Temporal stability		Ad definitions	
	2007-2009	2010-2012	Log(1+Ad $)	$I_{Ad\ \$>0}$
$AA(NP)_t$	0.00161***	0.00104***	0.00095***	0.00755***
	(0.00020)	(0.00015)	(0.00011)	(0.00108)
$AA(NP)_{t-1}$	0.00124***	0.00107***	0.00088***	0.00702***
	(0.00020)	(0.00013)	(0.00011)	(0.00100)
FEs and Controls	YES	YES	YES	YES
R^2	0.195	0.195	0.189	0.189
No. obs.	352,263	575,496	927,759	927,759

Table 6: Summary Statistics – Advertising and Financial Markets

This table reports summary statistics on financial market data and Kantar-advertising on the firm level. The cross-sectional summary statistics are based on within-firm time series averages. In order to keep TAQ-based variables (available 1996-2010 only) and other variables comparable, the sample includes observations from 1996 to 2010 only. Similarly, newspaper advertising observations are restricted to 1999-2010, since data from local paper ads are available only after 1998. Panel A reports statistics for all NYSE/AMEX/NASDAQ observations where last week's stock price is ≥ 5. Panel B additionally restricts the set of firms to those that have strictly positive Kantar-advertising at least once 1996-2010.

	Mean	Median	SD	10%ile	90%ile	N
Panel A: All public firms						
Market Cap (Million $)	1,422.78	174.34	8,192.04	20.72	2,016.58	12,220
Firm age	10.78	6.10	12.39	1.87	27.04	12,229
Return on assets (%)	3.35	8.38	23.62	-26.42	23.90	11,063
Advertising-to-sales (%)	6.69	1.33	19.65	0.06	12.03	5,733
Turnover_{t} (%)	173.37	133.25	151.39	29.87	364.65	12,216
Return_{t} (%)	-0.03	0.04	0.63	-0.39	0.18	12,216
$\text{Rea.Vola}_{t\text{-}7,t\text{-}36}$ (%)	62.16	55.23	31.02	29.84	108.53	12,200
News_{t} (%)	0.71	0.00	3.73	0.00	1.29	12,232
Effective Spread (%)	5.18	3.80	4.51	1.04	11.28	12,105
Price Impact (%)	4.33	3.33	3.94	1.22	8.35	12,168
Panel B: Public firms with TAQ data and Kantar ads						
Market Cap (Million $)	3,547.02	597.81	13,697.86	62.66	6,542.52	4,139
Firm age	15.08	8.58	16.01	2.60	34.69	4,139
Return on assets (%)	9.16	12.20	18.44	-7.47	25.71	3,998
Advertising-to-sales (%)	5.65	1.53	15.80	0.06	10.58	2,593
Turnover_{t} (%)	202.44	167.19	153.96	44.81	410.73	4,139
Return_{t} (%)	0.01	0.05	0.28	-0.17	0.13	4,139
$\text{Rea.Vola}_{t\text{-}7,t\text{-}36}$ (%)	52.43	46.51	24.23	28.50	86.01	4,139
News_{t} (%)	1.90	0.32	6.18	0.00	3.84	4,139
Effective Spread (%)	3.46	2.65	2.93	0.77	7.03	4,136
Price Impact (%)	4.07	2.92	4.08	1.07	8.20	4,139
TV Ad (daily $)	32,359.20	3.00	239,409.36	0.00	19,802.44	4,139
News TV Ad (daily $)	547.18	0.00	3,818.00	0.00	362.16	4,139
No-News TV Ad (daily $)	31,812.03	2.13	236,732.68	0.00	18,445.83	4,139
Newspaper Ad (daily $)	5,393.29	30.72	51,720.75	0.00	4,200.63	3,852
WSJ Newspaper Ad (daily $)	681.19	0.00	5,584.95	0.00	641.37	3,852
3 National Newspaper Ad (daily $)	883.48	0.00	6,837.88	0.00	505.56	3,852
Local Newspaper Ad (daily $)	3,828.63	7.04	43,875.06	0.00	1,863.94	3,852

Table 7: Impact on Financial Markets – TV Advertising

The analysis is done for 1995-2012 (1996-2010) common stocks from NYSE, AMEX and NASDAQ for Turnover and Returns (TAQ-based data), excluding stocks with last-week prices below 5 USD. Turnover is daily trading volume over shares outstanding. EffSpr is the effective spread, defined as daily transaction-weighted average of transaction prices relative to prevailing quotes. PrcImp is the price impact, defined as transaction-weighted average of 5-minute impacts on quote-midpoints. AA is abnormal advertising, defined as log-advertising-dollars today relative to log-advertising-dollars yesterday. EA is an earnings announcement dummy. News is a national newspaper article dummy. $\text{Turnover}_{\text{t-7,t-36}}$ is the trading volume over the 4 weeks up to t-7, divided by average shares outstanding. $\text{Return}_{\text{t-7,t-36}}$ is the holding period return over the 4 weeks up to t-7. $\text{ReaVola}_{\text{t-7,t-36}}$ is realized volatility, defined as average absolute return during the 4 weeks up to t-7. MarketCap is the firm's market capitalization. Standard-errors are shown in parentheses and clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_t)$	(2) $\ln(\text{EffSpr}_t)$	(3) $\ln(\text{PrcImp}_t)$	(4) $\text{Return}_t^{\text{excess}}$	(5) $\text{Return}_t^{\text{excess}}$
AA(TV)_t	0.00044**	-0.00047	-0.00024	-0.00001	-0.00001*
	(0.00019)	(0.00046)	(0.00046)	(0.00001)	(0.00001)
AA(TV)_{t-1}	0.00051**	-0.00066	-0.00041	-0.00000	0.00000
	(0.00021)	(0.00043)	(0.00044)	(0.00001)	(0.00001)
AA(TV)_{t-2}	0.00000	-0.00061*	-0.00049	0.00001**	0.00001
	(0.00019)	(0.00036)	(0.00038)	(0.00001)	(0.00001)
AA(TV)_{t-3}	0.00031*	-0.00053*	-0.00034	0.00000	-0.00000
	(0.00016)	(0.00031)	(0.00032)	(0.00001)	(0.00001)
EA_t	0.49717***	0.17299***	0.28054***	0.00159***	0.00109***
	(0.00833)	(0.00678)	(0.00687)	(0.00017)	(0.00028)
News_t	0.15947***	0.06243***	0.09491***	0.00022***	0.00022***
	(0.00617)	(0.00876)	(0.00918)	(0.00008)	(0.00007)
$\ln(\text{Turnover}_{\text{t-7,t-36}})$	0.61649***	-0.07114***	-0.01427	0.00007**	0.00008**
	(0.00517)	(0.01019)	(0.01103)	(0.00003)	(0.00004)
$\text{Return}_{\text{t-7,t-36}}$	-0.16202***	0.02087	-0.00051	-0.00092***	-0.00019
	(0.00846)	(0.01307)	(0.01392)	(0.00017)	(0.00031)
$\ln(\text{ReaVola}_{\text{t-7,t-36}})$	-0.05092***	0.16769***	0.19806***	-0.00012***	-0.00026**
	(0.00465)	(0.01089)	(0.01202)	(0.00004)	(0.00012)
$\ln(\text{MarketCap}_{\text{t-7}})$	0.03023***	-0.11901***	0.00660	-0.00088***	-0.00001
	(0.00587)	(0.01333)	(0.01384)	(0.00004)	(0.00002)
$\ln(\text{Turnover}_{\text{t-7}})$	0.16536***				
	(0.00161)				
$\ln(\text{EffSpr}_{\text{t-7}})$		0.34372***			
		(0.00509)			
$\ln(\text{PrcImp}_{\text{t-7}})$			0.31781***		
			(0.00622)		
Firm-FEs	YES	YES	YES	YES	NO
Week-FEs	YES	YES	YES	YES	NO
Day-of-Week-FEs	YES	YES	YES	YES	NO
Fama-MacBeth	NO	NO	NO	NO	YES
R^2	0.70	0.58	0.39	0.01	0.07
No. obs.	2871633	2287395	2363899	3009588	3009588

