Noise Trading: An Ad-based Measure*

Vivian W. Fang   Joshua Madsen   Xinyuan Shao†

March 9, 2019

Abstract

This paper proposes a novel measure of noise trading that aims to capture *uninformed* retail trading. The measure, an indicator of whether the firm placed advertisement(s) in the *Wall Street Journal* seven calendar days earlier, is motivated by evidence that retail trading spikes on ad days, that firms regularly place ads at weekly intervals, and that weekly ads frequently contain duplicate images. Instrumented retail trading is positively associated with informed trading and stock price efficiency, which suggests that informed investors anticipate increases in noise trading and trade accordingly.

JEL Classifications: G10, G12, G14, G23, M37

Keywords: Advertisement, Noise Trading, Uninformed Trading, Informed Trading, Retail Trading, Institutional Trading, Stock Liquidity, Price Efficiency, Image Analysis

*We are grateful for comments and suggestions from Anat Admati, Nick Guest, Iftekhar Hasan, Jeff McMullin, Yi Tang, Yihui Wang, seminar participants at Fordham University and the University of Minnesota, and conference participants at the 2018 Brigham Young University Accounting Research Symposium. We thank Jason Swan and Yifan Yan for excellent research assistance.

†*E-mail:* fangw@umn.edu; jmmadsen@umn.edu; shaox201@umn.edu

Mailing address: Carlson School of Management, University of Minnesota, Minneapolis, MN 55455.

1 Introduction

Noise trading is crucial in market microstructure models: simply put, trading would not take place without it (e.g., Kyle (1985); Admati and Pfleiderer (1988)). Noise trading, as defined by these models, is uninformed.[1] Truly random buys and sells by liquidity traders fit this theoretical definition but are difficult to capture. Other potential proxies—retail and small trades—are shown to be sometimes informed (Barber, Odean, and Zhu (2009); Brandt, Brav, Graham, and Kumar (2009); Boehmer, Jones, and Zhang (2017)), making them less-than-ideal measures of noise trading. In this paper, we propose a new measure of noise trading that aims to capture *uninformed* retail trading. Specifically, we measure noise trading using an indicator of whether the firm placed an advertisement (ad) in the *Wall Street Journal* (WSJ) seven calendar days earlier.

This measure exploits the rigidity in firms' print advertising timing—firms regularly place product ads at weekly intervals (Madsen and Niessner (2019))—as well as evidence that retail trading spikes on ad days. We confirm both findings using a sample of 9,620 WSJ ad days by 238 U.S. public firms between 2009 and 2013. First, there is a high probability (42.4%) that a firm advertises on a given day if it advertised seven calendar days earlier, consistent with advertising rigidity. Second, both the number and dollar amount of retail trades, calculated using the method of Boehmer et al. (2017), significantly increase on WSJ ad days. The spike in retail trading exhibits a cyclical pattern, repeating every five trading days, and thus mirrors firms' weekly advertising pattern. We find no significant increase in the number of retail trades immediately prior to ad days, increasing confidence that WSJ ads trigger retail trading.[2] To establish the relevance of our measure to retail trading, we document an increase of 34.5 retail trades (2.3% of the sample average) and $804,000 retail trading volume (3.5% of the sample average) seven calendar days after a WSJ ad day, with the largest effects occurring during the first and last trading hours.

[1] We consider a trade uninformed if it is not motivated by information and is also insensitive to price.

[2] Increased retail trading on ad days is consistent with Barber and Odean's (2008) finding that retail investors buy stocks that catch their attention, Madsen and Niessner's (2019) finding that Google searches for a firm's ticker rise on its ad days, and Liaukonyte and Zaldokas's (2019) finding that TV ads lead to increases in SEC EDGAR queries and Google searches for financial information.

We control for date and firm fixed effects, ad days with new images, days surrounding earnings announcements, other news days, market capitalization, and book-to-market.

Our measure arguably captures only uninformed retail trading for two reasons. First, advertising rigidity allows us to address the endogenous timing of ad placement, which may be correlated with firms' information events. It is unlikely that new information arrives every seven days or that firms intentionally bank information and release it on prescheduled ad days. Second, ads that are placed in the same newspaper every seven days likely contain minimal information content. To bolster this point, we perform image analysis using a combination of machine learning and manual verification. We find that WSJ ads placed seven days after a previous ad day have 61.8% probability of being a duplicate image of an ad that already appeared in the WSJ within the previous 60 days. Thus, while retail trading in response to general ads (or other information events) could be informed, retail trading in response to weekly recurring ads is likely uninformed and thus matches the theoretical definition of noise trading.

As an application of this measure, we study the association between noise trading and informed trading. Kyle (1985) shows that random noise trading provides camouflage, enabling informed traders to profit at the expense of uninformed traders. Admati and Pfleiderer (1988) allow for discretionary noise trading and predict a similar effect of noise trading on informed trading. Subsequent theories show that noise trading stimulates informed trading by allowing large investors to build positions at a low cost to monitor firms (Kyle and Vila (1991); Kahn and Winton (1998); Maug (1998)) and realize monitoring gains (Faure-Grimaud and Gromb (2004)). Additionally, noise trading prompts blockholders to acquire more information and trade aggressively on it, thus also increasing price efficiency (Edmans (2009); Edmans and Manso (2011)).

Prior empirical research sheds light on these predictions by documenting a positive effect of stock liquidity on block formation and trading (e.g., Edmans, Fang, and Zur (2013); Norli, Ostergaard, and Schindele (2014)). Common liquidity measures, however, do not capture variation in just noise trading. Instead, these measures are typically functions of both uninformed and informed trading.[3] We thus revisit the effect of noise trading on informed trading using the ad-based measure as an instrument for noise trading. As discussed earlier, this instrument is positively correlated with retail trading but unlikely to affect informed trading other than through its correlation with uninformed retail trading. The instrument also addresses the concern that a potentially omitted firm characteristic is correlated with both retail and informed trading, as any such characteristic is unlikely to fluctuate every seven days. Furthermore, the cyclical pattern in weekly advertising and retail trading suggests that informed traders can anticipate ad days (and associated changes in uninformed trading) and trade to their profit. This does not require informed traders to have knowledge about the specifics of firms' ad contracts, only that they are able to discern patterns in retail trading induced by weekly recurring ads. The predictability of our measure allows us to identify a portion of noise trading that is anticipatable to informed traders, making a causal link from noise trading to informed trading possible.

We document a cyclical pattern in informed trading that resembles the pattern in retail trading, albeit less regular: both the number and dollar amount of informed trades (defined as non-retail trades of $50,000 or greater) increase on WSJ ad days and the five trading days before and after ad days. Two-stage least squares (2SLS) regressions confirm a positive association between instrumented retail trading and informed trading—an increase of 34.5 instrumented retail trades (i.e., the increase associated with a WSJ ad seven days earlier) is associated with an increase of 14.3 informed trades (2.3% of the sample average), and an increase of $804,000 instrumented retail trading volume is associated with an increase of $2.2 million informed trading volume (2.6% of the sample average). Importantly, we control for the placement of a non-duplicate ad and continue to include a comprehensive set of controls and both date and firm fixed effects.[4] We interpret this result as informed traders rationally responding to expected and/or observed increases in noise trading, as predicted by market microstructure theories.

[3] See Goyenko, Holden, and Trzcinka (2009) for a summary of liquidity measures, including those based on trading costs (e.g., quoted or effective bid-ask spreads) or price impact (e.g., the Amihud measure of Amihud (2002)).

[4] The results are also robust to removing ad days that fall seven days after a previous ad day and release non-duplicate images.

One alternative interpretation is that information released on WSJ ad days drives both retail and informed trades, making them correlated and inducing a positive bias (information hypothesis). The use of the ad-based instrument alleviates this concern. A second alternative interpretation is that increased attention brought about by ads drives both retail and large non-retail trades, also inducing a positive bias. This would suggest that some large institutional trades are behavioral responses to attention (i.e., uninformed), which we view as less likely. We conduct two additional analyses to help rule out these hypotheses. First, we show that the positive relation between the ad-based measure and informed trading strengthens with the length of the firm's history of placing weekly recurring ads. Neither the information nor the attention hypothesis predicts this result. Instead, it is consistent with our interpretation that informed traders rationally anticipate and exploit increases in noise trading, as a longer history of recurring ads should make it easier to discern a pattern in noise trading. Second, we show that the ad-based measure is positively associated with price efficiency, particularly for firms with a longer history of placing recurring ads. We follow Chordia, Roll, and Subrahmanyam (2005, 2008) and measure price efficiency as the inverse of the short-term return predictability of order imbalance. Inconsistent with the attention hypothesis, this result suggests that ad-induced uninformed retail trading prompts informed investors to trade and that their trading in turn accelerates the incorporation of private information into stock prices.

Finally, we check the robustness of our results to alternative measures of noise trading and retail trading. Specifically, we show that the 2SLS results are robust to adding the existence of a WSJ ad fourteen calendar days earlier as a second instrument. This additional instrument is motivated by the observation that some firms advertise on a bi-weekly basis (Madsen and Niessner (2019)). The results are also robust to using only retail trades of $5,000 or less.

This study adds to the existing literature in two ways. First, we contribute a novel measure of noise trading. Compared to the liquidity measures used in prior studies, our ad-based measure of noise trading has two advantages. First, our measure is primitive. Edmans (2009) and Edmans and Manso (2011) define liquidity simply as the volume of noise trader demand, and our measure exactly maps to this notion of liquidity.[5] Second, our measure is likely correlated with only

[5] In contrast, Kyle (1985) defines liquidity as an increasing function of noise trading (relative to informed trading), and describes it as a "slippery and elusive concept" that encompasses three transactional properties: tightness,

uninformed retail trades and thus captures the essence of noise trading. These two advantages alleviate concerns that new information or other omitted firm characteristics drive both uninformed and informed trading and allow us to more forcibly establish a causal link from noise trading to informed trading. Our results show that informed traders strategically time their trades to expected and/or observed noise trades, and their trading in turn improves stock price efficiency. These results complement previous findings of a positive effect of stock market liquidity on block formation and trading (e.g., Edmans et al. (2013); Norli et al. (2014)).

The uninformed nature of our measure also makes it unique compared to non-liquidity based measures of noise trading. For example, retail trades are sometimes informed (Boehmer et al. (2017)) and small trades can result from order splitting by informed traders (Barber et al. (2009); Brandt et al. (2009)). Greene and Smart (1999) use the coverage of a stock in WSJ's "Investment Dartboard" column as a shock to noise trading, and find an increase in trading volume and a decrease in bid-ask spreads following the coverage. Although such coverages may drive mostly uninformed retail trading, lingering endogeneity concerns remain since this column is dedicated to publishing stock recommendations written by financial analysts. In contrast, our ad-based measure is arguably uninformed, generalizable, and potentially applicable in wider contexts.

By deriving a measure of noise trading from product ads, we also contribute to a growing literature on the financial market implications of corporate advertising. In addition to the aforementioned studies that document an effect of print and TV ads on investor attention, prior research finds that annual advertising expenditures are negatively associated with trading costs and price impact (Grullon, Kanatas, and Weston (2004)), and positively associated with breadth of ownership (Grullon et al. (2004); Frieder and Subrahmanyam (2005)), stock returns (Boyd and Schonfeld (1977); Chemmanur and Yan (2011); Lou (2014)), and firm value (Gurun and Butler (2012)). In contrast, we focus on daily ads and their effect on uninformed/informed trading and price efficiency.

depth, and resiliency. To capture this notion of liquidity, empirical literature typically uses either trading cost- or price impact-based measures. Some studies also utilize shocks that arguably increased one property of liquidity (such as decimalization as a shock to tightness in Fang, Noe, and Tice (2009) and financial crises as a shock to resiliency in Bharath, Jayaraman, and Nagar (2013)).

2 Data, variable measurement, and descriptive statistics

This section describes data, defines the main variables, and provides descriptive statistics for the sample. Detailed variable definitions are in appendix A.

