Is It All Noise? The Microstructure Implications of Corporate Recurring Advertisements

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Abstract

This paper studies the market microstructure implications of uninformed trading volume. We capture uninformed volume using spikes in retail trading triggered by weekly advertisements (ads) in the *Wall Street Journal* that are largely duplicates. We report three findings. First, consistent with a positive volume-volatility relation, stock price volatility amplifies on recurring ad days. Second, informed investors time liquidity to trade more aggressively on recurring ad days. Third, despite the increase in informed trading on such days, price impact is lower, yielding a negative volume-price impact relation. Collectively, the evidence supports the theoretical predictions of Collin-Dufresne and Fos (2016).

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

Keywords: Advertising, Retail Trading, Price Volatility, Informed Trading, Price Impact

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I Introduction

Advertising, a corporate action intended to promote products and brands, can have ripple effects on secondary market trading. Prior studies show that annual marketing expenditures are positively related to retail attention, stock liquidity, and ownership breadth (Grullon, Kanatas, and Weston (2004), Frieder and Subrahmanyam (2005), and Lou (2014)). Using more granular advertising measures, Madsen and Niessner (2019) show that retail attention and total trading volume rise on newspaper advertisement (ad) days, and Liaukonyte and Zaldokas (Liaukonyte and Zaldokas) show that TV ads trigger retail attention, trading, and information acquisition. This paper complements prior research by examining patterns of retail trading surrounding corporate recurring ads, but more important, probes the resemblance of recurring ad-induced retail trading to uninformed volume as modeled by theory and its implications for stock price volatility, informed trading, and price impact.

The use of recurring ad-induced retail trades as an instrument for uninformed volume—formally defined as an indicator for whether the firm placed an ad in the *Wall Street Journal* (WSJ) seven calendar days earlier—builds on Madsen and Niessner's (2019) observation that firms frequently advertise at weekly intervals and recurring ads attract retail attention. We focus on the WSJ because it is the most followed business newspaper and publishes the greatest percentage of ads among all business newspapers. As motivating evidence to support our instrument's relevance to retail trading, we first show that both the number and dollar volume of retail trades of $50,000 or less (measured using Boehmer, Jones, Zhang, and Zhang's (2021) "BJZZ" methodology) spike on ad days as well as seven days after ad days. Since each spike on average lasts for two days, we measure retail trading and all outcome variables over two-day rolling windows in our main tests. In regression analysis, we find that our instrument is associated with an increase of 26.1 retail trades and $305,000 retail dollar volume, 1.9% and 2.6% of the sample mean, respectively. The increase in retail dollar volume is economically comparable to the corresponding increase on other news days ($346,000) and smaller than the increase on earnings announcement days ($9.4 million).

[Insert Figure 1 approximately here]

Although retail trading in response to general ads could be driven by information, we argue that retail trading in response to weekly recurring ads is more likely driven by attention for two reasons. First, advertising rigidity mitigates concerns about the endogenous timing of ad placement, which may be correlated with firms' information events. New information is unlikely to arrive every seven days and firms are unlikely to intentionally bank new information and release it on prescheduled ad days. Second, image analysis indicates that ads placed in the WSJ at weekly intervals have a 62% probability of being duplicate images of previously placed ads, and thus likely contain minimal information content. As an example, Figure 1 displays images of the duplicate ads that Oracle Corporation placed in the WSJ every Thursday over ten consecutive weeks in 2013.[1]

[1] One may argue that even weekly duplicate ads contain information about a firm's growth and profitability. For weekly ads to be effective signals, market participants must update their beliefs about the firm every time an ad is placed and the firm must have full discretion over ad timing. We view both conditions as unlikely given the preponderance of duplicate images placed over relatively short horizons and the fact that multi-period ad contracts typically involve firms, ad agencies, and the journal.