Table 8: Impact on Financial Markets – Newspaper Advertising

The analysis is done for 1995-2012 (1996-2010) common stocks from NYSE, AMEX and NASDAQ for Turnover and Returns (TAQ-based data), excluding stocks with last-week prices below 5 USD. Turnover is daily trading volume over shares outstanding. EffSpr is the effective spread, defined as daily transaction-weighted average of transaction prices relative to prevailing quotes. PrcImp is the price impact, defined as transaction-weighted average of 5-minute impacts on quote-midpoints. AA is abnormal advertising, defined as log-advertising-dollars today relative to log-advertising-dollars' median of the same weekday during the last 8 weeks. EA is an earnings announcement dummy. News is a national newspaper article dummy. $\text{Turnover}_{\text{t-7,t-36}}$ is the trading volume over the 4 weeks up to t-7, divided by average shares outstanding. $\text{Return}_{\text{t-7,t-36}}$ is the holding period return over the 4 weeks up to t-7. $\text{ReaVola}_{\text{t-7,t-36}}$ is realized volatility, defined as average absolute return during the 4 weeks up to t-7. MarketCap is the firm's market capitalization. Standard-errors are shown in parentheses and clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_\text{t})$	(2) $\ln(\text{EffSpr}_\text{t})$	(3) $\ln(\text{PrcImp}_\text{t})$	(4) $\text{Return}_\text{t}^{\text{excess}}$	(5) $\text{Return}_\text{t}^{\text{excess}}$
AA(NP)_t	0.00032***	0.00012	-0.00006	0.00000	0.00000
	(0.00012)	(0.00023)	(0.00023)	(0.00000)	(0.00000)
$\text{AA(NP)}_\text{t-1}$	0.00046***	-0.00012	-0.00017	0.00000	0.00001
	(0.00011)	(0.00021)	(0.00022)	(0.00000)	(0.00000)
$\text{AA(NP)}_\text{t-2}$	0.00050***	-0.00039*	-0.00025	-0.00000	-0.00000
	(0.00012)	(0.00021)	(0.00022)	(0.00000)	(0.00000)
$\text{AA(NP)}_\text{t-3}$	0.00008	-0.00000	-0.00004	0.00000	0.00000
	(0.00012)	(0.00022)	(0.00021)	(0.00000)	(0.00000)
EA_t	0.47117***	0.17247***	0.26722***	0.00192***	0.00180***
	(0.00806)	(0.00614)	(0.00624)	(0.00018)	(0.00028)
News_t	0.15117***	0.06719***	0.09085***	0.00015*	0.00019***
	(0.00596)	(0.00915)	(0.00937)	(0.00008)	(0.00007)
$\ln(\text{Turnover}_{\text{t-7,t-36}})$	0.60876***	-0.09300***	-0.02423***	0.00010***	0.00011**
	(0.00476)	(0.00851)	(0.00932)	(0.00003)	(0.00004)
$\text{Return}_{\text{t-7,t-36}}$	-0.13887***	0.01454	-0.00741	-0.00064***	-0.00052
	(0.00785)	(0.01093)	(0.01160)	(0.00017)	(0.00034)
$\ln(\text{ReaVola}_{\text{t-7,t-36}})$	-0.03853***	0.17118***	0.19345***	-0.00018***	-0.00024**
	(0.00424)	(0.00951)	(0.01005)	(0.00004)	(0.00012)
$\ln(\text{MarketCap}_{\text{t-7}})$	0.03668***	-0.10655***	0.00371	-0.00111***	-0.00003
	(0.00512)	(0.01107)	(0.01161)	(0.00005)	(0.00002)
$\ln(\text{Turnover}_{\text{t-7}})$	0.17013***				
	(0.00158)				
$\ln(\text{EffSpr}_{\text{t-7}})$		0.35279***			
		(0.00482)			
$\ln(\text{PrcImp}_{\text{t-7}})$			0.33659***		
			(0.00571)		
Firm-FEs	YES	YES	YES	YES	NO
Week-FEs	YES	YES	YES	YES	NO
Day-of-Week-FEs	YES	YES	YES	YES	NO
Fama-MacBeth	NO	NO	NO	NO	YES
R^2	0.72	0.59	0.42	0.01	0.07
No. obs.	3051008	2575174	2638908	3218136	3218136

Table 9: Impact on Financial Markets – TV Advertising Channels

The analysis is done for 1995-2012 (1996-2010) common stocks from NYSE, AMEX and NASDAQ for Turnover and Returns (TAQ-based data), excluding stocks with last-week prices below 5 USD. Turnover is daily trading volume over shares outstanding. EffSpr is the effective spread, defined as daily transaction-weighted average of transaction prices relative to prevailing quotes. PrcImp is the price impact, defined as transaction-weighted average of 5-minute impacts on quote-midpoints. AA is abnormal advertising, defined as log-advertising-dollars today relative to log-advertising-dollars yesterday. Controls are included in the regressions (same as in the main regressions), but not reported. Standard-errors are shown in parentheses and clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_t)$	(2) $\ln(\text{EffSpr}_t)$	(3) $\ln(\text{PrcImp}_t)$	(4) $\text{Return}_t^{\text{excess}}$	(5) $\text{Return}_t^{\text{excess}}$
AA(TVNWS)_t	0.00001	-0.00135	-0.00126	-0.00001	-0.00001
	(0.00032)	(0.00090)	(0.00088)	(0.00001)	(0.00002)
$\text{AA(TVNWS)}_{t\text{-}1}$	0.00013	-0.00236***	-0.00195**	-0.00000	-0.00002
	(0.00036)	(0.00091)	(0.00093)	(0.00001)	(0.00002)
$\text{AA(TVNWS)}_{t\text{-}2}$	0.00025	-0.00138**	-0.00103*	0.00001	0.00001
	(0.00028)	(0.00064)	(0.00060)	(0.00001)	(0.00001)
$\text{AA(TVNWS)}_{t\text{-}3}$	0.00034	-0.00148***	-0.00063	-0.00001	-0.00000
	(0.00024)	(0.00051)	(0.00047)	(0.00001)	(0.00001)
AA(TVNONWS)_t	0.00054***	-0.00002	0.00044	-0.00001	-0.00001
	(0.00021)	(0.00045)	(0.00044)	(0.00001)	(0.00001)
$\text{AA(TVNONWS)}_{t\text{-}1}$	0.00035	-0.00055	-0.00003	-0.00000	-0.00001
	(0.00022)	(0.00047)	(0.00048)	(0.00001)	(0.00001)
$\text{AA(TVNONWS)}_{t\text{-}2}$	0.00028	-0.00068*	-0.00034	0.00001	0.00000
	(0.00019)	(0.00037)	(0.00038)	(0.00001)	(0.00001)
$\text{AA(TVNONWS)}_{t\text{-}3}$	0.00024	-0.00029	-0.00018	-0.00001	-0.00001
	(0.00016)	(0.00030)	(0.00032)	(0.00001)	(0.00001)
Firm-FEs	YES	YES	YES	YES	NO
Week-FEs	YES	YES	YES	YES	NO
Day-of-Week-FEs	YES	YES	YES	YES	NO
Fama-MacBeth	NO	NO	NO	NO	YES
Controls	YES	YES	YES	YES	YES
R^2	0.70	0.58	0.39	0.01	0.07
No. obs.	2870033	2286073	2362503	2870033	2870033