2.1 Ad days

We obtain ad data from MediaRadar Ad Sales Research Database, which covers ads published in a wide range of daily newspapers between February 2008 and October 2013. Compared to TV and online ads, print ads have a longer shelf life and their placement (both date and location) can be easily measured. Although readership of print newspapers has declined, the remaining subscribers represent the most engaged readers, a desirable feature for corporate advertisers.

Given our interest in how recurring ads affect trading, we focus our analysis on ads placed in the WSJ for three reasons. First, the WSJ is one of the most widely circulated newspapers in the U.S. With 1.4 million print copies sold daily in 2013,[6] the journal captures a significant amount of the ads covered by MediaRadar. Second, the WSJ is the most influential business newspaper in the U.S., so presumably, its subscribers are keen to learn about business and economics news and comfortable with trading. Third, focusing on one newspaper helps ensure that recurring ads contain minimal information content, particularly if these ads result from multi-week contracts.

To assess the effect of advertising on trading, we align each ad day in the WSJ to a trading day. While a majority of the sample ads (94%) fall on trading days, a small fraction are placed in the WSJ weekend issues and on holidays (i.e., non-trading days). We align each non-trading ad day to its first subsequent trading day, although inferences do not change if we remove these ads. We define an indicator for ad days, Ad_t, to equal one if the firm placed an ad in the WSJ on day t, and zero otherwise.

[6] Data on the 2013 average circulation rate for the top 25 U.S. newspapers are available through Alliance for Audited Media at https://web.archive.org/web/20151016155148/http://auditedmedia.com/news/blog/top-25-us-newspapers-for-march-2013.aspx.

2.2 Retail trading and informed trading

To construct measures of retail and informed trading, we retrieve intraday trading data from the Trade and Quote database (TAQ). We follow Boehmer et al. (2017) to detect retail trades. Their methodology exploits the fact that marketable retail orders are primarily executed either via internalization (i.e., filled from the broker's own inventory) or by wholesalers. These retail orders are often associated with a small price improvement (typically 0.01, 0.1, or 0.2 cents) relative to the National Best Bid or Offer (NBBO). In contrast, institutional orders, executed through either exchanges or dark pools, are generally prohibited from sub-pennying pricing after the decimalization of tick size in 2001. One exception is that institutional orders are allowed to be executed at the midpoint of the NBBO, so some are printed at 0.5 cents. Further, some institutional trades are printed at 0.4, 0.5, or 0.6 cents, which result from a dark pool that for a time allowed some negotiation around the midquote.

Boehmer et al. (2017) exploit these institutional features and track retail orders in two steps. First, they retrieve trades and quotes marked with exchange code "D" in TAQ, which are potential retail transactions reported to a Financial Industry Regulatory Authority Trade Reporting Facility (FINRA TRF). Second, they classify these transactions based on printed prices. Trades recorded at a price higher than a round penny by (0-0.4) cents are labeled retail seller-initiated trades, and trades recorded at a price higher than a round penny by (0.6-1) cent(s) are labeled retail buyer-initiated trades. Orders recorded at a price higher than a round penny by [0.4-0.6] cents may be institutional trades and are thus excluded. We closely follow this approach to identify retail trades, and define three measures of retail trading for a given trading day t: *Number of Retail Trades* (the total number of retail trades), *Retail Dollar Volume* (the aggregate dollar volume of retail trades), and *Retail Trading PC* (the first principal component of the two, standardized to have a mean of zero and standard deviation of one).

To proxy for informed trades, we identify non-retail trades of $50,000 or more; the choice of using $50,000 as the cutoff level follows Lee and Radhakrishna (2000) and Barber et al. (2009). Thus, we argue that large institutional trades are likely motivated by information. This definition likely represents a lower bound of informed trading, as it excludes any informed retail trades as well as informed institutional trades below \$50,000.[7] Similar to retail trading, we calculate two measures of informed trading for day t: *Number of Informed Trades* (the total number of informed trades) and *Informed Dollar Volume* (the aggregate dollar volume of informed trades).

2.3 Control variables

One important control that we include in our multivariate analyses is an indicator for WSJ ads that are *not* duplicate images of a previous ad. We create this indicator in three steps. First, we capture the image of every WSJ ad in our sample. Second, we apply Scale Invariant Feature Transform (SIFT) and Speed Up Robust Feature (SURF), two common feature detection algorithms in computer vision, to compare each ad's image (Ad_i) to images of previous ads placed by the firm for the same brand ($Ad_{j\neq i}$). These algorithms take an image and transform it into a "large collection of local feature vectors" known as keypoints (Lowe (1999)). Each keypoint is invariant to any scaling, rotation, or translation of the image. SIFT and SURF then calculate the Euclidean distances between all the keypoints of two images (Ad_i, Ad_j) and produce a similarity measure.[8] Third, we code the indicator $Non\text{-}duplicate\, Ad_t$ as one if any Ad_i on day t is not a duplicate image of any Ad_j that already appeared in the WSJ within the previous 60 days (i.e., similarity measures produced by SIFT and SURF equal 5 or less for any Ad_i, Ad_j pair), and zero if it is a duplicate image (i.e., similarity measure from both SIFT and SURF is greater than 15 for at least one Ad_i, Ad_j pair) or if there was no ad on day t. We manually check ad images for which either technique produces a similarity measure between 5 and 15 and classify them into duplicate and non-duplicate ads.[9]

[7] This definition possibly includes portfolio-rebalancing trades by institutions. Such trades might not be related to fundamentals of the holding companies per se, but still fall under our definition of informed trades because they are motivated by institutions' private information and are not pure noise trades. In other words, institutions can anticipate and exploit the recurring ad-induced noise trading and execute rebalancing trades to their profit.

[8] The similarity measure is calculated using the ratio of distances test proposed by Lowe (2004). Specifically, to identify a match for $Keypoint_{i,k}$ (where i indexes the ad and k indexes the keypoints within Ad_i), the Euclidean distance between $Keypoint_{i,k}$ and its closest neighbor $Keypoint_{j,k}$ must be significantly smaller than the distance between $Keypoint_{i,k}$ and its second-closest neighbor $Keypoint_{j,m\neq k}$. Following prior research, we define a match as good if the distance from $Keypoint_{i,k}$ to the closest neighbor $Keypoint_{j,k}$ is 60% or less of the distance from $Keypoint_{i,k}$ to its second-closest neighbor. If no $Keypoint_{j,k}$ meets this criterion, then $Keypoint_{i,k}$ is not matched. The resulting similarity measure is the percentage of all good matches across all keypoints k in Ad_i.

[9] The choice of using 5 and 15 as cutoff thresholds seems reasonable based on manual verification of two random samples of 100 ads each—94% of the ads for which both techniques produce similarity measures of 5 or less are

As additional controls, we include four indicators to control for the effect of earnings announcements and other news releases on retail and informed trading. These indicators denote quarterly earnings announcement days (QEA_t); the two days prior to an earnings announcement ($QEA_{[t-2,t-1]}$); the two days after an earnings announcement ($QEA_{[t+1,t+2]}$); and the days with non-earnings announcement news releases ($Other\,News_t$), respectively. Similar to ad days, we align a non-trading earnings announcement/news day with its first subsequent trading day in defining these indicators. We also include two controls for size and growth: the natural logarithm of market capitalization ($ln(Market\,Cap)$) and book-to-market ratio ($Book/Market$), both measured at the end of prior quarter. In terms of data sources for these controls, firm financials are from the Compustat quarterly files, quarterly earnings announcement days are from I/B/E/S, other news events are from Ravenpack, and market capitalization and listing status are from CRSP daily stock files.

2.4 Summary statistics

We restrict the sample to U.S. domiciled firms with exchange-listed common shares. After aligning advertising and trading days, we merge the advertising data with trading measures and controls. The final sample consists of 139,656 trading days by 238 unique firms between April 2009 (the month in which MediaRadar begins coverage of the WSJ) and October 2013. Of these firm-trading days, 9,620 (6.9%) are marked as WSJ ad days, which are associated with 10,225 individual ads. Table 1 reports descriptive statistics for our sample. To ease the presentation of coefficient estimates in the regression analyses reported below, we divide the number of trades by one hundred and dollar trading volume by one million.

An average firm-day in our sample is associated with 1,491 retail trades and $23.1 million in retail dollar volume. The average retail trade size is 348.5 shares or $13,725, with the latter number falling within the interquartile range of $2,000 to $25,000 quoted by Boehmer et al. (2017) for a

confirmed to be non-duplicate images, and 97% of the ads for which both techniques produce similarity measures greater than 15 are confirmed to be duplicate images. Since we manually check all ads for which at least one of the techniques produces a similarity measure between 5 and 15, results are not sensitive to using cutoff levels that are close to these thresholds.

larger sample of firms. The average trade size is also consistent with the observation by Boehmer et al. (2017) that retail trades are not necessarily small and sometimes informed. In Section 5, we report results using modified measures of retail trading that limit trade size to $5,000 or less. As expected, informed trades are significantly larger than retail trades. In our sample, an average firm-day is associated with 622.6 informed trades and $85.7 million in informed dollar volume, with an average trade size of 7,249 shares or $177,260. Finally, our sample firms tend to be large, with an average market capitalization of $14.2 billion and a book-to-market ratio of 0.78.

3 Empirical results

3.1 Ad days and retail trading

We start by examining patterns in retail investors' trading around ad days. Figure 1 plots the average number of retail trades and retail dollar volume from trading day -7 to trading day 7, with day 0 representing the 9,620 WSJ ad days in our sample. The first pattern that emerges from Figure 1 is that both the number and dollar volume of retail trades spike on ad days. Extending this result to multivariate regression, we study the relation between ad days and retail trading by estimating the following ordinary least squares (OLS) model:

$$Retail\ Trading_t = \alpha + \beta Ad_t + \gamma Controls_t + \epsilon_t. \tag{1}$$

Again, the sample is at the firm-trading day level, with subscript t indexing day and the subscript for firm omitted for brevity. The dependent variable is one of the three measures of retail trading, all defined in Section 2.2, and the key independent variable is Ad_t. $Controls_t$ includes those discussed in Section 2.3, date fixed effects to control for time-series variation in retail trading due to common shocks (such as market conditions), and firm fixed effects to control for firm-level heterogeneity in advertising and retail trading. To examine when the increase in retail trading occurs and how long it lasts, we also include indicators for the days immediately before and after ad days. Specifically, we include $n\ Days\ Before\ Ad_t$ (which denotes whether trading day t is the n^{th} trading day before a subsequent ad day, with $n = 1, 2$) and *n Days After* Ad_t (which denotes whether day t is the n^{th} trading day after a previous ad day, with $n = 1, 2$).[10] In all regressions henceforth, we cluster standard errors by trading days.[11]

Columns (1)-(3) of Table 2 report the regression results of equation (1) with *Number of Retail Trades* (in hundreds), *Retail Dollar Volume* (in millions), and *Retail Trading PC* (the first principal component of the two) as the dependent variable, respectively. The coefficient estimate on Ad_t is positive in all three columns and significant at the 5% or 1% level, confirming the univariate observation that retail trading increases on ad days. In terms of economic significance, an average WSJ ad day is associated with an increase of 27.6 retail trades and $844,000 retail trading volume, and an increase of 1.7% in the first principal component of retail trading.[12]

Compared to Ad_t, the indicators for adjacent ad days are generally less significant. Specifically, the two indicators denoting whether trading day t is immediately before an ad day, i.e., *2 Days Before* Ad_t and *1 Day Before* Ad_t, are insignificant in Columns (1) and (3); a one-tailed t-test shows that the coefficient estimate on Ad_t is significantly larger than the coefficient estimates on both of these indicators. Although the indicators for days before an ad day are significant in Column (2), their coefficient estimates are much smaller in magnitude than the coefficient estimate on Ad_t. This result is reassuring: if ads trigger retail trading, we should not expect a rise in retail trading before ad days. In contrast, the two indicators for days immediately after an ad day are generally significant. *1 Day After* Ad_t is significant in all three columns, and the magnitude of its coefficient estimate is comparable to the coefficient estimate for Ad_t. *2 Days After* Ad_t is significant in two out of the three columns, albeit with a smaller magnitude. The results suggest that ad-induced retail trading persists for two trading days (day 0 and 1) and starts to fade on day 2.