Recurring ad-induced retail trades share similar properties with uninformed volume (or interchangeably, "noise trading"), a crucial construct in microstructure theory. First, these trades exhibit no significant order imbalance, consistent with their uninformed and non-directional nature.[2] Second, these trades exhibit time-varying volatility, as both the level and uncertainty of retail trading volatility (proxied using the intraday realized mean and standard deviation) increase on recurring ad days, with a notable amplification during the opening hour. Collin-Dufresne and Fos (2016) (henceforth "CF") assume that noise trading volatility is stochastic, a feature that differentiates their model from Kyle (1985), which assumes that noise trading volatility is constant. Since our evidence suggests that recurring ad-induced retail trades resemble the construct of noise trading modeled by CF, we utilize these trades to test CF's predictions regarding the microstructure implications of shocks to uninformed volume.

The first prediction we test is the "positive volume-volatility relation" (CF, p. 1442). CF show that, with stochastic noise trading volatility, informed investors trade aggressively in the presence of positive shocks to uninformed volume. Because the market maker rationally anticipates such trading, stock price volatility rises. This prediction distinguishes CF from Kyle (1985), as stock price volatility is constant in the latter. To test this prediction, we use recurring ad-instrumented retail trades to study how shocks to uninformed volume affect stock price volatility (empirically measured as stock return volatility).

[2] We discuss the limitations of the BJZZ retail trade measure in Section II.B and the implications for the order imbalance result in Section III.B.

We regress measures of stock return volatility on our instrument for uninformed volume, controls for non-duplicate images, market capitalization, market-to-book, releases of earnings announcements and other news, past stock returns, idiosyncratic price volatility, and return skewness as well as firm and date fixed effects. We find that seven days after WSJ ad days, intraday stock return volatility increases over a two-day window relative to other two-day windows. Specifically, the instrument is associated with an increase of 1.4% (2%) in the two-day rolling average volatility of five- (thirty-) minute intraday stock returns relative to their respective sample mean. This increase represents 55.2% (66.7%) of the corresponding increase on other news days and 2.4% (3%) of the increase on earnings announcement days. Overall, these findings support CF's prediction of a "positive volume-volatility relation."[3]

The second prediction we test concerns informed investors' optimal trading strategy. Earlier market microstructure theories (e.g., Kyle (1985)) predict a positive relation between uninformed and informed trading; however, the precise timing for when informed investors trade on their private information is nuanced. Informed investors generally demand immediacy given competition (e.g., Holden and Subrahmanyam (1992), Foster and Viswanathan (1993)), particularly if they are assumed to trade only on short-lived private information (e.g., Admati and Pfleiderer (1988), Foster and Viswanathan (1993)). CF show that, given time-varying noise trading volatility, informed investors can benefit from timing

[3] Several other theories (e.g., Ho and Stoll (1980), Grossman and Miller (1988), De Long, Shleifer, Summers, and Waldmann (1990), and Hendershott and Menkveld (2014)) also predict a positive volume-volatility relation, but their predictions concern inventory costs or other noise trader risk, whereas CF's prediction arises due to adverse selection. In additional analysis, we show that the positive volume-volatility relation concentrates in firms with above-sample-median price impact in the past four weeks, suggesting that adverse selection risk is a main driver for the relation that we document as opposed to noise trader risk. These theories also diverge from CF regarding their predictions for price impact, which we discuss below.

liquidity (or transient shocks to uninformed volume) when they possess relatively long-lived information. To test this prediction, we again use recurring ad-instrumented retail trades to study how positive shocks to uninformed volume affect informed trading. Our approach assumes that informed traders are able to form expectations about noise trading volatility on recurring ad days ex ante and trade accordingly.

To capture informed trading, we first utilize the informed trading intensity measure introduced by Bogousslavsky, Fos, and Muravyev (2024). Given the limited observability of informed trades, Bogousslavsky et al. (2024) use machine learning to extrapolate from patterns of known informed trades to estimate the universe of informed trades and then build a measure of trading intensity. We find that seven days after WSJ ad days, informed trading intensity increases over a two-day window relative to other two-day windows. Our ad-based instrument is associated with an increase of 0.7% in the two-day rolling average informed trading intensity relative to its sample mean. This increase represents 25% of the corresponding increase on other news days and 1.9% of the increase on earnings announcement days.