Table 10: Impact on Financial Markets – Newspapers Advertising Channels

The analysis is done for 1999-2012 (1999-2010) common stocks from NYSE, AMEX and NASDAQ for Turnover and Returns (TAQ-based data), excluding stocks with last-week prices below 5 USD. Turnover is daily trading volume over shares outstanding. EffSpr is the effective spread, defined as daily transaction-weighted average of transaction prices relative to prevailing quotes. PrcImp is the price impact, defined as transaction-weighted average of 5-minute impacts on quote-midpoints. AA_{paper} is abnormal newspaper advertising, defined as log-advertising-dollars today relative to log-advertising-dollars' median of the same weekday during the last 8 weeks. Controls are included in the regressions (same as in the main regressions), but not reported. Standard-errors are clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_t)$	(2) $\ln(\text{EffSpr}_t)$	(3) $\ln(\text{PrcImp}_t)$	(4) $\text{Return}_t^{\text{excess}}$	(5) $\text{Return}_t^{\text{excess}}$
$AA(NPWSJ)_t$	0.00006	-0.00075	-0.00044	0.00000	-0.00001
	(0.00021)	(0.00057)	(0.00049)	(0.00001)	(0.00001)
$AA(NPWSJ)_{t-1}$	0.00070***	-0.00035	-0.00021	-0.00002**	-0.00001
	(0.00023)	(0.00064)	(0.00061)	(0.00001)	(0.00001)
$AA(NPWSJ)_{t-2}$	0.00069***	-0.00082	-0.00030	-0.00001	-0.00009
	(0.00027)	(0.00066)	(0.00058)	(0.00001)	(0.00006)
$AA(NPWSJ)_{t-3}$	0.00065**	0.00150**	0.00157***	0.00001	0.00007
	(0.00028)	(0.00064)	(0.00057)	(0.00001)	(0.00014)
$AA(NP3NAT)_t$	0.00028	0.00007	0.00070	-0.00000	-0.00001
	(0.00019)	(0.00047)	(0.00044)	(0.00001)	(0.00001)
$AA(NP3NAT)_{t-1}$	-0.00003	0.00016	0.00038	-0.00000	-0.00001
	(0.00020)	(0.00041)	(0.00039)	(0.00001)	(0.00001)
$AA(NP3NAT)_{t-2}$	0.00019	-0.00025	0.00025	0.00001	0.00000
	(0.00020)	(0.00037)	(0.00039)	(0.00001)	(0.00001)
$AA(NP3NAT)_{t-3}$	0.00025	0.00008	0.00010	0.00001	0.00001
	(0.00020)	(0.00042)	(0.00040)	(0.00001)	(0.00001)
$AA(NPLOC)_t$	0.00030**	-0.00009	-0.00016	0.00000	0.00000
	(0.00014)	(0.00025)	(0.00024)	(0.00001)	(0.00001)
$AA(NPLOC)_{t-1}$	0.00037***	-0.00005	0.00005	0.00001**	0.00001
	(0.00013)	(0.00022)	(0.00022)	(0.00000)	(0.00001)
$AA(NPLOC)_{t-2}$	0.00043***	-0.00034	-0.00019	-0.00000	-0.00000
	(0.00013)	(0.00022)	(0.00022)	(0.00001)	(0.00001)
$AA(NPLOC)_{t-3}$	-0.00003	0.00001	-0.00008	-0.00000	-0.00000
	(0.00013)	(0.00023)	(0.00023)	(0.00001)	(0.00001)
Firm-FEs	YES	YES	YES	YES	NO
Week-FEs	YES	YES	YES	YES	NO
Day-of-Week-FEs	YES	YES	YES	YES	NO
Fama-MacBeth	NO	NO	NO	NO	YES
Controls	YES	YES	YES	YES	YES
R^2	0.72	0.62	0.45	0.01	0.08
No. obs.	2801776	2404404	2449408	2801776	2801776

Table 11: Impact on Financial Markets – TV Advertising Sensitivity

The data requirements and regression specifications are equivalent to those in the main analysis. For ease of presentation, only the advertising coefficients are reported. Advertising sensitivity is the firm's average coefficient for the 4 advertising-regressors in a firm-by-firm regression of $AWIKI_t$ on AA_t through AA_{t-3}, day-of-week dummies, $AWIKI_{t-7}$ and the usual control variables. Split is done at the cross-sectional median of advertising sensitivity. Standard-errors are clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(Turnover_t)$	(2) $\ln(EffSpr_t)$	(3) $\ln(PrcImp_t)$	(4) $Return_t^{excess}$	(5) $Return_t^{excess}$
Panel A: Low Advertising Sensitivity					
$AA(TV)_t$	0.00030	-0.00064	-0.00061	-0.00001	-0.00003**
	(0.00026)	(0.00069)	(0.00064)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00046	-0.00021	-0.00011	0.00000	0.00000
	(0.00029)	(0.00062)	(0.00061)	(0.00001)	(0.00001)
$AA(TV)_{t-2}$	0.00010	-0.00031	0.00000	0.00002	0.00001
	(0.00028)	(0.00051)	(0.00051)	(0.00001)	(0.00001)
$AA(TV)_{t-3}$	0.00036	0.00046	0.00054	0.00000	0.00000
	(0.00023)	(0.00044)	(0.00045)	(0.00001)	(0.00001)
Panel B: High Advertising Sensitivity					
$AA(TV)_t$	0.00019	-0.00111	-0.00085	-0.00002	-0.00002
	(0.00031)	(0.00082)	(0.00079)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00046	-0.00140*	-0.00099	0.00001	0.00001
	(0.00033)	(0.00077)	(0.00076)	(0.00001)	(0.00001)
$AA(TV)_{t-2}$	0.00031	-0.00117*	-0.00092	0.00002*	0.00001
	(0.00028)	(0.00064)	(0.00065)	(0.00001)	(0.00001)
$AA(TV)_{t-3}$	0.00050**	-0.00110**	-0.00075	0.00001	0.00001
	(0.00023)	(0.00052)	(0.00054)	(0.00001)	(0.00001)
Firm-FEs	YES	YES	YES	YES	NO
Week-FEs	YES	YES	YES	YES	NO
Day-of-Week-FEs	YES	YES	YES	YES	NO
Fama-MacBeth	NO	NO	NO	NO	YES
Controls	YES	YES	YES	YES	YES

Table 12: Impact on Financial Markets – Newspaper Advertising Sensitivity

The data requirements and regression specifications are equivalent to those in the main analysis. For ease of presentation, only the advertising coefficients are reported. Advertising sensitivity is the firm's average coefficient for the 4 advertising-regressors in a firm-by-firm regression of $AWIKI_t$ on AA_t through AA_{t-3}, day-of-week dummies, $AWIKI_{t-7}$ and the usual control variables. Split is done at the cross-sectional median of advertising sensitivity. Standard-errors are clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(Turnover_t)$	(2) $\ln(EffSpr_t)$	(3) $\ln(PrcImp_t)$	(4) $Return_t^{excess}$	(5) $Return_t^{excess}$
Panel A: Low Advertising Sensitivity					
$AA(NP)_t$	-0.00001	0.00021	-0.00014	0.00001	0.00000
	(0.00016)	(0.00036)	(0.00034)	(0.00001)	(0.00001)
$AA(NP)_{t-1}$	0.00016	-0.00015	-0.00016	0.00000	-0.00001
	(0.00015)	(0.00031)	(0.00030)	(0.00001)	(0.00001)
$AA(NP)_{t-2}$	0.00029*	-0.00031	-0.00023	-0.00000	0.00001
	(0.00016)	(0.00032)	(0.00033)	(0.00001)	(0.00001)
$AA(NP)_{t-3}$	-0.00010	-0.00020	-0.00020	0.00001	0.00000
	(0.00017)	(0.00033)	(0.00030)	(0.00001)	(0.00001)
Panel B: High Advertising Sensitivity					
$AA(NP)_t$	0.00070***	0.00001	-0.00003	-0.00001	-0.00002*
	(0.00016)	(0.00037)	(0.00035)	(0.00001)	(0.00001)
$AA(NP)_{t-1}$	0.00057***	0.00007	-0.00000	0.00001	0.00001*
	(0.00017)	(0.00037)	(0.00037)	(0.00001)	(0.00001)
$AA(NP)_{t-2}$	0.00033*	-0.00036	-0.00024	0.00000	0.00000
	(0.00017)	(0.00035)	(0.00038)	(0.00001)	(0.00001)
$AA(NP)_{t-3}$	0.00026	0.00012	0.00001	0.00000	-0.00000
	(0.00018)	(0.00037)	(0.00037)	(0.00001)	(0.00001)
Firm-FEs	YES	YES	YES	YES	NO
Week-FEs	YES	YES	YES	YES	NO
Day-of-Week-FEs	YES	YES	YES	YES	NO
Fama-MacBeth	NO	NO	NO	NO	YES
Controls	YES	YES	YES	YES	YES