Examining the controls related to firms' earnings releases, we find that the indicators for quarterly earnings announcement days and the two days before and after earnings announcements

[10] Because of the weekly pattern in ad placement and the fact that a week has no more than five trading days, we include indicators only for the two trading days before and after ad days.

[11] Our measure exploits the autocorrelation in firms' timing of ad placement and the variation in retail trading induced by recurring ads. In order to preserve this variation, we do not cluster standard errors by firm.

[12] The standardized change (coefficient estimate divided by standard deviation of the variable) in the number of retail trades is 27.6/2,285=1.2% and the standardized change in retail dollar volume is $844,000/$43.79M=1.9%.

are highly significant in all three columns, consistent with earnings releases significantly influencing market expectations and trading (Kothari (2001)). The coefficient estimate on QEA_t, the indicator for earnings announcement days, also provides a useful benchmark for Ad_t. The increase in the number of retail trades on ad days is $1/40^{\text{th}}$ of the increase on earnings announcement days (27.6 vs. 1,101.8), and the increase in the retail dollar volume on ad days is $1/23^{\text{rd}}$ of the increase on earnings announcement days ($844,000 vs. $19.7 million). Thus, the increase in retail trading on ad days is economically meaningful but also plausible.

Turning to the remaining controls, the indicator for other news days is positively associated with all three measures of retail trading, but as expected, its coefficient estimate is much smaller in magnitude than the coefficient estimate on QEA_t. Market capitalization is negatively associated with the number of retail trades but positively associated with retail dollar volume and the first principal component of retail trading. This result suggests fewer but larger retail trades, on average, for larger firms. Book-to-market is negative in all three columns, suggesting that retail investors tend to chase growth firms.

The second pattern that emerges from Figure 1 is that retail trading increases on the five trading days (typically corresponding to seven calendar days) before and after ad days, exhibiting a cyclical pattern. The two patterns observed from Figure 1, combined with prior evidence that firms frequently place product ads at weekly intervals (Madsen and Niessner (2019)), suggest the possibility that the cyclical spike in retail trading reflects retail investors' attention to weekly recurring ads. To explore this possibility, we first examine the timing of WSJ ads in our sample. Table 3 Panel A shows that conditional on a firm placing an ad in the WSJ on calendar day $t-7$, the probability of the firm placing an ad on calendar day t is 42.4%. In contrast, the probability that the firm places an ad any other day during the week is only 7% -12.1%.

The same pattern holds for duplicate ads as well as non-duplicate ads, with both types frequently placed every seven days. Importantly, there is a high probability of observing a duplicate ad in the WSJ on a given day if the firm also placed a WSJ ad seven calendar days earlier. Conditional on a firm placing WSJ ads on both day $t-7$ and day t, the probability that the ad already appeared in the WSJ within the previous 60 days is 61.8% (i.e., 26.2%/(26.2%+16.2%)).

This pattern supports our conjecture that ads placed in the WSJ every seven days likely contain minimal information content.

We also examine the frequency of the 10,225 individual ads in our sample by days of the week in Table 3 Panel B. As shown, a majority of the WSJ ads fall on weekdays, representing 94.6% of the sample. Weekday ads are spread evenly between Mondays and Wednesdays (22.2%, 20.2%, and 22.2%, respectively), slightly decrease in numbers on Thursdays (17.5%), and further decrease on Fridays (12.4%). Frequencies are comparable between duplicate and non-duplicate ads, suggesting that neither type of ads concentrate on a specific day of the week. The distribution of WSJ ad days strengthens the argument that the observed cyclical pattern in retail trading is driven by weekly recurring ads rather than confounding effects such as the day-of-the week effects (e.g., French (1980); Gibbons and Hess (1981); Lakonishok and Levi (1982)). We also include date fixed effects in all regression analyses to help address any unobservable differences across days of the week.

3.2 Recurring ad days and retail trading

The previous section shows that (1) retail trading spikes on WSJ ad days; (2) the cyclical spike in retail trading that takes place every five trading days corresponds to the weekly pattern in firms' ads placement; and (3) weekly ads frequently contain duplicate images. Building on these findings, we introduce an instrument for noise trading: the existence of a WSJ ad seven calendar days earlier. Intuitively, this instrument is designed to capture the increase in retail trading induced by weekly recurring ads, which is arguably uninformed. We verify the relevance of the instrument by estimating the following OLS model, which we use as the first-stage regression of a 2SLS analysis linking instrumented retail trading to informed trading:

$$Retail\ Trading_t = \alpha + \beta Ad_{t-7} + \gamma Controls_t + \epsilon_t. \tag{2}$$

The dependent variable is one of the three measures of retail trading for trading day t. The instrument Ad_{t-7} equals one if the firm placed an ad in the WSJ seven calendar days earlier and zero otherwise. We continue to include the control for ad days with non-duplicate images, basic controls, as well as date and firm fixed effects.

Table 4 reports the results of estimating equation (2) with *Number of Retail Trades*, *Retail Dollar Volume*, and *Retail Trading PC* as the dependent variable in Columns (1)-(3), respectively. As shown, Ad_{t-7} is positive in all three columns and its coefficient estimate is significant at the 1% level, which confirms the relevance of this instrument to retail trading. The weak instrument test from the 2SLS analysis strongly rejects the null of no correlation between Ad_{t-7} and retail trading, with the Cragg-Donald F-statistic exceeding the 10% maximal bias of the instrumental variable estimator relative to OLS in Columns (2)-(3) and the 20% maximal bias of the instrumental variable estimator relative to OLS in Column (1). In terms of economic significance, the existence of an ad seven days earlier is associated with an increase of 34.5 retail trades (2.3% of the sample average) and $804,000 retail trading volume (3.5% of the sample average), and an increase of 1.8% in the first principal component of retail trading (also comparable to the standardized change in the number and dollar volume of retail trades). Coefficient estimates on the controls are similar to those reported in Table 2. In particular, the coefficient estimate on $Non\text{-}duplicate\,Ad_t$ is positive in all three columns and statistically significant in Columns (2)-(3), which suggests that ads with non-duplicate images stimulate more trading by retail investors. More importantly, controlling for ad days that release non-duplicate images or removing them does not affect the positive relation between Ad_{t-7} and retail trading.

3.3 Ad days and informed trading

In this section, we examine the effect of noise trading on informed trading. We start with a univariate analysis that plots the average number and dollar volume of informed trades (defined as non-retail trades of $50,000 or greater) for the 15-day window centered on WSJ ad days. If informed traders rationally anticipate the increased noise trading on ad days and trade to their profit as theory predicts, then we expect to see a pattern in informed trading similar to the pattern in retail trading. As expected, Figure 2 illustrates a cyclical pattern in informed trading: both measures of informed trading increase on ad days and the five trading days before and after ad days. Although this pattern is less regular than the pattern from Figure 1, the similarity between the two suggests that informed traders likely take into account retail traders' response to recurring ads, and trade accordingly.

One alternative interpretation of the pattern illustrated above is the information hypothesis: if information drives both retail and informed trades on ad days, then this will induce a positive bias. A less obvious alternative interpretation is the attention hypothesis: if increased attention brought about by ads drives both retail and large non-retail trades (our proxy for informed trades), then this will also induce a positive bias. These alternative interpretations present endogeneity challenges. We first use an instrumental variable approach to help rule out the information hypothesis, and then conduct additional analyses in Section 4 to address both hypotheses.

We estimate a 2SLS model using the existence of an ad seven days earlier as an instrument for uninformed retail trading. As shown earlier, the instrument is highly correlated with retail trading, thus satisfying the relevance criterion. Given the repetitive nature of weekly recurring ads, which is the main motivation of the instrument, it is unlikely correlated with informed trading except through its correlation with uninformed trading (the exclusion restriction). The first-stage of the 2SLS model is specified in equation (2) and the second-stage is specified below as:

$$Informed\ Trading_t = \alpha + \beta Fitted\ Retail\ Trading_t + \gamma Controls_t + \epsilon_t. \tag{3}$$

where *Fitted Retail Trading* is the fitted value of *Retail Trading* from equation (2) and controls are previously defined.

Table 5 reports the results of estimating equation (3) and confirms a positive association between instrumented retail trading and informed trading. The economic magnitudes from the 2SLS analysis suggest that an increase of 34.5 instrumented retail trades (i.e., the increase associated with an ad seven days earlier from Table 4) is associated with an increase of 14.3 informed trades (2.3% of the sample average), and an increase of \$804,000 instrumented retail trading volume is associated with an increase of \$2.2 million informed trading volume (2.6% of the sample average). An interquartile increase in the principal component of retail trading is associated with an increase of 483.5 informed trades and \$74.5 million informed trading volume.

Noticeably, $Non\text{-}duplicate\,Ad_t$ is insignificant in all columns. This result casts doubt on the two alternative interpretations: although new ads trigger more retail trading, they do not appear to directly motivate large trades by institutional investors, making it less likely that these trades are responses to either the information contained in the WSJ ads or the attention brought about by them. Instead, it supports our interpretation that informed traders exploit expected and/or observed increases in noise trading on recurring ad days and trade accordingly. For the remaining controls, size and book-to-market are both positively related to informed trading. Indicators for days surrounding earnings announcements and other news days are insignificant.[13]

3.4 Ad days and intraday trading

In this section, we examine intraday trading intervals to more precisely measure when informed traders react to recurring ad-induced noise trading. To do so, we divide a regular trading day into six one-hour intervals and one thirty-minute interval, namely [9:30 to 10:30), [10:30 to 11:30), [11:30 to 12:30), [12:30 to 13:00), [13:00 to 14:00), [14:00 to 15:00), and [15:00 to 16:00] Eastern Time (ET).

We continue to hypothesize a positive relation between recurring ad days and retail trading in each of these intervals. We run a 2SLS model with the first-stage specified below as:

$$Retail\ Trading_{t,k} \quad = \quad \alpha + \beta Ad_{t-7} + \gamma Controls_t + \epsilon_t. \tag{4}$$

Subscript t indexes day and subscript k indexes trading intervals. For brevity, we measure retail trading using only *Retail Trading PC*, which integrates both the number of retail trades and retail dollar volume. If the increase in retail trading on recurring ad days is a behavioral response to attention, then we expect to see a positive β across all trading intervals.

Table 6 reports the results of estimating equation (4) and provides additional evidence that recurring ads induce noise trading. Consistent with our expectations, β is significantly positive

[13] In untabulated analysis, we document significantly positive coefficient estimates on these indicators if we exclude the fitted retail trading measures from the regressions. This result suggests that, earnings announcements and other news releases have an insignificant effect on our measures of informed trading after controlling for retail traders' responses to these news events, at least for our sample of relatively large firms.

in all seven columns, suggesting that the increase in retail trading on recurring ad days occurs throughout the day, with the largest effects occurring during the first and last trading hours. As the WSJ is published and available before markets open, this pattern is consistent with at least some retail traders immediately responding to recurring ads. $Non\text{-}duplicate\,Ad_t$ is also positive in all seven columns and statistically significant for three time intervals, suggesting that ads with new images trigger incremental retail trading.

The second-stage of the 2SLS model is specified below as:

$$Informed\,Trading_{t,k} \;=\; \alpha + \beta Fitted\ Retail\ Trading_{t,k} + \gamma Controls_t + \epsilon_t. \tag{5}$$

Table 7 reports the results of estimating equation (5) and shows a positive association between instrumented retail trading and informed trading in six out of the seven trading intervals. Informed traders' response to recurring ad-induced retail trading is the most pronounced during the first trading hour, when ad-induced retail trading is also high. $Non\text{-}duplicate\,Ad_t$ is negative in all columns, and marginally significant in two. Again, this result is inconsistent with the alternative interpretations that the increase in informed trades on recurring ad days is a response to information released by the firm or a result of increased attention.

4 Additional analyses for alternative interpretations

In this section, we conduct two additional analyses to further shed light on the information and attention hypotheses.