We also consider two less refined measures of informed trading: option and insider trades. Prior research shows that option volume, particularly from out-of-the-money (OTM) contracts, predicts future stock price movements (Pan and Poteshman (2006)) and that insider trades, particularly opportunistic ones, reflect managers' private information (Cohen, Malloy, and Pomorski (2012)). We separately calculate the number of total and OTM option contracts and the number of opportunistic and routine insider trades over two-day rolling windows. Results show that our instrument is strongly associated with an increase in both total and OTM option contracts and weakly associated with an increase in opportunistic insider trades. Together, these findings are consistent with CF's prediction that informed investors strategically time at least some trades to periods of high uninformed volume.

The final prediction we test involves price impact. CF model time-varying volatility of noise trading and show that positive shocks to this volatility lead to both lower price impact and higher informed trading, and that any price impact that does result from increased informed trading is unlikely to exhibit reversals since the price movement ultimately reflects the private information possessed by informed traders. In contrast, models like De Long et al. (1990) and Foucault, Sraer, and Thesmar (2011) assume noise trading volatility to be an exogenous parameter so an increase in this parameter permanently increases price impact. Grossman and Miller (1988) and other models of inventory holding costs similarly predict a positive effect of noise trader risk on price impact and such price impact (as a result of compensating for liquidity suppliers) is followed by reversals.

To distinguish between these predictions, we first show that our ad-based instrument is negatively associated with a value-weighted measure of price impact, averaged over a two-day rolling window (i.e., price impact is lower seven days after a WSJ ad day). Replacing price impact with λ, a common measure of adverse selection that increases with price impact in theory (Kyle (1985)), yields similar results. Our instrument is associated with a decrease of 2.3% in the two-day rolling average price impact relative to its sample mean, and a decrease of 1.8% in the two-day rolling average λ relative to its standard deviation. This result is more consistent with CF's prediction of a negative relation between noise trading and price impact, as opposed to a positive relation predicted by other models of trading costs. Furthermore, an analysis of firms' return autocorrelation reveals no evidence of increased price reversals on recurring ad days compared to other trading days. This finding is consistent with CF's prediction that informed investors trade on private information on days with increased uninformed volume.

Our results are robust to removing the control for non-duplicate ads, double clustering standard errors, or using Newey and West (1987) standard errors throughout. In additional analyses, we show that our results are robust to conducting two-stage least squares (2SLS) analyses and estimating a system of simultaneous equations to examine the effect of uninformed volume on informed trading and price impact. The last analysis reveals that an exogenous increase in uninformed retail trading, instrumented with recurring ads, encourages informed trading while reducing price impact. This result provides further support for the theoretical predictions of CF, which posit that higher informed trading and lower price impact can co-exist in equilibrium.

This study makes three contributions. First, it contributes to understanding the market implications of uninformed retail trading. While the finding of a positive volume-volatility relation aligns with prior evidence (e.g., Foucault et al. (2011), Fedyk (2024), and Peress and Schmidt (2020)), the findings on how uninformed volume relates to price impact are novel. As discussed earlier, theories predict a negative relation between uninformed volume and price impact if noise trading volatility is modeled as time-varying (as in CF) but a positive relation if noise trading volatility is assumed to be an exogenous parameter (as in De Long et al. (1990) and Foucault et al. (2011)). Theories also predict price reversals if trading costs stem from noise trader risk (such as inventory holding costs in Grossman and Miller (1988)) but no reversals if trading costs instead stem from adverse selection risk (as in CF).