Table 13: Impact on Financial Markets – TV Advertising Robustness I

The data requirements and regression specifications are equivalent to those in the main analysis. For ease of presentation, only the contemporary and first lag effects of advertising expenditures are reported. Splits are done at the cross-sectional median except for the consumer industry split. Consumer industry is defined according to the Fama French five industry classification as in Lou (2014). Media coverage is the number of national newspaper articles on the firm in the previous 12 months.Standard-errors are clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_t)$	(2) $\ln(\text{EffSpr}_t)$	(3) $\ln(\text{PrcImp}_t)$	(4) $\text{Return}_t^{\text{excess}}$	(5) $\text{Return}_t^{\text{excess}}$
			Panel A: Low Analyst Coverage		
$AA(TV)_t$	0.00060**	-0.00072	-0.00037	-0.00001	-0.00002*
	(0.00030)	(0.00053)	(0.00056)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00087***	-0.00059	-0.00028	-0.00001	-0.00000
	(0.00032)	(0.00049)	(0.00053)	(0.00001)	(0.00001)
			Panel B: High Analyst Coverage		
$AA(TV)_t$	0.00001	-0.00039	-0.00035	-0.00001	-0.00001
	(0.00022)	(0.00070)	(0.00066)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00012	-0.00062	-0.00050	0.00000	0.00000
	(0.00024)	(0.00067)	(0.00065)	(0.00001)	(0.00001)
			Panel C: Low Media Coverage		
$AA(TV)_t$	0.00068**	-0.00024	0.00003	-0.00000	-0.00001
	(0.00028)	(0.00054)	(0.00060)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00051*	-0.00011	0.00012	-0.00001	-0.00000
	(0.00030)	(0.00050)	(0.00057)	(0.00001)	(0.00001)
			Panel D: High Media Coverage		
$AA(TV)_t$	-0.00010	-0.00070	-0.00065	-0.00001	-0.00003**
	(0.00023)	(0.00070)	(0.00065)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00040	-0.00129*	-0.00111*	0.00001	-0.00000
	(0.00026)	(0.00067)	(0.00062)	(0.00001)	(0.00001)
			Panel E: Consumer Industry		
$AA(TV)_t$	0.00045	-0.00017	0.00008	-0.00001	-0.00002
	(0.00036)	(0.00075)	(0.00079)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00059	-0.00072	-0.00078	0.00001	0.00000
	(0.00038)	(0.00069)	(0.00073)	(0.00001)	(0.00001)
			Panel F: Non-Consumer Industry		
$AA(TV)_t$	0.00041*	-0.00057	-0.00027	-0.00001	-0.00001
	(0.00023)	(0.00058)	(0.00056)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00048*	-0.00060	-0.00016	-0.00001	0.00000
	(0.00025)	(0.00054)	(0.00055)	(0.00001)	(0.00001)

Table 14: Impact on Financial Markets – TV Advertising Robustness II

The data requirements and regression specifications are equivalent to those in the main analysis. For ease of presentation, only the contemporary and first lag effects of advertising expenditures are reported.Standard-errors are clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_t)$	(2) $\ln(\text{EffSpr}_t)$	(3) $\ln(\text{PrcImp}_t)$	(4) $\text{Return}_t^{\text{excess}}$	(5) $\text{Return}_t^{\text{excess}}$
	Panel A: Controlling for Newspaper Advertising				
$AA(TV)_t$	0.00051***	-0.00028	-0.00002	-0.00001**	-0.00002**
	(0.00019)	(0.00047)	(0.00046)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00054***	-0.00045	-0.00015	-0.00000	-0.00000
	(0.00021)	(0.00043)	(0.00045)	(0.00001)	(0.00001)
	Panel B: 1995-2003				
$AA(TV)_t$	0.00078***	-0.00044	-0.00026	-0.00002	-0.00001
	(0.00029)	(0.00069)	(0.00070)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00097***	-0.00112*	-0.00105	0.00000	0.00000
	(0.00032)	(0.00065)	(0.00067)	(0.00001)	(0.00001)
	Panel C: 2004-2012				
$AA(TV)_t$	-0.00009	-0.00088***	-0.00077***	0.00000	-0.00002*
	(0.00023)	(0.00032)	(0.00028)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	-0.00011	-0.00049	-0.00022	-0.00001	-0.00000
	(0.00024)	(0.00032)	(0.00028)	(0.00001)	(0.00001)
	Panel D: NYSE/AMEX				
$AA(TV)_t$	0.00029	-0.00039	-0.00015	-0.00002**	-0.00002**
	(0.00021)	(0.00058)	(0.00055)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00055**	-0.00048	-0.00045	-0.00000	-0.00000
	(0.00023)	(0.00054)	(0.00053)	(0.00001)	(0.00001)
	Panel E: NASDAQ				
$AA(TV)_t$	0.00064	-0.00086	-0.00083	0.00002	-0.00001
	(0.00039)	(0.00058)	(0.00070)	(0.00001)	(0.00001)
$AA(TV)_{t-1}$	0.00042	-0.00125**	-0.00075	0.00000	0.00000
	(0.00040)	(0.00056)	(0.00069)	(0.00001)	(0.00001)
	Panel F: Ln(1+$Advertising)				
$\ln(Ad(TV)_t)$	0.00045**	-0.00039	-0.00005	-0.00001	-0.00001
	(0.00022)	(0.00052)	(0.00051)	(0.00001)	(0.00001)
$\ln(Ad(TV)_{t-1})$	-0.00019	-0.00068*	-0.00065	0.00001	0.00000
	(0.00018)	(0.00037)	(0.00040)	(0.00001)	(0.00001)
	Panel G: Advertising-Dummy				
$I_{Ad(TV),t}$	0.00299*	-0.00130	0.00101	-0.00003	-0.00005
	(0.00169)	(0.00404)	(0.00416)	(0.00005)	(0.00005)
$I_{Ad(TV),t-1}$	-0.00068	-0.00267	-0.00199	-0.00001	0.00001
	(0.00143)	(0.00282)	(0.00313)	(0.00006)	(0.00006)