4.1 Length of advertising history

First, we examine whether the positive relation between our measure and informed trading varies with the length of the firm's history of placing recurring ads. Arguably, a longer history of recurring ads makes it easier for informed investors to discern a pattern in noise trading. If informed traders are able to anticipate increases in noise trading on recurring ad days ex ante, then they would have incentives to acquire more information about the firm and trade more aggressively on that information ex post (Edmans (2009), Edmans and Manso (2011)).

To test this premise, we first calculate, conditional on the firm placing an ad in the WSJ seven calendar days earlier (i.e., $Ad_{t-7} = 1$), the frequency (in weeks) of the firm placing recurring ads at weekly intervals during the twelve weeks prior to day $t-7$. The sample median of this frequency is three weeks. We then define two separate measures: $Ad_{t-7,\,long\,history}$, which equals one if the firm placed an ad in the WSJ seven calendar days earlier and also placed recurring ads at weekly intervals for at least three of the prior twelve weeks, and zero otherwise; and $Ad_{t-7,\,short\,history}$, which equals one if the firm placed an ad in the WSJ seven calendar days earlier and also placed recurring ads at weekly intervals for less than three of the prior twelve weeks, and zero otherwise.

We study the relation between these two measures and informed trading by estimating the following OLS model:

$$Informed\,Trading_t \quad = \quad \alpha + \beta_1 Ad_{t-7,\,long\,history} + \beta_2 Ad_{t-7,\,short\,history} + \gamma Controls_t + \epsilon_t. \quad (6)$$

Table 8 reports the regression results of estimating equation (6). As shown, the coefficient estimate on $Ad_{t-7,\,long\,history}$ is significantly positive in both columns, whereas the coefficient estimate on $Ad_{t-7,\,short\,history}$ is insignificant. This result is consistent with our interpretation of informed trading being a rational response to increased uninformed retail trading on ad days, as a longer history of recurring ads makes it easier for informed investors to form rational expectations of recurring ad-induced noise trading. It is inconsistent with the two alternative interpretations, as a positive correlation between the ad-based measure and informed trading, induced by either information or attention, should not vary with the length of the recurring ad history.

4.2 Ad days and stock price efficiency

Second, we assess the effect of recurring ad days on stock price efficiency. Our interpretation of the results suggests a positive association between the ad-based measure and price efficiency. If informed traders rationally anticipate increased noise trading on recurring ad days and trade to their profit, then their trading should incorporate private information about the firm into price and enhance price efficiency. In contrast, the attention hypothesis would imply no effect of the measure on price efficiency, as the large non-retail trades would themselves be uninformed.

Chordia, Roll, and Subrahmanyam (2005, 2008) show that the capacity of an asset market to accommodate order imbalances is inversely related to the short-term predictability of stock returns from previous order flows, and propose an approach to measure price efficiency based on this relation. Following their approach, we first calculate a measure of order imbalance, $OIB\$$, the dollar amount paid by buyer-initiated trades minus the dollar amount received by seller-initiated trades divided by the dollar volume of trading. Trades are classified as buyer- or seller-initiated using the Lee and Ready (1991) algorithm. We then match $OIB\$$ to stock returns. Our sample is at the firm-day level. To avoid artificially inflating sample size and t-statistics, we limit the calculation of $OIB\$$ to the first hour of each trading day (when informed traders' response to retail trading is strongest, see Table 7), i.e., over the eleven five-minute intervals from 9:30 to 10:25 ET, and match them to the corresponding *Stock Return* over the eleven five-minute intervals from 9:35 to 10:30 ET. *Stock Return* are stock returns calculated using the midpoints of the best bid and offer. This procedure yields a sample of 1,494,432 observations at the firm-trading interval level.

We study the relation between the ad-based measure and price efficiency by estimating the following OLS model:

$$\begin{aligned} \mathit{Stock\ Return}_{t,k+1} &= \alpha + \beta OIB\$_{t,k} \times Ad_{t-7} + \eta OIB\$_{t,k} \\ &+ \mu Ad_{t-7} + \gamma Controls_t + \epsilon_t. \end{aligned} \tag{7}$$

Subscript t indexes day and subscript k indexes five-minute trading intervals. $OIB\$$ measures order imbalance, and Ad_{t-7} and controls are previously defined. Chordia et al. (2008) use the coefficient estimate on $OIB\$$, η, to capture the degree of price inefficiency, with a more positive value of $\hat{\eta}$ indicating less price efficiency. If the increase in informed trading is a rational response to increased noise trading on recurring ad days, then we predict $\beta < 0$; that is, we expect the ad-based measure to be positively associated with price efficiency (or negatively associated with price inefficiency) and thus decrease the return predictability of order imbalance.

Table 9 Column (1) reports the regression results of estimating equation (7). With both date and firm fixed effects included, $OIB\$$ is positive but statistically insignificant. Importantly, the coefficient estimate of interest, β, is negative and statistically significant at the 5% level. In Column (2), we modify equation (7) by separating Ad_{t-7} into $Ad_{t-7,\,long\,history}$ and $Ad_{t-7,\,short\,history}$ and include the interactions between these two measures and $OIB\$$. Similar to the results in Table 8, the interaction between $Ad_{t-7,\,long\,history}$ and $OIB\$$ is significantly negative, whereas the interaction between $Ad_{t-7,\,short\,history}$ and $OIB\$$ is statistically insignificant. These results suggest that recurring ads induce informed trading and enhance price efficiency, particularly for firms with a longer history of placing recurring ads.

To examine the sensitivity of these results to other lagged ad days, we repeat the analyses in Column (1) of Table 9, replacing Ad_{t-7} with Ad_{t-n}, which equals one if the firm placed an ad in the WSJ n calendar days earlier and zero otherwise, $n = 5, 6, 8, 9$. The results are reported in Table IA1 of the Internet Appendix. For the ease of comparison, we reproduce the results with Ad_{t-7} from Column (1) of Table 9. Interestingly, only the coefficient estimate on the interaction between order imbalance and Ad_{t-7} is significantly negative, which further supports our interpretation of increased price efficiency driven by trading on recurring ad days.

The results in this section are thus inconsistent with the attention hypothesis. Rather, they are consistent with either our interpretation that recurring ad-induced noise trading prompts informed investors to trade and their trading enhances price efficiency, or the information hypothesis.

5 Robustness checks

We conduct two additional analyses to check the robustness of the main results in Section 3 to alternative definitions of ad-based instruments and alternative measures of retail trading. Some of these robustness tests also shed light on the two alternative interpretations. First, we add Ad_{t-14}, the existence of a WSJ ad fourteen calendar days earlier, as a second instrument for noise trading. This instrument is motivated by the finding in Madsen and Niessner (2019) that some firms advertise at bi-weekly intervals. We rerun the 2SLS model in Tables 4-5, using both Ad_{t-7} and Ad_{t-14} as instruments for noise trading.

Table IA2 of the Internet Appendix reports the first-stage regression results of the 2SLS model, and Table IA3 reports the second-stage results. As Table IA2 shows, both Ad_{t-7} and Ad_{t-14} are positive and significant in all three columns, with the coefficient estimate on Ad_{t-14} significant at the 1% level, which confirms the relevance of the additional instrument to retail trading. The weak instrument test from the 2SLS analysis strongly rejects the null of no correlation between both instruments and retail trading, with the Cragg-Donald F-statistic exceeding the 10% maximal bias of the instrumental variable estimator relative to OLS in Columns (2)-(3) and the 20% maximal bias of the instrumental variable estimator relative to OLS in Column (1). The p-value of an F-test for the joint significance of the two instruments is well below 1%. Importantly, we continue to observe a positive association between instrumented retail trading and informed trading. Although IV exogeneity cannot be conclusively tested, the Hansen's J-statistic for the test of overidentifying restrictions is insignificant. This provides some comfort. Assuming that one of the two instruments is a valid IV, we cannot reject the null of no correlation between the other instrument and the 2SLS residuals.

As a second robustness check, we modify the retail trading measures by limiting trade size to $5,000 or less. Boehmer et al. (2017) find that retail trades can be sizable and sometimes informed, which motivates our use of an instrument for uninformed retail trading. Limiting the sample to only small retail trades further helps rule out the information hypothesis. The results with the modified retail trading measures are reported in Tables IA4-5 of the Internet Appendix and are qualitatively similar to those reported in Tables 4-5.

6 Conclusion

Noise trading is a standard feature in market microstructure models but tricky to empirically measure. Common liquidity measures are typically functions of both noise and informed trading. Non-liquidity based measures of noise trading, such as small and retail trades, are sometimes informed themselves. Motivated by evidence that retail trading spikes on ad days, that firms regularly place ads at weekly intervals, and that weekly ads frequently contain duplicate images, we introduce a novel measure of noise trading: an indicator of whether the firm placed an ad in the *Wall Street Journal* seven calendar days earlier.

We revisit the effect of noise trading on informed trading using the ad-based measure as an instrument. We show that the instrument is positively associated with daily and intraday retail trading, after controlling for date and firm fixed effects, firm characteristics, ad days with new images, and earnings and news releases. This significant association establishes the relevance of this instrument to retail trading. The repetitive nature of weekly recurring ads makes our instrument plausibly exogenous to informed trading other than through its correlation with retail trading. We find that instrumented retail trading is significantly positively related to large institutional trades, our proxy for informed trading, after including the controls as well as date and firm fixed effects.

To the extent that our instrument captures exogenous variation in noise trading, these results suggest that informed traders rationally respond to noise trading. However, information or attention could also induce an endogenous positive relation between retail and informed trading. We conduct two additional analyses to further rule out these alternative interpretations. First, we show that a longer history of the firm placing weekly recurring ads strengthens the positive relation between the ad-based measure and informed trading. This result is inconsistent with either the information or the attention hypothesis. Second, we show that the ad-based measure is positively related to stock price efficiency, particularly for firms with a longer history of placing recurring ads, which is inconsistent with the attention hypothesis. Additional tests show that our results are robust to adding a second instrument to indicate the existence of a WSJ ad fourteen calendar days earlier or using measures of retail trading that limit trade size to $5,000 or less.

Overall, the results support the theoretical predictions and highlight one important financial market implication of corporate advertising: ads influence retail and institutional investors' trading behavior and market efficiency. More broadly, our instrument—the existence of a product ad seven calendar days earlier—represents a primitive measure of noise trading that captures the uninformed essence of noise trading that is generalizable to other contexts.

References

Admati, A. R. and P. Pfleiderer (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial Studies 1*(1), 3–40.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Barber, B. M. and T. Odean (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*(2), 785–818.

Barber, B. M., T. Odean, and N. Zhu (2009). Do retail trades move markets? *Review of Financial Studies 22*(1), 151–186.

Bharath, S. T., S. Jayaraman, and V. Nagar (2013). Exit as governance: An empirical analysis. *Journal of Finance 68*(6), 2515–2547.

Boehmer, E., C. M. Jones, and X. Zhang (2017). Tracking retail investor activity. Working paper.

Boyd, J. H. and E. P. Schonfeld (1977). The effect of financial press advertising on stock prices. *Financial Management 6*(2), 42–51.

Brandt, M. W., A. Brav, J. R. Graham, and A. Kumar (2009). The idiosyncratic volatility puzzle: Time trend or speculative episodes? *Review of Financial Studies 23*(2), 863–899.

Chemmanur, T. J. and A. Yan (2011). Advertising, investor recognition, and stock returns. Working paper.

Chordia, T., R. Roll, and A. Subrahmanyam (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics 76*(2), 271–292.

Chordia, T., R. Roll, and A. Subrahmanyam (2008). Liquidity and market efficiency. *Journal of Financial Economics 87*(2), 249–268.

Edmans, A. (2009). Blockholder trading, market efficiency, and managerial myopia. *Journal of Finance 64*(6), 2481–2513.

Edmans, A., V. W. Fang, and E. Zur (2013). The effect of liquidity on governance. *Review of Financial Studies 26*(6), 1443–1482.