Empirical evidence is also mixed: Foucault et al. (2011) find that an exogenous reduction in retail trading leads to a drop in price impact, while Greene and Smart (1999) find that increased retail trading in response to coverage in the WSJ is associated with decreased adverse selection costs and Bloomfield, O'hara, and Saar (2009) provide laboratory evidence that noise trades decrease bid-ask spreads. The two latter studies thus suggest that price impact decreases with noise trading. Additionally, Collin-Dufresne and Fos (2015) show that measures of price impact are lower on days with known informed trades from 13-D filings. While our finding of a negative volume-price impact relation is complementary, our use of a recurring ad-based instrument captures transient shocks to noise trading volatility, enabling more direct tests of CF's theoretical predictions. As such, our results do not align well with the predictions of De Long et al. (1990) and Foucault et al. (2011) as our instrument may not capture the permanent shifts in noise trading volatility that they model.

Second, this study adds to research on the market implications of corporate advertising. Prior studies find that advertising is negatively associated with trading costs and price impact (Grullon et al. (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), and Lou (2014)), firm value (Gurun and Butler (2012)), and searches for financial information (Madsen and Niessner (2019), Liaukonyte and Zaldokas (Liaukonyte and Zaldokas)). Our study departs from these studies by deriving a recurring ad-based instrument for uninformed volume to test microstructure theory predictions.

Finally, this study aligns with existing evidence that retail investors may interpret stale news as new information (e.g., Barber and Loeffler (1993), Huberman and Regev (2001), Tetlock (2011), Gilbert, Kogan, Lochstoer, and Ozyildirim (2012), and Chawla, Da, Xu, and Ye (2022)). Our results similarly indicate that retail investors respond to recurring, duplicate ads by trading more actively even though these ads arguably contain little information. Despite being uninformative themselves, recurring ads can have real market implications for stock price volatility, informed trading, and price impact through triggering retail trading.

II Data, Variable Measurement, and Descriptive Statistics

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

II.A Ad Days

We obtain ad data from MediaRadar Ad Sales Research database and focus on a sample of ads printed in the WSJ between April 2009 (the month in which MediaRadar begins coverage of the journal) and October 2013. With the aim to examine the microstructure implications of uninformed volume (or noise trading), we choose this sample for three reasons. First, we study print ads because our instrument for noise trading hinges on corporate advertising patterns, which are easier to capture using print ads than digital ads. This choice need not sacrifice the generalizability of our inferences as we have no reason to suspect that digital ads are less attention-grabbing than print ads or that they affect markets differently. Second, we end our sample in 2013 because print ads likely had the broadest reach before 2013 due to declining readership of print newspapers in recent years.[4] Third, we focus on the WSJ because it is one of the most widely circulated U.S. newspapers. Among the business journals covered by MediaRadar, the WSJ publishes 85% of the ads. Moreover, because the WSJ is arguably the most influential business newspaper in the world, its subscribers are presumably keen to learn about business and economics news and comfortable with trading. Focusing on one newspaper also helps ensure that recurring ads contain minimal information content, particularly if these ads result from multi-week contracts.

After identifying ad days in the WSJ, we align them to trading days. While a majority of the sample ads (94.6%) fall on trading days, a small fraction are placed in the WSJ weekend issues (published on Saturdays) and on holidays (i.e., non-trading days). We align each non-trading ad day to the first subsequent trading day, although inferences do not change if we remove these ads. We define our recurring ad-based instrument for uninformed volume, $Ad_{i,t-7}$, as an indicator that equals one if firm i placed an ad in the WSJ seven calendar days earlier and zero otherwise.

[4] Based on data from *Editor and Publisher*, the total estimated circulation of U.S. weekday daily newspapers has increased steadily from 1940, peaked in the early 1990s, and has been dropping since, with 2013 being the first year in which this number is below the 1940's level. That said, the WSJ allows its subscribers to access the "Print Edition" of the daily newspaper through either its website or mobile application, giving its print ads a broader reach.

II.B Retail Trading

We follow Boehmer et al. (2021) to detect retail trades using intraday data from the Trade and Quote database (TAQ). The BJZZ methodology builds on the observation 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 minimum 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. (2021) 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. 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 the BJZZ methodology to identify retail trades.