Table 15: Impact on Financial Markets – Newspaper Advertising Robustness I

The data requirements and regression specifications are equivalent to those in the main analysis. For ease of presentation, only the contemporary and first lag effects of advertising expenditures are reported. Splits are done at the cross-sectional median except for the consumer industry split. Consumer industry is defined according to the Fama French five industry classification as in Lou (2014). Media coverage is the number of national newspaper articles on the firm in the previous 12 months.Standard-errors are clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_t)$	(2) $\ln(\text{EffSpr}_t)$	(3) $\ln(\text{PrcImp}_t)$	(4) $\text{Return}_t^{\text{excess}}$	(5) $\text{Return}_t^{\text{excess}}$
Panel A: Low Analyst Coverage					
$\text{AA(NP)}_{\text{t-1}}$	0.00030	0.00040	0.00013	0.00000	-0.00000
	(0.00022)	(0.00031)	(0.00035)	(0.00001)	(0.00001)
$\text{AA(NP)}_{\text{t-1}}$	0.00019	-0.00033	-0.00032	0.00001	0.00001
	(0.00021)	(0.00028)	(0.00033)	(0.00001)	(0.00001)
Panel B: High Analyst Coverage					
$\text{AA(NP)}_{\text{t-1}}$	0.00031***	0.00008	-0.00003	0.00001	0.00001
	(0.00011)	(0.00032)	(0.00029)	(0.00001)	(0.00001)
$\text{AA(NP)}_{\text{t-1}}$	0.00058***	0.00014	-0.00000	0.00000	0.00000
	(0.00011)	(0.00028)	(0.00027)	(0.00001)	(0.00000)
Panel C: Low Media Coverage					
AA(NP)_{t}	0.00038*	-0.00008	0.00016	0.00000	0.00000
	(0.00021)	(0.00032)	(0.00036)	(0.00001)	(0.00001)
$\text{AA(NP)}_{\text{t-1}}$	0.00029	-0.00049*	-0.00044	0.00001	0.00002**
	(0.00020)	(0.00029)	(0.00031)	(0.00001)	(0.00001)
Panel D: High Media Coverage					
AA(NP)_{t}	0.00021*	0.00021	-0.00025	0.00000	-0.00000
	(0.00012)	(0.00030)	(0.00027)	(0.00001)	(0.00001)
$\text{AA(NP)}_{\text{t-1}}$	0.00054***	0.00013	0.00001	0.00000	0.00000
	(0.00012)	(0.00028)	(0.00027)	(0.00001)	(0.00001)
Panel E: Consumer Industry					
$\text{AA(NP)}_{\text{t-1}}$	0.00030	0.00037	0.00019	-0.00000	0.00002
	(0.00022)	(0.00038)	(0.00037)	(0.00001)	(0.00002)
$\text{AA(NP)}_{\text{t-1}}$	0.00013	0.00050	0.00068*	-0.00000	-0.00001
	(0.00021)	(0.00037)	(0.00037)	(0.00001)	(0.00002)
Panel F: Non-Consumer Industry					
$\text{AA(NP)}_{\text{t-1}}$	0.00028**	-0.00003	-0.00021	0.00001*	0.00000
	(0.00014)	(0.00029)	(0.00028)	(0.00000)	(0.00000)
$\text{AA(NP)}_{\text{t-1}}$	0.00052***	-0.00038	-0.00052**	0.00001	0.00001*
	(0.00013)	(0.00025)	(0.00026)	(0.00000)	(0.00000)

Table 16: Impact on Financial Markets – Newspaper Advertising Robustness II

The data requirements and regression specifications are equivalent to those in the main analysis. For ease of presentation, only the contemporary and first lag effects of advertising expenditures are reported.Standard-errors are clustered by firm for the panel-regressions. Fama-MacBeth regression standard-errors are Newey-West corrected (5 lags). 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(\text{Turnover}_t)$	(2) $\ln(\text{EffSpr}_t)$	(3) $\ln(\text{PrcImp}_t)$	(4) $\text{Return}_t^{\text{excess}}$	(5) $\text{Return}_t^{\text{excess}}$
		Panel A: Controlling for TV Advertising			
$AA(NP)_t$	0.00040***	0.00017	0.00006	0.00000	0.00000
	(0.00012)	(0.00024)	(0.00024)	(0.00000)	(0.00000)
$AA(NP)_{t-1}$	0.00054***	-0.00005	-0.00004	0.00001	0.00001
	(0.00011)	(0.00022)	(0.00022)	(0.00000)	(0.00000)
		Panel B: 1995-2003			
$AA(NP)_{t-1}$	0.00048***	0.00046	0.00016	0.00000	-0.00000
	(0.00018)	(0.00039)	(0.00038)	(0.00001)	(0.00001)
$AA(NP)_{t-1}$	0.00077***	-0.00011	-0.00012	0.00001	0.00001
	(0.00017)	(0.00037)	(0.00039)	(0.00001)	(0.00001)
		Panel C: 2004-2012			
$AA(NP)_{t-1}$	0.00024*	-0.00006	0.00001	0.00001	0.00000
	(0.00014)	(0.00019)	(0.00016)	(0.00001)	(0.00000)
$AA(NP)_{t-1}$	0.00027*	0.00007	0.00008	0.00000	0.00000
	(0.00014)	(0.00017)	(0.00015)	(0.00000)	(0.00001)
		Panel D: NYSE/AMEX			
$AA(NP)_t$	0.00032**	0.00009	-0.00005	-0.00000	-0.00001
	(0.00013)	(0.00028)	(0.00027)	(0.00000)	(0.00000)
$AA(NP)_{t-1}$	0.00048***	0.00018	-0.00002	0.00001	0.00000
	(0.00012)	(0.00026)	(0.00026)	(0.00000)	(0.00000)
		Panel E: NASDAQ			
$AA(NP)_t$	0.00029	0.00027	-0.00003	0.00001*	0.00003
	(0.00023)	(0.00037)	(0.00037)	(0.00001)	(0.00002)
$AA(NP)_{t-1}$	0.00039	-0.00072**	-0.00061*	0.00000	0.00002
	(0.00024)	(0.00031)	(0.00033)	(0.00001)	(0.00001)
		Panel F: Ln(1+$Advertising)			
$\ln(Ad(NP)_t)$	-0.00008	-0.00008	-0.00061	0.00000	0.00000
	(0.00016)	(0.00045)	(0.00049)	(0.00000)	(0.00000)
$\ln(Ad(NP)_{t-1})$	0.00022	-0.00020	-0.00029	-0.00000	0.00000
	(0.00014)	(0.00038)	(0.00041)	(0.00000)	(0.00000)
		Panel G: Advertising-Dummy			
$I_{Ad(NP),t}$	-0.00010	0.00116	-0.00227	0.00002	0.00002
	(0.00148)	(0.00388)	(0.00423)	(0.00004)	(0.00005)
$I_{Ad(NP),t-1}$	0.00247*	-0.00057	0.00065	-0.00001	0.00004
	(0.00130)	(0.00332)	(0.00359)	(0.00004)	(0.00004)

A Appendix: Variable Description

The following table briefly defines the main variables used in our empirical analysis. Abbreviations for the data sources are:

(i) Kantar: Kantar Stradegy database

(ii) WIKI: Wikipedia page count database

(iii) SVI: Google SVI data

(iv) TAQ: Trade and Quote database

(v) CRSP: CRSP's Stocks Database

(vi) CS: Compustat

(vii) OP: The homepages of authors of the respective original papers

EST indicates that the variable is estimated or computed based on original variables from the respective data sources.