Edmans, A. and G. Manso (2011). Governance through trading and intervention: A theory of multiple blockholders. *Review of Financial Studies 24*(7), 2395–2428.

Fang, V. W., T. H. Noe, and S. Tice (2009). Stock market liquidity and firm value. *Journal of Financial Economics 94*(1), 150–169.

Faure-Grimaud, A. and D. Gromb (2004). Public trading and private incentives. *Review of Financial Studies 17*(4), 985–1014.

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics 8*(1), 55–69.

Frieder, L. and A. Subrahmanyam (2005). Brand perceptions and the market for common stock. *The Journal of Financial and Quantitative Analysis 40*(1), 57–85.

Gibbons, M. R. and P. Hess (1981). Day of the week effects and asset returns. *Journal of Business 54*(4), 579–596.

Goyenko, R. Y., C. W. Holden, and C. A. Trzcinka (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics 92*(2), 153–181.

Greene, J. and S. Smart (1999). Liquidity provision and noise trading: Evidence from the "investment dartboard" column. *Journal of Finance 54*(5), 1885–1899.

Grullon, G., G. Kanatas, and J. P. Weston (2004). Advertising, breadth of ownership, and liquidity. *Review of Financial Studies 17*(2), 439–461.

Gurun, U. G. and A. W. Butler (2012). Don't believe the hype: Local media slant, local advertising, and firm value. *Journal of Finance 67*(2), 561–598.

Kahn, C. and A. Winton (1998). Ownership structure, speculation, and shareholder intervention. *Journal of Finance 53*(1), 99–129.

Kothari, S. P. (2001). Capital markets research in accounting. *Journal of Accounting and Economics 31*(1-3), 105–231.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica 53*(6), 1315–1335.

Kyle, A. S. and J.-L. Vila (1991). Noise trading and takeovers. *RAND Journal of Economics 22*(1), 54–71.

Lakonishok, J. and M. Levi (1982). Weekend effects on stock returns: a note. *Journal of Finance 37*(3), 883–889.

Lee, C. M. C. and B. Radhakrishna (2000). Inferring investor behavior: Evidence from torq data. *Journal of Financial Markets 3*(2), 83–111.

Lee, C. M. C. and M. J. Ready (1991). Inferring trade direction from intraday data. *Journal of Finance 46*(2), 733–746.

Liaukonyte, J. and A. Zaldokas (2019). Background noise? tv advertising affects real timeinvestor behavior. Working paper, Cornell University.

Lou, D. (2014). Attracting investor attention through advertising. *Review of Financial Studies 27*(6), 1797–1829.

Lowe, D. G. (1999). Object recognition from local scale-invariant features.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision 60*(2), 91–110.

Madsen, J. M. and M. Niessner (2019). Is investor attention for sale? the role of advertising in financial markets. *Journal of Accounting Research*, forthcoming.

Maug, E. (1998). Large shareholders as monitors: Is there a tradeoff between liquidity and control? *Journal of Finance 53*(1), 65–98.

Norli, Ø., C. Ostergaard, and I. Schindele (2014). Liquidity and shareholder activism. *Review of Financial Studies 28*(2), 486–520.

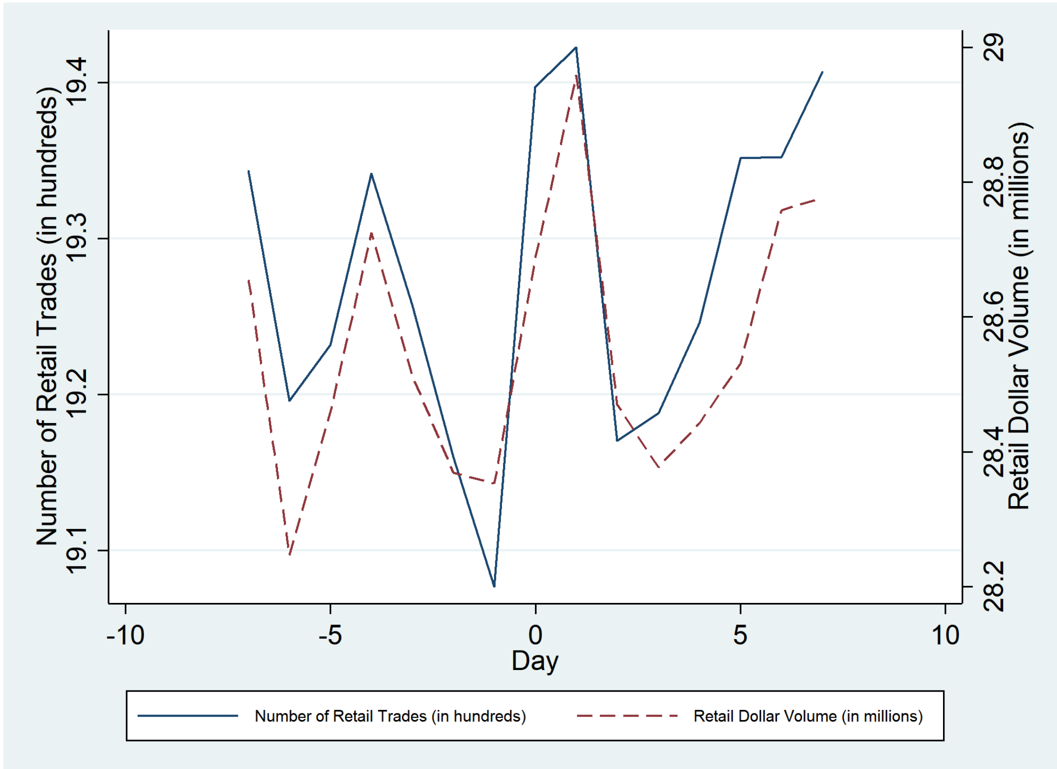
Appendix A:
Definition of Variables

This appendix describes the calculation of variables used in the core analyses. Underlined variables refer to variable names within Compustat. t indexes days, q indexes the quarter to which day t belongs, and k indexes the five-minute trading intervals within the first hour of each trading day. Firm subscript is omitted for brevity. To code the ad and news-related variables, we first align each ad/news day to a trading day in CRSP, with a non-trading ad/news day aligned with its first subsequent trading day.

Variable	Definition
Indicators for ad days and ad-based instrument	
Ad_t	An indicator variable that equals one if trading day t is an ad day of the firm in the WSJ, and zero otherwise.
n Days Before Ad_t	An indicator variable that equals one if day t is the n^{th} trading day before a subsequent ad day of the firm in the WSJ, and zero otherwise, $n = 1, 2$.
n Days After Ad_t	An indicator variable that equals one if day t is the n^{th} trading day after a previous ad day of the firm in the WSJ, and zero otherwise, $n = 1, 2$.
Non-duplicate Ad_t	An indicator variable that equals one if trading day t is an ad day of the firm in the WSJ and the ad contains a non-duplicate image, and zero otherwise. We identify duplicate images by comparing the ad to all ads for the same brand that were placed in the WSJ within the previous 60 days. See Section 2.3 for a detailed description of the image analysis.
Ad_{t-7}	An indicator variable that equals one if day $t-7$ (i.e., seven calendar days before trading day t) is an ad day of the firm in the WSJ, and zero otherwise.
$Ad_{t-7,\, long\, history}$	An indicator variable that equals one if day $t-7$ is an ad day of the firm in the WSJ and the firm placed recurring ads at weekly intervals for at least three of the prior twelve weeks, and zero otherwise.
$Ad_{t-7,\, short\, history}$	An indicator variable that equals one if day $t-7$ is an ad day of the firm in the WSJ and the firm placed recurring ads at weekly intervals for less than three of the prior twelve weeks, and zero otherwise.
Measures of retail trading and informed trading	
Number of Retail Trades$_t$	The total number of retail trades on day t, calculated following the methodology of Boehmer et al. (2017). Specifically, we identify retail trades in two steps. First, we retrieve trades and quotes marked with exchange code "D" in TAQ. Second, we classify these transactions based on printed prices. Trades recorded at a price higher than a round penny by (0-0.4) cents are labeled retail seller-initiated trades, and trades recorded at a price higher than a round penny by (0.6-1) cent(s) are labeled retail buy-initiated trades.
Retail Dollar Volume$_t$	The aggregate dollar volume of retail trades on day t, calculated following the methodology of Boehmer et al. (2017).
Retail Trading PC$_t$	The first principal component of *Number of Retail Trades* and *Retail Dollar Volume*, standardized by subtracting its sample mean and then scaled by its sample standard deviation.
Number of Informed Trades$_t$	The total number of informed trades on day t, with informed trades defined as non-retail trades of $50,000 or greater.
Informed Dollar Volume$_t$	The aggregate dollar volume of informed trades on day t, with informed trades defined as non-retail trades of $50,000 or greater.
Controls	
$QEA_{[t-2,t-1]}$	An indicator variable that equals one if day t is the first or second trading day before a quarterly earnings announcement day of the firm, and zero otherwise.
QEA_t	An indicator variable that equals one if day t is a quarterly earnings announcement day of the firm, and zero otherwise.
$QEA_{[t+1,t+2]}$	An indicator variable that equals one if day t is the first or second trading day after a quarterly earnings announcement day of the firm, and zero otherwise.
Other News$_t$	An indicator variable that equals one if day t is a news release day (excluding earnings announcements) of the firm, and zero otherwise.

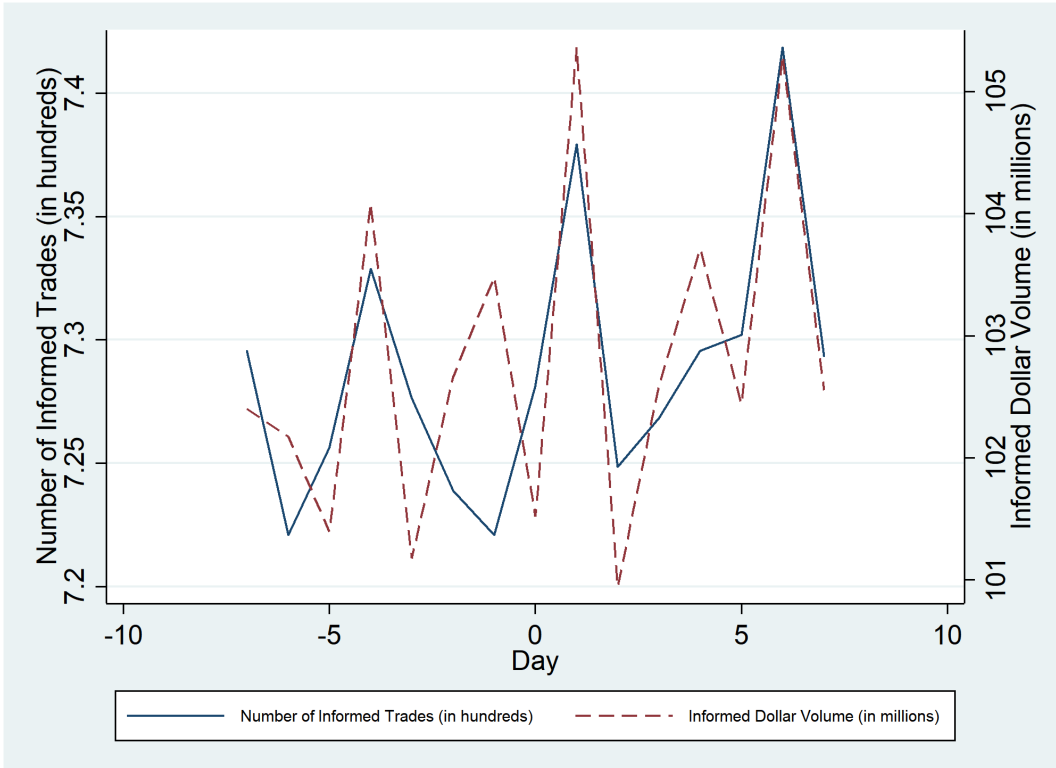
ln(Market Cap)$_{q-1}$	Natural logarithm of market capitalization (abs(PRC) × SHROUT) at the end of quarter $q-1$.
$Book/Market_{q-1}$	The ratio of book value of assets to market value of assets, calculated as total assets (ATQ) divided by [market capitalization plus total liability (LTQ)], both at the end of quarter $q-1$.
Measures of price efficiency	
OIB\$$_{t,k}$	The dollar amount paid by buyer-initiators minus the dollar amount received by seller-initiators divided by the dollar volume of trading, calculated over one of the eleven five-minute intervals from 9:30 to 10:25 ET.
Stock Return$_{t,k+1}$	Stock return, calculated using the midpoints of the best bid and offer over one of the eleven five-minute intervals from 9:35 to 10:30 ET.