[Insert Figure 2 approximately here]

Using the identified trades, we first examine patterns of retail trading around WSJ ad days. Figure 2, which plots the average number of retail trades and retail dollar volume from seven trading days before a WSJ ad to seven trading days after, reveals two patterns. First, both the number and dollar volume of retail trades spike on ad days and last for two days before declining. Second, retail trading exhibits a weekly cyclical pattern, increasing five trading days (typically corresponding to seven calendar days) before and after ad days.

Based on the first pattern shown in Figure 2, we define two measures of retail trading over the two-day window $[t,\, t+1]$ for each firm-trading day i, t: *Retail Trades* (the aggregate number of retail trades divided by two) and *Retail Volume* (the aggregate retail dollar volume divided by two). In constructing these measures, we limit trade sizes to \$50,000 to exclude large retail trades that are potentially motivated by information; this empirical choice follows Barber, Odean, and Zhu (2008). Based on the second pattern shown in Figure 2, we use $Ad_{i,t-7}$ as an instrument to capture uninformed retail trades.

Recent studies suggest that the BJZZ methodology is prone to Type II errors (Barber, Huang, Jorion, Odean, and Schwarz (2024)), Type I errors (Battalio, Jennings, Saglam, and Wu (2023)), and signing errors (Barber et al. (2024)) if applied to recent sample periods. Specifically, Barber et al. (2024) analyze a sample of 85,000 retail trades executed between December 2021 and June 2022 and find that the BJZZ methodology identifies 35% of these trades while incorrectly signing 28% of the identified trades. However, they find minimal error rates before 2016 and thus attribute this temporal variability to recent trading innovations that have influenced market structures, including the Securities and Exchange Commission (SEC) Tick Size Pilot introduced in 2016 and zero-commission trading introduced in 2019. Topbas and Ye (2023) suggest that the

Alternative Trading Systems Trade Transparency implemented in 2014 could have also contributed. As our sample period predates 2014, error rates should be low. Additionally, Barardehi, Bernhardt, Da, and Warachka (2023) suggest that the BJZZ methodology exhibits bias towards identifying retail orders executed under poor liquidity conditions. Our results should also be less prone to this bias, as our sample firms lean towards larger sizes and their observed stock liquidity further improves on recurring ad days. Nevertheless, we conduct robustness checks with two additional measures of retail orders (i.e., off-exchange one-share orders in Da, Fang, and Lin (2024) or all orders of $5,000 or less in Lou (2014)).

II.C Outcome Variables

We study three main outcome variables: stock price volatility, informed trading, and price impact. We first calculate intraday stock price volatility as the variance of stock returns across five- and thirty-minute intervals averaged over the two-day window $[t,\, t+1]$ for each firm-trading day i, t, and label the resulting measures $\textit{Return Volatility}_{i,5,t}$ and $\textit{Return Volatility}_{i,30,t}$, respectively. We winsorize inputs daily at the 1% and 99% level in calculating these two measures.

We then turn to measure informed trading. Capturing high-frequency informed trades is inherently difficult because informed investors have strong incentives to hide their trades to avoid price impact and prevent front-running. For this reason, prior literature typically uses institutional trades to proxy for informed trades. One challenge with this approach is that no existing database provides comprehensive coverage of granular-level institutional trades. Another challenge is that not all institutional trades are informed if they are executed for liquidity or rebalancing needs (Coval and Stafford (2007), Chinco and Fos (2021)).

Bogousslavsky et al. (2024) introduce a measure of informed trading intensity to address these challenges. They develop this measure by applying machine learning techniques to extrapolate from patterns of Schedule 13D trades to estimate the universe of informed trades. They cross-validate the measure using days with known opportunistic insider trades and days with large changes in short selling activity. The advantage of this measure is that it is generated from a small sample of known informed trades and thus does not require the availability of all informed trades. Based on the observed pattern of two-day spikes in retail trading following recurring ads, we calculate our measure of informed trading, $\textit{Informed Trading Intensity}_{i,t}$, as the daily measure of Bogousslavsky et al. (2024) averaged over the two-day window $[t, t+1]$ for each firm-trading day i, t.