Panel A: Advertising variables		
Variable Name	Description	Source
TV Ad $	Daily dollar amount spent on TV advertising in 990 US TV stations, estimated using rate cards that give information on prices for different parts of the day and/or programs. Available from 1995 to 2012.	Kantar
News TV Ad $	Daily dollar amount spent on TV advertising in US News TV stations. These stations are CNN, CNBC, Fox News, MSNBC and CNN headline news. Available from 1995 to 2012.	Kantar
Newspaper Ad $	Daily dollar amount spent on newspaper advertising in 155 US newspapers, estimated using rate cards that give information on prices based on size, product categories, and days of week or sections. Available from 1995 to 2012.	Kantar
National newspaper Ad $	Daily dollar amount spent on newspaper advertising in four national US newspapers, namely the Wall Street Journal, New York Times, USA Today and Washington Post. Includes the Wall Street Journal and the USA Today from 1995 to 2012 and the Wall Street Journal, USA Today, New York Times and Washington Post from 1999 to 2012.	Kantar
Local newspaper Ad $	Daily dollar amount spent on newspaper advertising in 151 local US newspapers. Available from 1999 to 2012.	Kantar
WSJ Ad $	Daily dollar amount spent on newspaper advertising in the Wall Street Journal. Available from 1995 to 2012.	Kantar
3 National newspaper Ad $	Daily dollar amount spent on newspaper advertising in the three other national newspapers (New York Times, USA Today and Washington Post). Includes the USA Today from 1995 to 2012 and the New York Times, USA Today and Washington Post from 1999 to 2012.	Kantar
$AA(TV)_t$	Abnormal TV advertising on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars t-1.	Kantar, EST
$AA(TVNWS)_t$	Abnormal news TV advertising on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars t-1.	Kantar, EST
$AA(TVNONWS)_t$	Abnormal TV advertising in non-news channels on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars t-1.	Kantar, EST
$AA(NP)_t$	Abnormal newspaper advertising on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars' median of the same weekday during the last 8 weeks.	Kantar, EST
$AA(NPNAT)_t$	Abnormal national newspaper advertising on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars' median of the same weekday during the last 8 weeks.	Kantar, EST
$AA(NPLOC)_t$	Abnormal local newspaper advertising on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars' median of the same weekday during the last 8 weeks.	Kantar, EST

$AA(NPWSJ)_t$	Abnormal newspaper advertising in the Wall Street Journal on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars' median of the same weekday during the last 8 weeks.	Kantar, EST
$AA(NP3NAT)_t$	Abnormal newspaper advertising in the three other national newspapers (New York Times, USA Today and Washington Post) on day t, defined as log-advertising-dollars on day t relative to log-advertising-dollars' median of the same weekday during the last 8 weeks.	Kantar, EST

Panel B: Investor attention variables

Variable Name	Description	Source
$Wiki_t$	Number of times the Wikipedia page of a company was visited on day t.	WIKI
$AWIKI_t$	Abnormal wikipedia page views on day t, defined as log-wiki on day t relative to the log of the median of the same weekday during the last 8 weeks. The definition follows Da, Engelberg, and Gao (2011), with the only difference being that we consider daily instead of weekly data.	WIKI, EST
SVI_t	Google search volume index of the company ticker on day t relative to the search volume at the first time company ticker searches were recorded in Google Trends. The data comes from Drake, Roulstone, and Thornock (2012).	SVI, OP
$ASVI_t$	Abnormal Google search volume index on day t, defined as log-svi on day t relative to the log of the median of the same weekday during the last 8 weeks. The definition follows Da, Engelberg, and Gao (2011), with the only difference being that we consider daily instead of weekly data. The data comes from Drake, Roulstone, and Thornock (2012).	SVI, OP, EST

Panel C: Financial market variables		
Variable Name	Description	Source
Turnover_{t}	Turnover is daily trading volume over shares outstanding on day t.	CRSP, EST
EffSpr_{t}	EffSpr is the effective spread, defined as daily transaction-weighted average of transaction prices relative to prevailing quotes on day t. Specifically, $EffSpr_t = 2\|P_t - Q_t\|/Q_t$ for each transaction, with P_t being the transaction price and Q_t the quote midpoint price, which is the average of the prevailing bid and ask quotes ($Q_t = \frac{A_t+B_t}{2}$). $EffSpr_t$ is then averaged over the day for each stock. We would like to thank Olga Lebedeva and Stefan Obernberger for providing us with their data set. This data set has also been used in Lebedeva (2012) and Hillert, Maug, and Obernberger (2014).	TAQ, EST, OP
PrcImp_{t}	PrcImp is the price impact, defined as transaction-weighted average of 5-minute impacts on quote-midpoints on day t. Specifically, $PrcImp_t = 2\|Q_{t+5} - Q_t\|/Q_t$ for each transaction, where Q_{t+5} represents the quote midpoint price of the stock after five minutes (300 seconds) and Q_t is defined as above. $PrcImp_t$ is then averaged over the day for each stock. We would like to thank Olga Lebedeva and Stefan Obernberger for providing us with their data set. This data set has also been used in Lebedeva (2012) and Hillert, Maug, and Obernberger (2014).	TAQ, EST, OP
$\text{Return}_{t}^{\text{excess}}$	Raw excess return of a stock over the risk-free rate on day t.	CRSP, EST
$\text{Turnover}_{\text{t-7,t-36}}$	$\text{Turnover}_{\text{t-7,t-36}}$ is the trading volume over the 4 weeks up to t-7, divided by average shares outstanding.	CRSP, EST
$\text{Return}_{\text{t-7,t-36}}$	$\text{Return}_{\text{t-7,t-36}}$ is the holding period return over the 4 weeks up to t-7.	CRSP, EST
$\text{ReaVola}_{\text{t-7,t-36}}$	$\text{ReaVola}_{\text{t-7,t-36}}$ is realized volatility, defined as average absolute return during the 4 weeks up to t-7.	CRSP, EST
MarketCap_{t}	MarketCap is the firm's market capitalization in million USD on day t.	CRSP, EST

Panel D: Other variables		
Variable Name	Description	Source
News_{t}	Dummy variable equal to one if the firm is covered in at least one of four national newspapers (Wall Street Journal, New York Times, USA Today, Washington Post) on day t. The data comes from Hillert, Jacobs, and Mueller (2014).	OP
Earnings Announcement_{t}	Dummy variable equal to one if the firm has an earnings announcement on day t.	IBES

B Appendix: Wikipedia Page View Data

This section briefly describes the procedure we use to extract Wikipedia page view counts on the firm-day level.

1. Download of full set of page count data from December 2007 to December 2012, as provided by Wikipedia. The data can be accessed from https://dumps.wikimedia.org/other/pagecounts-raw/.This data shows the unscaled, hourly number of page views for each redirect (URL) that was used at least once in this hour to access a Wikipedia page. We have checked the precision of this data set by calling an infrequently visited Wikipedia page 10 (20) times shortly before (after) the full hour. This led to a count of 10 (20) for the Wikipedia page we called in the correct hour.

2. Construction of a set of firms (permco-level) that are of interest in the context of our analysis: We use all firms available in CRSP anytime between December 2007 and December 2012 (variables used for link: name, ticker, headquarter state, time period of availability in CRSP).

3. Identification of firms' Wikipedia pages by searching English-language Wikipedia for the company name. If a page is found, information on ticker and headquarter state are used to make sure this actually is the Wikipedia page of the firm from CRSP. If there are separate pages for product and firm ('Coca-Cola' and 'The Coca-Cola Company'), only the firm page is used.

4. Manual selection of redirects that directly relate to firm name. For instance, 'Apple Computer', 'Option-Shift-K' and 'Jobs and Wozniak' all redirect to 'Apple Inc.'. We only classify the first redirect as 'directly related to firm name'.

5. For each hour, page counts for all redirects of each permco are added up. Then a dataset on the firm-day level is constructed by adding up hourly counts for Eastern Time (NYC) days.