Figure 1
Retail Trading Surrounding Advertisement (Ad) Days



This figure plots the average number (solid line) and dollar volume (dashed line) of retail trades, from seven trading days before to seven trading days after ad days (day 0). Retail trades are defined using the Boehmer et al. (2017) classification. The sample comprises 9,620 ad days by 238 firms in the Wall Street Journal (WSJ) between April 2009 and October 2013.

Figure 2
Informed Trading Surrounding Ad Days



This figure plots the average number (solid line) and dollar volume (dashed line) of informed trades, from seven trading days before to seven trading days after ad days (day 0). Informed trades are defined as non-retail trades of $50,000 or greater. The sample is the same as in Figure 1.

Table 1
Summary Statistics

	(1)					
	Obs	Mean	SD	P25	P50	P75
Ad_t	139,656	0.069	0.253	0.000	0.000	0.000
$Non\text{-}duplicate\ Ad_t$	139,656	0.036	0.187	0.000	0.000	0.000
$Number\ of\ Retail\ Trades_t$ (100's)	139,656	14.910	22.852	2.200	6.680	16.380
$Retail\ Dollar\ Volume_t$ ($mil)	139,656	23.069	43.793	1.885	6.883	21.997
$Retail\ Trade\ Size_t$ ($)	139,656	13,724.939	15,199.914	6,465.612	10,359.662	15,332.683
$Retail\ Shares\ per\ Trade_t$	139,656	348.528	261.510	221.243	282.733	396.043
$Retail\ \ Trading\ PC_t$	139,656	0.007	1.006	-0.540	-0.372	0.059
$Number\ of\ Informed\ Trades_t$ (100's)	139,656	6.226	17.084	0.230	1.160	4.400
$Informed\ Dollar\ Volume_t$ ($mil)	139,656	85.703	214.433	4.090	17.934	65.880
$Informed\ Trade\ Size_t$ ($)	135,077	177,259.742	176,140.712	111,113.953	133,493.141	181550.953
$Informed\ Shares\ per\ Trade_t$	135,077	7248.975	13,009.352	2,355.564	4,221.472	7,956.804
$QEA_{[t-2,t-1]}$	139,656	0.025	0.155	0.000	0.000	0.000
QEA_t	139,656	0.016	0.124	0.000	0.000	0.000
$QEA_{[t+1,t+2]}$	139,656	0.023	0.151	0.000	0.000	0.000
$Other\ News_t$ s	139,656	0.459	0.498	0.000	0.000	1.000
$ln(MarketCap)_t$	139,656	16.470	1.671	15.426	16.533	17.642
$Book/Market_t$	139,656	0.778	0.266	0.581	0.821	0.989

This table reports summary statistics of the main variables used in the multivariate analyses and other variables for descriptive purpose. Ad_t indicates trading days with an ad in the WSJ, or the first subsequent trading day after a non-trading ad day. $Non\text{-}duplicate\ Ad_t$ indicates ad days with at least one non-duplicate image. *Number of Retail Trades*$_t$ and *Retail Dollar Volume*$_t$ are defined using the Boehmer et al. (2017) classification. *Retail Trade Size*$_t$ is the dollar value per retail trade, and *Retail Shares per Trade*$_t$ is the number of shares per retail trade. *Retail Trading PC*$_t$ is the standardized first principal component of *Number of Retail Trades*$_t$ and *Retail Dollar Volume*$_t$. *Number of Informed Trades*$_t$ and *Informed Dollar Volume*$_t$ are defined using non-retail trades of $50,000 or greater. *Informed Trade Size*$_t$ is the dollar value per informed trade, and *Informed Shares per Trade*$_t$ is the number of shares per informed trade. Number of trades are in hundreds, and dollar volumes are in millions. QEA_t indicates days with quarterly earnings announcements, $QEA_{[t-2,t-1]}$ ($QEA_{[t+1,t+2]}$) indicates the two days before (after) quarterly earnings announcements, and *Other News*$_t$ indicates days with news other than earnings announcements. *ln(Market Cap)*$_t$ is the natural algorithm of market capitalization (in thousands), and *Book/Market*$_t$ is the book-to-market ratio, both measured at the end of prior quarter. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. All continuous variables are winsorized at the 1% and 99% levels.

Table 2
Ad Days and Retail Trading

	(1) *Number of Retail* $Trades_t$	(2) *Retail Dollar* $Volume_t$	(3) *Retail Trading* PC_t
$2\ Days\ Before\ Ad_t$	0.021	0.460**	0.006
	(0.17)	(2.04)	(1.18)
$1\ Day\ Before\ Ad_t$	-0.008	0.569**	0.007
	(-0.07)	(2.54)	(1.30)
Ad_t	0.276**	0.844***	0.017***
	(2.20)	(3.76)	(3.24)
$1\ Day\ After\ Ad_t$	0.229*	0.973***	0.017***
	(1.92)	(4.26)	(3.40)
$2\ Days\ After\ Ad_t$	0.090	0.584**	0.009*
	(0.72)	(2.52)	(1.74)
$QEA_{[t-2,t-1]}$	0.700***	1.160***	0.030***
	(4.05)	(3.60)	(4.17)
QEA_t	11.018***	19.680***	0.494***
	(30.40)	(25.97)	(29.67)
$QEA_{[t+1,t+2]}$	8.212***	15.205***	0.375***
	(24.19)	(21.05)	(23.42)
$Other\ News_t$	0.789***	0.710***	0.027***
	(14.66)	(7.85)	(12.56)
$ln(Market\ Cap)_{q-1}$	-1.034***	6.652***	0.057***
	(-4.03)	(16.00)	(5.88)
$Book/Market_{q-1}$	-8.122***	-2.731***	-0.222***
	(-13.48)	(-2.79)	(-9.56)
Observations	139,656	139,656	139,656
Adj R-Squared	0.81	0.83	0.83
Date Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
One-tailed P-value (Ad_t > 2 Days Before Ad_t)	0.07	0.11	0.07
One-tailed P-value (Ad_t > 1 Day Before Ad_t)	0.05	0.19	0.08
One-tailed P-value (Ad_t > 1 Day After Ad_t)	0.40	0.34	0.47
One-tailed P-value (Ad_t > 2 Days After Ad_t)	0.14	0.21	0.15

This table reports the ordinary least squares (OLS) regression results on the relation between ad days and retail trading. Ad_t indicates days with an ad in the WSJ, $n\,Day(s)\,Before\,Ad_t$ are set equal to one if the firm placed an ad in n trading days and zero otherwise, and $n\,Day(s)\,After\,Ad_t$ are set equal to one if the firm placed an ad n trading days earlier and zero otherwise, $n = 1, 2$. Retail trading is measured using *Number of Retail Trades* in column (1); *Retail Dollar Volume* in column (2); and *Retail Trading PC* in column (3). Number of trades are in hundreds, and dollar volumes are in millions. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table 3
Sample Distribution of Ad Days

Panel A: Advertising probability conditional on the firm placing an ad seven calendar days earlier

	All	Duplicate Ads	Non-Duplicate Ads
Day_t	42.4%	26.2%	16.2%
Day_{t-1}	12.1%	6.0%	6.2%
Day_{t-2}	10.0%	4.6%	5.3%
Day_{t-3}	7.4%	3.3%	4.2%
Day_{t-4}	7.0%	3.4%	3.6%
Day_{t-5}	9.9%	4.5%	5.3%
Day_{t-6}	11.5%	5.8%	5.7%

Panel B: Frequency by Day of the Week

	All Ads		Duplicate Ads		Non-Duplicate Ads	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Monday	2,272	22.2%	837	19.3%	1,435	24.4%
Tuesday	2,073	20.3%	957	22.0%	1,116	19.0%
Wednesday	2,267	22.2%	991	22.8%	1,276	21.7%
Thursday	1,788	17.5%	829	19.1%	959	16.3%
Friday	1,271	12.4%	541	12.4%	730	12.4%
Weekend	554	5.4%	193	4.4%	361	6.1%
Total	10,225	100.00%	4,348	100%	5,877	100%

This table reports sample distribution of ad days, duplicate ad days, and non-duplicate ad days. Panel A tabulates the percentage of firms advertising in the WSJ on calendar days t through $t-6$ conditional on placing an ad on day $t-7$. Panel B tabulates the number and percentage of ads placed on each weekday and on weekends.

Table 4
Lagged Ad Days and Retail Trading

	(1) *Number of Retail* $Trades_t$	(2) *Retail Dollar* $Volume_t$	(3) *Retail Trading* PC_t
Ad_{t-7}	0.345***	0.804***	0.018***
	(2.83)	(3.43)	(3.43)
Non-duplicate Ad_t	0.188	0.687**	0.013*
	(1.12)	(2.26)	(1.83)
$QEA_{[t-2,t-1]}$	0.700***	1.160***	0.030***
	(4.06)	(3.60)	(4.17)
QEA_t	11.016***	19.671***	0.494***
	(30.39)	(25.96)	(29.66)
$QEA_{[t+1,t+2]}$	8.212***	15.204***	0.375***
	(24.17)	(21.03)	(23.40)
Other $News_t$	0.789***	0.714***	0.027***
	(14.66)	(7.88)	(12.57)
$ln(Market\,Cap)_{q-1}$	-1.032***	6.669***	0.057***
	(-4.03)	(16.00)	(5.91)
$Book/Market_{q-1}$	-8.120***	-2.732***	-0.222***
	(-13.47)	(-2.79)	(-9.56)
Observations	139,656	139,656	139,656
Adj R-Squared	0.81	0.83	0.83
Date Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes

This table reports the first-stage regression results of the two-stage least squares (2SLS) analysis on the relation between retail trading and informed trading, using Ad_{t-7} as an instrument for retail trading. Ad_{t-7} indicates days with an ad placed seven calendar days earlier in the WSJ. Retail trading is measured using *Number of Retail Trades* in column (1); *Retail Dollar Volume* in column (2); and *Retail Trading PC* in column (3). Number of trades are in hundreds, and dollar volumes are in millions. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table 5
Instrumented Retail Trading and Informed Trading

	(1) *Number of Informed* $Trades_t$	(2) *Informed Dollar* $Volume_t$	(3) *Number of Informed* $Trades_t$	(4) *Informed Dollar* $Volume_t$
$Fitted\ Retail\ Number\ of\ Trades_t$	0.415*			
	(1.95)			
$Fitted\ Retail\ Dollar\ Volume_t$		2.747**		
		(2.42)		
$Fitted\ Retail\ Trading\ PC_t$			8.072**	124.320**
			(2.10)	(2.45)
$Non\text{-}duplicate\ Ad_t$	0.011	-1.700	-0.014	-1.389
	(0.10)	(-1.16)	(-0.13)	(-1.00)
$QEA_{[t-2,t-1]}$	-0.093	0.254	-0.048	-0.327
	(-0.51)	(0.14)	(-0.31)	(-0.17)
QEA_t	-0.151	8.952	0.432	1.557
	(-0.06)	(0.40)	(0.23)	(0.06)
$QEA_{[t+1,t+2]}$	0.193	11.833	0.575	6.992
	(0.11)	(0.68)	(0.39)	(0.36)
$Other\ News_t$	-0.115	1.523*	-0.005	0.131
	(-0.68)	(1.74)	(-0.05)	(0.09)
$ln(Market\ Cap)_{q-1}$	3.306***	18.985**	2.419***	30.238***
	(12.29)	(2.49)	(9.76)	(9.34)
$Book/Market_{q-1}$	4.836***	20.772***	3.255***	40.822***
	(2.73)	(3.85)	(3.57)	(3.35)
Observations	139,656	139,656	139,656	139,656
Adj R-Squared	0.89	0.89	0.90	0.89
Date Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	9.29	15.17	14.43	14.43

This table reports the second-stage regression results of the 2SLS analysis on the relation between retail trading and informed trading, using Ad_{t-7} as an instrument for retail trading. Retail trading is measured using *Number of Retail Trades* in column (1); *Retail Dollar Volume* in column (2); and *Retail Trading PC* in columns (3) and (4). Informed trading is measured using *Number of Informed Trades* in columns (1) and (3), and *Informed Dollar Volume* in columns (2) and (4). Number of trades are in hundreds, and dollar volumes are in millions. Variables with prefix 'Fitted' are the fitted values of their respective variables from the first-stage regressions (see Table 4). Controls, in both stages, include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table 6
Lagged Ad Days and Retail Trading: Intraday

	(1) *Retail Trading* $PC_{t,k}$ *[9:30,10:30)*	(2) *Retail Trading* $PC_{t,k}$ *[10:30,11:30)*	(3) *Retail Trading* $PC_{t,k}$ *[11:30,12:30)*	(4) *Retail Trading* $PC_{t,k}$ *[12:30,13:00)*	(5) *Retail Trading* $PC_{t,k}$ *[13:00,14:00)*	(6) *Retail Trading* $PC_{t,k}$ *[14:00,15:00)*	(7) *Retail Trading* $PC_{t,k}$ *[15:00,16:00]*
Ad_{t-7}	0.020**	0.017***	0.016***	0.006**	0.014***	0.011**	0.025***
	(2.57)	(2.73)	(2.96)	(2.21)	(2.85)	(2.23)	(3.84)
Non-duplicate Ad_t	0.014	0.009	0.015**	0.002	0.009	0.017**	0.023***
	(1.41)	(1.11)	(2.16)	(0.65)	(1.39)	(2.51)	(2.69)
$QEA_{[t-2,t-1]}$	0.012	0.003	0.006	0.011**	0.029***	0.040***	0.106***
	(1.09)	(0.35)	(0.84)	(2.44)	(4.26)	(4.94)	(10.43)
QEA_t	0.816***	0.476***	0.367***	0.184***	0.320***	0.347***	0.624***
	(30.24)	(25.30)	(24.55)	(21.81)	(25.17)	(25.62)	(29.49)
$QEA_{[t+1,t+2]}$	0.676***	0.420***	0.312***	0.150***	0.248***	0.259***	0.337***
	(26.43)	(23.14)	(21.89)	(20.98)	(20.50)	(19.53)	(21.39)
$Other\ News_t$	0.054***	0.033***	0.024***	0.012***	0.022***	0.023***	0.027***
	(15.39)	(12.23)	(10.88)	(10.40)	(11.04)	(10.87)	(10.04)
$ln(Market\ Cap)_{q-1}$	0.029*	0.061***	0.070***	0.038***	0.070***	0.095***	0.096***
	(1.87)	(5.01)	(6.85)	(7.10)	(8.06)	(9.52)	(8.30)
$Book/Market_{q-1}$	-0.445***	-0.334***	-0.236***	-0.107***	-0.214***	-0.207***	-0.297***
	(-11.19)	(-10.21)	(-8.67)	(-7.22)	(-9.03)	(-7.56)	(-9.41)
Observations	127,233	116,117	113,395	100,728	111,961	113,641	125,951
Adj R-Squared	0.81	0.79	0.78	0.74	0.77	0.78	0.82
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the first-stage regression results of the 2SLS analysis on the relation between intraday retail trading and intraday informed trading, using Ad_{t-7} as an instrument for retail trading. Ad_{t-7} indicates days with an ad placed seven calendar days earlier in the WSJ. Retail trading is measured using *Retail Trading PC*. Columns (1) through (7) report the results for the time intervals [9:30,10:30), [10:30,11:30), [11:30,12:30), [12:30,13:00), [13:00,14:00), [14:00,15:00), and [15:00,16:00] ET, respectively. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table 7
Instrumented Retail Trading and Informed Trading: Intraday

	(1) *Informed Dollar* $Volume_{t,k}$ *[9:30,10:30)*	(2) *Informed Dollar* $Volume_{t,k}$ *[10:30,11:30)*	(3) *Informed Dollar* $Volume_{t,k}$ *[11:30,12:30)*	(4) *Informed Dollar* $Volume_{t,k}$ *[12:30,13:00)*	(5) *Informed Dollar* $Volume_{t,k}$ *[13:00,14:00)*	(6) *Informed Dollar* $Volume_{t,k}$ *[14:00,15:00)*	(7) *Informed Dollar* $Volume_{t,k}$ *[15:00,16:00]*
Fitted Retail Tradng PC_t	44.293***	9.121	20.438**	30.627**	26.515***	31.473**	20.350**
	(3.11)	(0.87)	(2.26)	(2.38)	(2.82)	(2.43)	(2.36)
Non-duplicate Ad_t	-0.438	-0.203	-0.338	-0.151	-0.329*	-0.493*	-0.382
	(-0.98)	(-0.78)	(-1.39)	(-1.29)	(-1.69)	(-1.69)	(-1.10)
$QEA_{[t-2,t-1]}$	-0.236	0.096	0.177	-0.122	-0.190	-0.629	-0.500
	(-0.65)	(0.36)	(0.83)	(-0.66)	(-0.57)	(-1.16)	(-0.51)
QEA_t	-14.956	5.316	-0.387	-2.583	-2.784	-4.750	-1.830
	(-1.28)	(1.06)	(-0.12)	(-1.09)	(-0.92)	(-1.06)	(-0.34)
$QEA_{[t+1,t+2]}$	-13.157	4.951	-0.473	-1.906	-1.420	-2.852	0.401
	(-1.36)	(1.11)	(-0.17)	(-0.99)	(-0.60)	(-0.84)	(0.14)
$Other\ News_t$	-1.179	0.210	-0.166	-0.248	-0.268	-0.397	0.330
	(-1.53)	(0.61)	(-0.75)	(-1.58)	(-1.28)	(-1.30)	(1.29)
$ln(Market\ Cap)_{q-1}$	7.143***	5.796***	3.745***	1.364***	2.455***	2.089*	5.855***
	(11.17)	(8.35)	(5.61)	(2.74)	(3.56)	(1.67)	(6.75)
$Book/Market_{q-1}$	15.866**	4.387	5.126**	3.808***	5.673***	6.606**	6.311**
	(2.44)	(1.19)	(2.30)	(2.61)	(2.67)	(2.36)	(2.27)
Observations	127,233	116,117	113,395	100,728	111,961	113,641	125,951
Adj R-Squared	0.79	0.83	0.83	0.75	0.80	0.80	0.86
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	7.24	8.55	10.38	5.82	10.53	5.96	18.54

This table reports the second-stage regression results of the 2SLS analysis on the relation between intraday retail trading and informed trading, using Ad_{t-7} as an instrument for retail trading. Retail trading is measured using *Retail Trading PC*. Informed trading is measured using *Informed Dollar Volume*. *Fitted Retail Trading PC* is the fitted values of *Retail Trading PC* from the first-stage regressions (see Table 6). Columns (1) through (7) report the results for the time intervals [9:30,10:30), [10:30,11:30), [11:30,12:30), [12:30,13:00), [13:00,14:00), [14:00,15:00), and [15:00,16:00] ET, respectively. Controls, in both stages, include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table 8
Lagged Ad Days and Informed Trading: History of Recurring Ads

	(1) $Number\,of$ $Informed$ $Trades_t$	(2) $Informed$ $Dollar$ $Volume_t$
$Ad_{t-7,\,long\,history}$	0.186*	3.045**
	(1.76)	(2.07)
$Ad_{t-7,\,short\,history}$	0.082	1.004
	(0.58)	(0.54)
$Non\text{-}duplicate\ Ad_t$	0.083	0.107
	(0.69)	(0.07)
$QEA_{[t-2,t-1]}$	0.197	3.449**
	(1.56)	(2.10)
QEA_t	4.420***	62.983***
	(17.54)	(19.53)
$QEA_{[t+1,t+2]}$	3.601***	53.603***
	(15.71)	(16.85)
$Other\ News_t$	0.212***	3.483***
	(7.76)	(8.36)
$ln(Market\,Cap)_{q-1}$	2.877***	37.294***
	(16.57)	(17.06)
$Book/Market_{q-1}$	1.465***	13.242**
	(3.78)	(2.52)
Observations	139,656	139,656
Adj R-Squared	0.85	0.82
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

This table reports the OLS analysis on the relation between lagged ad days (based on the length of recurring ad history) and informed trading. $Ad_{t-7,\,long\,history}$ ($Ad_{t-7,\,short\,history}$) indicates days with an ad placed seven calendar days earlier in the WSJ, and requires the same firm to place ads at weekly intervals for equal to or more (less) than three of the prior twelve weeks in the WSJ. Informed trading is measured using *Number of Informed Trades* in column (1), and *Informed Dollar Volume* in column (2). Number of trades are in hundreds, and dollar volumes are in millions. Controls include those described in Table 1 as well as firm and date fixed effects. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table 9
Lagged Ad Days and Price Efficiency

	(1)	(2)
	Stock Return$_{t,k+1}$	
$OIB\$_{t,k} \times Ad_{t-7}$	-0.937**	
	(-2.05)	
$OIB\$_{t,k} \times Ad_{t-7,\ long\ history}$		-1.410**
		(-2.33)
$OIB\$_{t,k} \times Ad_{t-7,\ short\ history}$		-0.205
		(-0.30)
$OIB\$_{t,k}$	0.017	0.017
	(0.12)	(0.12)
Ad_{t-7}	-0.085	
	(-0.85)	
$Ad_{t-7,\ long\ history}$		-0.143
		(-1.18)
$Ad_{t-7,\ short\ history}$		-0.001
		(-0.01)
$Non\text{-}duplicate\ Ad_t$	-0.155	-0.150
	(-1.25)	(-1.21)
$QEA_{[t-2,t-1]}$	-0.093	-0.094
	(-0.62)	(-0.62)
QEA_t	-0.662*	-0.662*
	(-1.95)	(-1.95)
$QEA_{[t+1,t+2]}$	-0.720***	-0.721***
	(-2.98)	(-2.98)
$Other\ News_t$	0.126**	0.126**
	(2.20)	(2.20)
$ln(Market\ Cap)_{q-1}$	-0.610**	-0.609**
	(-2.14)	(-2.13)
$Book/Market_{q-1}$	-0.010	-0.009
	(-0.01)	(-0.01)
Observations	1,494,432	1,494,432
Adj R-Squared	0.01	0.01
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

This table reports the OLS analysis on the relation between lagged ad days and price efficiency. Ad_{t-7} indicates days with an ad placed seven calendar days earlier in the WSJ, and $Ad_{t-7,\ long\ history}$ ($Ad_{t-7,\ short\ history}$) indicates days with an ad placed seven calendar days earlier, and requires the same firm to place ads at weekly intervals for equal to or more (less) than three of the prior twelve weeks. $OIB\$_{t,k}$ is the dollar order imbalance on day t for the five-minute interval k calculated over the eleven five-minute intervals k from 9:30 to 10:25 ET, and *Stock Return*$_{t,k+1}$ are stock returns calculated using the midpoints of the best bid and offer over the eleven five-minute intervals $k+1$ from 9:35 to 10:30 ET. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table IA1
Lagged Ad Days and Price Efficiency: Different Lags