C Appendix: Additional Tables

Table A1: Summary Statistics - Advertising and Investor Attention

This table gives summary statistics on Wikipedia page visits and Kantar advertising expenditure. The sample goes from 2007 until 2012. Wiki page visits and the advertising variables are per day. $AA(i)_t$ is abnormal newspaper advertising, i = {TV,TVNWS,TVNONWS,NP,NPLOC, NPNAT, NPWSJ, NP3NAT}. TV refers to all TV channels, TVNWS to news channels (CNN, CNBC, Fox News, MSNBC, CNN headline news), TVNONWS to all non-news TV channels, NP to all newspapers, NPLOC to local newspapers, NPNAT to national newspapers (Wall Street Journal, New York Times, USA Today and Washington Post), NPWSJ to the Wall Street Journal and NP3NAT to the other three national newspapers. News is a national newspaper article dummy. $Turnover_{t-7,t-36}$ is the trading volume over the 4 weeks up to t-7, divided by average shares outstanding. $Return_{t-7,t-36}$ is the holding period return over the 4 weeks up to t-7. $ReaVola_{t-7,t-36}$ is realized volatility, defined as average absolute return during the 4 weeks up to t-7. MarketCap is the firm's market capitalization. Panel A and B report statistics at the firm-day level on the regression samples for our TV and newspaper analyses, respectively.

	Mean	Median	SD	10%ile	90%ile	N
Panel A: TV regression sample						
Market Cap (Million $)	14,608.23	3,108.25	35,826.63	217.58	34,022.50	946,215
Firm age	29.85	22.92	22.46	6.33	65.25	946,467
Return on assets (%)	0.14	0.12	0.11	0.02	0.27	922,753
Advertising-to-sales (%)	0.03	0.02	0.04	0.00	0.08	780,702
$ReaVola_{t-7,t-36}$ (%)	46.05	35.46	35.67	16.77	86.53	945,457
$Turnover_{t-7,t-36}$ (%)	308.02	240.54	235.68	93.78	609.51	945,499
$Return_{t-7,t-36}$ (%)	0.91	0.93	14.40	-14.50	15.13	945,457
$News_t$ (%)	3.44	0.00	18.23	0.00	0.00	947,982
Wiki page count	540.89	116.00	2,572.65	17.00	1,135.00	947,982
TV Ad (daily $)	206,163.55	1,757.00	775,621.24	0.00	430,238.00	947,982
News TV Ad (daily $)	3,099.62	0.00	12,706.67	0.00	6,215.00	947,982
$AA(TV)_t$	-0.02	0.00	2.16	-1.48	1.44	947,982
$AA(TVNWS)_t$	-0.00	0.00	1.23	0.00	0.00	947,982
$AA(TVNONWS)_t$	-0.02	0.00	2.17	-1.49	1.46	947,982
Panel B: Newspaper regression sample						
Market Cap (Million $)	14,926.38	3,261.33	35,464.06	229.40	34,855.18	928,416
Firm age	29.53	22.75	22.00	6.75	63.92	928,613
Return on assets (%)	0.13	0.12	0.11	0.02	0.26	908,973
Advertising-to-sales (%)	0.03	0.01	0.04	0.00	0.06	760,751
$ReaVola_{t-7,t-36}$ (%)	46.49	35.76	35.88	17.07	87.44	927,759
$Turnover_{t-7,t-36}$ (%)	310.24	243.80	234.06	96.28	614.21	927,799
$Return_{t-7,t-36}$ (%)	0.90	0.90	14.46	-14.58	15.27	927,759
$News_t$ (%)	3.67	0.00	18.79	0.00	0.00	930,230
Wiki page count	543.21	107.00	2,637.73	16.00	1,157.00	930,230
Newspaper Ad (daily $)	30,667.02	0.00	265,019.90	0.00	22,407.00	930,230
National Newspaper Ad (daily $)	6,183.43	0.00	46,386.81	0.00	0.00	930,230
Local Newspaper Ad (daily $)	24,483.59	0.00	237,697.16	0.00	13,443.50	930,230
3 national newspaper Ad (daily $)	3,984.24	0.00	35,541.67	0.00	0.00	930,230
WSJ Ad (daily $)	2,199.19	0.00	24,778.52	0.00	0.00	930,230
$AA(NP)_t$	0.18	0.00	3.18	-0.30	1.22	930,230
$AA(NPLOC)_t$	0.16	0.00	2.96	-0.16	0.90	930,230
$AA(NPNAT)_t$	0.10	0.00	1.99	0.00	0.00	930,230
$AA(NPWSJ)_t$	0.06	0.00	1.26	0.00	0.00	930,230
$AA(NP3NAT)_t$	0.07	0.00	1.74	0.00	0.00	930,230

Table A2: Summary Statistics – Advertising and Financial Markets

This table reports summary statistics on financial market data and Kantar-advertising on the firm-day level. The observations are restricted NYSE/AMEX/NASDAQ stocks, to those days when a firm's price was $\geq$ 5 last week and when it advertised at least once during the last 8 weeks, i.e. when the main data requirements for the panel regressions are fulfilled. In order to keep TAQ-based variables (available 1996-2010 only) and other variables comparable, the sample includes observations from 1996 to 2010 only. Statistics for newspaper subcategories (local papers, Wall Street Journal and the other national papers) are further restricted to the $\geq$ 1999 period, as local paper ads are available only after 1998.

	Mean	Median	SD	10%ile	90%ile	N
Panel A: TV Regression sample						
Market Cap (Million $)	11,320.41	2,184.80	28,057.57	244.11	27,337.38	2,576,578
Firm age	24.96	17.71	20.90	5.23	58.05	2,576,578
Return on assets (%)	14.41	14.26	10.57	2.95	25.79	2,564,494
Advertising-to-sales (%)	4.10	1.89	7.82	0.02	9.25	2,094,648
Turnover_{t} (%)	196.52	118.24	240.00	26.03	442.11	2,562,647
Return_{t} (%)	0.05	0.00	2.63	-2.72	2.83	2,562,323
$\text{Rea.Vola}_{t\text{-}7,t\text{-}36}$ (%)	39.43	32.79	24.98	16.54	69.97	2,555,867
News_{t} (%)	5.19	0.00	22.17	0.00	0.00	2,576,578
Effective Spread_{t} (%)	2.58	2.23	1.80	0.78	4.71	2,576,546
Price Impact_{t} (%)	4.01	2.85	3.74	1.04	8.43	2,576,578
TV Ad (daily $)	147,807.43	1,133.00	597,339.53	0.00	255,458.00	2,576,578
News TV Ad (daily $)	2,299.67	0.00	10,946.95	0.00	3,203.00	2,576,578
No-News TV Ad (daily $)	145,507.76	909.00	592,619.74	0.00	248,489.00	2,576,578
AA(TV)_{t}	0.02	0.00	2.28	-1.70	1.76	2,576,578
AA(TVNWS)_{t}	0.02	0.00	1.22	0.00	0.00	2,576,188
AA(TVNONWS)_{t}	-0.04	0.00	2.22	-1.39	1.26	2,576,188
Panel B: Newspaper Regression sample						
Market Cap (Million $)	10,191.61	1,875.77	26,597.27	177.24	22,816.52	2,879,703
Firm age	22.74	15.55	20.00	4.83	54.37	2,879,703
Return on assets (%)	13.08	13.24	11.57	2.35	25.04	2,866,347
Advertising-to-sales (%)	3.45	1.50	7.64	0.01	7.51	2,280,072
Turnover_{t} (%)	204.04	123.59	247.70	23.33	462.80	2,864,976
Return_{t} (%)	0.04	0.00	2.78	-2.88	2.98	2,864,557
$\text{Rea.Vola}_{t\text{-}7,t\text{-}36}$ (%)	41.82	34.18	27.55	16.87	76.08	2,855,942
News_{t} (%)	4.86	0.00	21.50	0.00	0.00	2,879,703
Effective Spread_{t} (%)	2.52	2.23	1.64	0.80	4.48	2,879,703
Price Impact_{t} (%)	3.86	2.80	3.48	1.05	7.99	2,879,703
Newspaper Ad (daily $)	20,991.65	0.00	168,195.85	0.00	14,714.00	2,675,054
WSJ Newspaper Ad (daily $)	2,066.51	0.00	22,955.88	0.00	0.00	2,675,054
3 National Newspaper Ad (daily $)	3,224.47	0.00	27,801.07	0.00	0.00	2,675,054
Local Newspaper Ad (daily $)	15,700.66	0.00	145,939.92	0.00	8,168.00	2,675,054
AA(NP)_{t}	0.21	0.00	3.01	-0.12	1.06	2,879,703
AA(NPWSJ)_{t}	0.06	0.00	1.34	0.00	0.00	2,675,054
AA(NP3NAT)_{t}	0.07	0.00	1.63	0.00	0.00	2,675,054
AA(NPLOC)_{t}	0.17	0.00	2.70	-0.03	0.74	2,675,054