	(1)	(2)	(3)	(4)	(5)
			Stock Return$_{t,k+1}$		
$OIB\$_{t,k} \times Ad_{t-5}$	-0.017				
	(-0.03)				
$OIB\$_{t,k} \times Ad_{t-6}$		-0.317			
		(-0.51)			
$OIB\$_{t,k} \times Ad_{t-7}$			-0.937**		
			(-2.05)		
$OIB\$_{t,k} \times Ad_{t-8}$				-0.796	
				(-1.51)	
$OIB\$_{t,k} \times Ad_{t-9}$					-0.475
					(-0.77)
$OIB\$_{t,k}$	-0.040	-0.021	0.017	0.008	-0.011
	(-0.30)	(-0.16)	(0.12)	(0.06)	(-0.09)
Ad_{t-5}	-0.016				
	(-0.13)				
Ad_{t-6}		-0.057			
		(-0.57)			
Ad_{t-7}			-0.085		
			(-0.85)		
Ad_{t-8}				-0.002	
				(-0.02)	
Ad_{t-9}					-0.101
					(-1.00)
Observations	1,494,432	1,494,432	1,494,432	1,494,432	1,494,432
Adj R-Squared	0.01	0.01	0.01	0.01	0.01
Control Variables	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

This table reports the OLS analysis on the relation between lagged ad days and price efficiency. Ad_{t-n} indicates days with an ad placed n calendar days earlier in the WSJ, where n = 5, 6, 7, 8, 9. $OIB\$_{t,k}$ is the dollar order imbalance on day t for the five-minute interval k calculated over the eleven five-minute intervals k from 9:30 to 10:25 ET, and *Stock Return*$_{t,k+1}$ are stock returns calculated using the midpoints of the best bid and offer over the eleven five-minute intervals $k+1$ from 9:35 to 10:30 ET. Controls include those described in Table 1 of the paper as well as date and firm fixed effects; their coefficient estimates are not reported for brevity. Detailed variable definitions are in Appendix A of the paper. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table IA2
Lagged Ad Days and Retail Trading: Weekly and Bi-Weekly Ads

	(1) *Number of Retail* $Trades_t$	(2) *Retail Dollar* $Volume_t$	(3) *Retail Trading* PC_t
Ad_{t-7}	0.233*	0.638**	0.013**
	(1.84)	(2.57)	(2.42)
Ad_{t-14}	0.349***	0.515**	0.014***
	(2.66)	(2.10)	(2.62)
Non-duplicate Ad_t	0.130	0.597*	0.010
	(0.76)	(1.95)	(1.46)
$QEA_{[t-2,t-1]}$	0.701***	1.161***	0.030***
	(4.06)	(3.60)	(4.17)
QEA_t	11.015***	19.669***	0.494***
	(30.39)	(25.96)	(29.66)
$QEA\_[t+1,t+2]$	8.212***	15.204***	0.375***
	(24.16)	(21.02)	(23.39)
Other $News_t$	0.788***	0.713***	0.027***
	(14.64)	(7.87)	(12.56)
$ln(Market\,Cap)_{q-1}$	-1.034***	6.667***	0.057***
	(-4.03)	(16.00)	(5.90)
$Book/Market_{q-1}$	-8.119***	-2.731***	-0.222***
	(-13.47)	(-2.78)	(-9.56)
Observations	139,656	139,656	139,656
Adj R-Squared	0.81	0.83	0.83
Date Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
P($\text{Ad}_{t-7} = \text{Ad}_{t-14} = 0$)	0.00	0.00	0.00

This table reports the first-stage regression results of the 2SLS analysis on the relation between retail trading and informed trading, using Ad_{t-7} and Ad_{t-14} as instruments for retail trading. Ad_{t-7} (Ad_{t-14}) indicates days with an ad placed seven (fourteen) calendar days earlier in the WSJ. Retail trading is measured using *Number of Retail Trades* in column (1); *Retail Dollar Volume* in column (2); and *Retail Trading PC* in column (3). Number of trades are in hundreds, and dollar volumes are in millions. Controls include those described in Table 1 of the paper as well as date and firm fixed effects. Detailed variable definitions are in Appendix A of the paper and Table IA6 of the Internet Appendix. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table IA3

Instrumented Retail Trading and Informed Trading: Weekly and Bi-weekly Ads

	(1) *Number of Informed* $Trades_t$	(2) *Informed Dollar* $Volume_t$	(3) *Number of Informed* $Trades_t$	(4) *Informed Dollar* $Volume_t$
$Fitted\ Retail\ Number\ of\ Trades_t$	0.271*			
	(1.74)			
$Fitted\ Retail\ Dollar\ Volume_t$		2.403**		
		(2.36)		
$Fitted\ Retail\ Trading\ PC_t$			6.108*	98.030**
			(1.91)	(2.32)
$Non\text{-}duplicate\ Ad_t$	0.047	-1.373	0.018	-0.932
	(0.44)	(-0.96)	(0.17)	(-0.68)
$QEA_{[t-2,t-1]}$	0.007	0.652	0.012	0.466
	(0.05)	(0.38)	(0.08)	(0.26)
QEA_t	1.435	15.731	1.402	14.549
	(0.83)	(0.78)	(0.88)	(0.69)
$QEA_{[t+1,t+2]}$	1.376	17.073	1.311	16.850
	(1.05)	(1.09)	(1.07)	(1.05)
$Other\ News_t$	-0.001	1.768**	0.048	0.840
	(-0.01)	(2.22)	(0.54)	(0.71)
$ln(Market\ Cap)_{q-1}$	3.158***	21.284***	2.531***	31.735***
	(13.83)	(3.10)	(11.60)	(11.21)
$Book/Market_{q-1}$	3.666***	19.828***	2.819***	34.990***
	(2.76)	(3.75)	(3.56)	(3.30)
Observations	139,656	139,656	139,656	139,656
Adj R-Squared	0.89	0.89	0.90	0.89
Date Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	8.85	10.37	11.41	11.41
Sargan-Hansen p-value	0.34	0.55	0.42	0.40

This table reports the second-stage regression results of the 2SLS analysis on the relation between retail trading and informed trading, using Ad_{t-7} and Ad_{t-14} as instruments for retail trading. Retail trading is measured using *Number of Retail Trades* in column (1); *Retail Dollar Volume* in column (2); and *Retail Trading PC* in columns (3) and (4). Informed trading is measured using *Number of Informed Trades* in columns (1) and (3); and *Informed Dollar Volume* in columns (2) and (4). Number of trades are in hundreds, and dollar volumes are in millions. Variables with prefix 'Fitted' are the fitted values of their respective variables from the first-stage regressions (see Table IA2). Controls, in both stages, include those described in Table 1 of the paper as well as date and firm fixed effects. Detailed variable definitions are in Appendix A of the paper. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table IA4
Lagged Ad Days and Retail Trading: Small Retail Trades

	(1) *Number of Small Retail* $Trades_t$	(2) *Small Retail Dollar* $Volume_t$	(3) *Small Retail Trading* PC_t
Ad_{t-7}	0.163**	0.072***	0.019***
	(2.35)	(4.10)	(3.31)
Non-duplicate Ad_t	0.136	0.052**	0.015*
	(1.42)	(2.18)	(1.84)
$QEA_{[t-2,t-1]}$	0.225**	0.077***	0.022***
	(2.32)	(3.01)	(2.71)
QEA_t	4.101***	1.134***	0.363***
	(22.62)	(23.49)	(23.44)
$QEA_{[t+1,t+2]}$	2.990***	0.834***	0.266***
	(18.60)	(19.37)	(19.27)
Other $News_t$	0.403***	0.090***	0.032***
	(12.75)	(11.05)	(12.15)
$ln(Market\ Cap)_{q-1}$	-2.028***	-0.098***	-0.102***
	(-12.17)	(-2.70)	(-7.98)
$Book/Market_{q-1}$	-3.690***	-0.612***	-0.259***
	(-10.49)	(-7.55)	(-9.29)
Observations	139,656	139,656	139,656
Adj R-Squared	0.78	0.78	0.79
Date Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes

This table reports the first-stage regression results of the 2SLS analysis on the relation between small retail trading and informed trading, using Ad_{t-7} as an instrument for small retail trading. Ad_{t-7} indicates days with an ad placed seven calendar days earlier in the WSJ. Retail trading is measured using *Number of Small Retail Trades* in column (1); *Small Retail Dollar Volume* in column (2); and *Small Retail Trading PC* in column (3). Number of trades are in hundreds, and dollar volumes are in millions. Controls include those described in Table 1 of the paper as well as date and firm fixed effects. Detailed variable definitions are in Appendix A of the paper and Table IA6 of the Internet Appendix. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table IA5
Instrumented Retail Trading and Informed Trading: Small Retail Trades

	(1) *Number of Institutional Trades$_t$*	(2) *Institutional Dollar Volume$_t$*	(3) *Number of Institutional Trades$_t$*	(4) *Institutional Dollar Volume$_t$*
Fitted Retail Number of Trades$_t$	1.196*			
	(1.93)			
Fitted Retail Dollar Volume$_t$		36.191**		
		(2.24)		
Fitted Retail Trading PC$_t$			10.265**	137.973**
			(2.14)	(2.19)
Non-duplicate Ad$_t$	-0.016	-1.201	-0.002	-1.308
	(-0.10)	(-0.67)	(-0.02)	(-0.70)
$QEA_{[t-2,t-1]}$	-0.023	1.169	0.017	0.861
	(-0.12)	(0.55)	(0.10)	(0.39)
QEA_t	0.345	30.692	1.521	21.627
	(0.13)	(1.64)	(0.86)	(0.93)
$QEA_{[t+1,t+2]}$	0.682	30.399**	1.526	23.891
	(0.36)	(2.17)	(1.16)	(1.39)
Other News$_t$	-0.250	0.410	-0.099	-0.759
	(-1.00)	(0.27)	(-0.63)	(-0.37)
$ln(Market\ Cap)_{q-1}$	5.634***	44.363***	4.260***	54.944***
	(4.38)	(16.97)	(8.02)	(8.00)
$Book/Market_{q-1}$	5.830**	35.223***	4.073***	48.757***
	(2.49)	(3.12)	(3.10)	(2.82)
Observations	139,656	139,656	139,656	139,656
Adj R-Squared	0.83	0.85	0.86	0.84
Date Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	6.61	20.21	13.00	13.00

This table reports the second-stage regression results of the 2SLS analysis on the relation between small retail trading and informed trading, using Ad_{t-7} as an instrument for small retail trading. Retail trading is measured using *Number of Small Retail Trades* in column (1); *Small Retail Dollar Volume* in column (2); and *Small Retail Trading PC* in columns (3) and (4). Informed trading is measured using *Number of Informed Trades* in columns (1) and (3); and *Informed Dollar Volume* in columns (2) and (4). Number of trades are in hundreds, and dollar volumes are in millions. Variables with prefix 'Fitted' are the fitted values of their respective variables from the first-stage regressions (see Table IA4). Controls, in both stages, include those described in Table 1 of the paper as well as date and firm fixed effects. Detailed variable definitions are in Appendix A of the paper. The sample period is April 2009 to October 2013. Standard errors are clustered by date, t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Table IA6
Definition of Variables Used in This Internet Appendix

This table describes the calculation of variables used only in this Internet Appendix. Variables also used in the core analyses are described in Appendix A of the paper. t indexes days, and q indexes the quarter to which day t belongs. Firm subscript is omitted for brevity. To code the ad-related variables, we first align each ad day to a trading day in CRSP, with a non-trading ad day aligned with its first subsequent trading day.

Variable	Definition
Alternative ad-based instruments	
Ad_{t-n}	An indicator variable that equals one if day $t-n$ (i.e., n calendar days before trading day t) is an ad day of the firm in the WSJ, and zero otherwise, with $n = 5, 6, 8, 9$.
Ad_{t-14}	An indicator variable that equals one if day $t-14$ (i.e., fourteen calendar days before trading day t) is an ad day of the firm in the WSJ, and zero otherwise.
Alternative measures of retail trading	
Number of Small Retail Trades$_t$	Similar to *Number of Retail Trades*$_t$, except that trade size is limited to be $5,000 or less.
Small Retail Dollar Volume$_t$	Similar to *Retail Dollar Volume*$_t$, except that trade size is limited to be $5,000 or less.
Small Retail Trading PC$_t$	The first principal component of *Number of Small Retail Trades* and *Small Retail Dollar Volume*.