Table A3: AR-Model Advertising

The analysis is done for 1995-2012 firm-day observations for firms with common stocks on NYSE, AMEX and NASDAQ. Advertising is daily advertising expenditure in dollars. Nontrading days are excluded, but results are stable when all days are used. Standard-errors are clustered by firm. Controls are as in Table 7 and include EA_t, $News_t$, $Turnover_{t\text{-}7,t\text{-}36}$, $Return_{t\text{-}7,t\text{-}36}$, $ReaVola_{t\text{-}7,t\text{-}36}$ and $MarketCap_{t\text{-}7}$. 1/2/3 stars denote significance at the 10/5/1%-level.

	(1) $\ln(1{+}Adv(TV)_t)$	(2) $\ln(1{+}Adv(TV)_t)$	(3) $\ln(1{+}Adv(NP)_t)$	(4) $\ln(1{+}Adv(NP)_t)$
$\ln(1{+}Adv(TV)_{t\text{-}1})$	0.534***	0.534***		
	(0.006)	(0.006)		
$\ln(1{+}Adv(TV)_{t\text{-}2})$	0.128***	0.128***		
	(0.003)	(0.003)		
$\ln(1{+}Adv(TV)_{t\text{-}3})$	0.055***	0.054***		
	(0.002)	(0.002)		
$\ln(1{+}Adv(TV)_{t\text{-}4})$	0.030***	0.029***		
	(0.002)	(0.002)		
$\ln(1{+}Adv(TV)_{t\text{-}5})$	0.010***	0.010***		
	(0.003)	(0.003)		
$\ln(1{+}Adv(TV)_{t\text{-}6})$	0.024***	0.024***		
	(0.003)	(0.003)		
$\ln(1{+}Adv(TV)_{t\text{-}7})$	0.124***	0.124***		
	(0.005)	(0.005)		
$\ln(1{+}Adv(NP)_{t\text{-}1})$			0.099***	0.099***
			(0.003)	(0.003)
$\ln(1{+}Adv(NP)_{t\text{-}2})$			0.063***	0.063***
			(0.003)	(0.003)
$\ln(1{+}Adv(NP)_{t\text{-}3})$			0.039***	0.038***
			(0.003)	(0.003)
$\ln(1{+}Adv(NP)_{t\text{-}4})$			0.028***	0.028***
			(0.002)	(0.002)
$\ln(1{+}Adv(NP)_{t\text{-}5})$			0.045***	0.044***
			(0.003)	(0.003)
$\ln(1{+}Adv(NP)_{t\text{-}6})$			0.072***	0.071***
			(0.003)	(0.003)
$\ln(1{+}Adv(NP)_{t\text{-}7})$			0.374***	0.374***
			(0.006)	(0.006)
Controls	YES	YES	YES	YES
Firm-FEs	YES	YES	YES	YES
Week-FEs	YES	YES	YES	YES
Day-of-Week-FEs	YES	YES	YES	YES
R^2	0.83	0.83	0.52	0.52
No. obs.	3007878	3007878	3218153	3218153

Table A4: Summary Statistics - Advertising and Google SVI

This table gives summary statistics on Google SVI and Kantar advertising expenditure. The sample goes from 2005 until 2008. Google search volume (SVI) and the advertising variables are per day. News is a national newspaper article dummy. $\text{Turnover}_{t\text{-}7,t\text{-}36}$ is the trading volume over the 4 weeks up to t-7, divided by average shares outstanding. $\text{Return}_{t\text{-}7,t\text{-}36}$ is the holding period return over the 4 weeks up to t-7. $\text{ReaVola}_{t\text{-}7,t\text{-}36}$ is realized volatility, defined as average absolute return during the 4 weeks up to t-7. MarketCap is the firm's market capitalization. Panel A to C report cross-sectional summary statistics that are based on within-firm time series averages.

	Mean	Median	SD	10%ile	90%ile	N
Panel A: All public firms						
Market Cap (Million $)	2,777.08	301.59	13,569.90	32.31	4,237.46	5,845
Firm age	15.53	11.38	14.68	2.13	35.13	5,845
Return on assets (%)	4.59	8.52	22.66	-18.97	24.18	5,521
Advertising-to-sales (%)	4.99	1.08	17.82	0.03	7.44	3,583
$\text{Turnover}_{t\text{-}7,t\text{-}36}$ (%)	195.42	156.54	166.52	28.03	420.17	5,841
$\text{ReaVola}_{t\text{-}7,t\text{-}36}$ (%)	50.39	45.18	25.31	24.82	82.48	5,841
$\text{Return}_{t\text{-}7,t\text{-}36}$ (%)	-0.67	-0.23	4.21	-4.66	2.76	5,841
News_t (%)	0.77	0.00	4.19	0.00	1.00	5,845
Panel B: Public firms with Google SVI data						
Market Cap (Million $)	21,499.06	9,777.12	38,391.94	3,071.42	44,616.23	547
Firm age	33.04	31.59	22.59	8.21	71.21	547
Return on assets (%)	15.30	14.07	10.56	3.62	27.55	541
Advertising-to-sales (%)	2.18	0.95	4.27	0.00	5.40	401
$\text{Turnover}_{t\text{-}7,t\text{-}36}$ (%)	274.45	230.66	160.34	126.35	494.23	547
$\text{ReaVola}_{t\text{-}7,t\text{-}36}$ (%)	32.77	30.63	11.42	20.13	48.03	547
$\text{Return}_{t\text{-}7,t\text{-}36}$ (%)	-0.07	0.14	1.85	-2.28	1.75	547
News_t (%)	5.67	1.64	11.29	0.07	14.37	547
Google SVI	0.95	1.00	0.87	0.15	1.34	547
Panel C: Public firms with Google SVI data and Kantar ads						
Market Cap (Million $)	21,821.49	10,706.37	36,820.04	3,387.31	44,958.48	502
Firm age	34.08	34.64	22.79	8.21	74.63	502
Return on assets (%)	15.37	13.96	9.33	3.62	27.33	498
Advertising-to-sales (%)	2.22	1.05	4.33	0.00	5.52	378
$\text{Turnover}_{t\text{-}7,t\text{-}36}$ (%)	266.37	222.69	155.16	126.31	470.02	502
$\text{ReaVola}_{t\text{-}7,t\text{-}36}$ (%)	32.12	30.19	10.82	20.08	46.69	502
$\text{Return}_{t\text{-}7,t\text{-}36}$ (%)	-0.08	0.13	1.81	-2.17	1.66	502
News_t (%)	6.00	1.85	11.64	0.07	14.99	502
Google SVI	0.97	1.00	0.90	0.17	1.34	502
TV Ad (daily $)	209,017.55	2,562.28	693,131.91	0.00	447,204.86	502
News TV Ad (daily $)	2,725.78	0.00	8,319.84	0.00	8,132.62	502
Newspaper (daily $)	43,215.55	1,443.89	193,419.03	10.24	58,540.44	502
WSJ Ad (daily $)	2,072.01	0.00	6,201.25	0.00	5,380.21	502
3 National newspaper Ad (daily $)	5,471.50	65.63	21,772.95	0.00	11,079.70	502
Local Newspaper Ad (daily $)	35,672.04	472.27	170,977.64	4.40	38,668.12	502