Finally, we follow Collin-Dufresne and Fos (2015) to calculate two measures of price impact. The first measure is the daily value-weighted price impact, $\textit{Price Impact}_{i,t}$. To calculate it, we first measure the price impact of each trade during a firm-trading day i, t as $\frac{2D_{i,q}(M_{i,q+5}-M_{i,q})}{M_{i,q}}$, where $M_{i,q}$ is the midpoint at the time of the qth trade and $M_{i,q+5}$ is the consolidated best bid and ask offer (BBO) midpoint prevailing five minutes after the qth trade; $D_{i,q}$ equals 1 (-1) if the qth trade is a buy (sell) order. We then aggregate the trade-level price impact values into the daily measure by taking the weighted average, using the dollar value of each trade as the weight.

The second measure, $\lambda_{i,t}$, is the coefficient estimate from the following model:

$$Ln\frac{M_{i,k}}{M_{i,k-5}} = \alpha + \lambda \times Sgn(\sum_{k-5}^{k} BuyShare_i - \sum_{k-5}^{k} SellShare_i) \times \sqrt{|\sum_{k-5}^{k} BuyShare_i - \sum_{k-5}^{k} SellShare_i|},$$

where $M_{i,k}$ is the prevailing bid-ask midpoint at second k, $M_{i,k-5}$ is the prevailing bid-ask midpoint five minutes earlier, and *BuyShare (SellShare)* indicates the number of shares bought (sold) during the five-minute window for firm i. As before, we winsorize inputs daily at the 1% and 99% level in calculating both price impact measures, and average them over the two-day window $[t, t+1]$.

II.D Control Variables

We include an important control for non-duplicate WSJ ads and create it in three steps. First, we extract the image of every WSJ ad in our sample. Second, we apply two feature detection algorithms—Scale Invariant Feature Transform (SIFT) and Speeded up Robust Feature (SURF)—to compare the image of $Ad_{i,l}$ (where l indexes ad image) to images of previous ads placed by the same firm i for the same brand, $Ad_{i,j \neq l}$. 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 scaling, rotation, or translation of the image. SIFT and SURF then calculate pairwise Euclidean distances among all the keypoints of the two images and produce a similarity measure. Figure 3 presents a sample SIFT analysis of the images of two WSJ ads placed by Oracle Corporation.[5] Third, we code the indicator $Non\text{-}duplicate\,Ad_{i,t}$ as one if any $Ad_{i,l}$ of firm i

[5] The similarity measure is calculated using the ratio of distances test proposed by Lowe (2004). Specifically, to identify a match for $Keypoint_{i,l,k}$ (where l indexes the ad and k indexes the keypoints within $Ad_{i,l}$), the Euclidean distance between $Keypoint_{i,l,k}$ and its closest neighbor $Keypoint_{i,j,k}$ must be significantly

on day t is not a duplicate image of any $Ad_{i,j}$ of the firm that appeared in the WSJ within the previous 60 days (i.e., similarity measures produced by SIFT and SURF equal 5 or less for any $Ad_{i,l} - Ad_{i,j}$ 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 $Ad_{i,l} - Ad_{i,j}$ 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.[6]

[Insert Figure 3 approximately here]

As additional controls, we include four indicators for a firm's information releases. These indicators denote quarterly earnings announcement days ($QEA_{i,t}$); the two days prior to an earnings announcement ($QEA_{i,[t-2,t-1]}$); the two days after an earnings announcement ($QEA_{i,[t+1,t+2]}$); and days with non-earnings announcement news ($Other\,News_{i,t}$), respectively. We align non-trading earnings announcement/news days to the first subsequent trading days in defining these indicators. We also include two controls for firm size and growth: the natural logarithm of market capitalization ($ln(Market\,Cap)_{i,q-1}$) and book-to-market ($Book/Market_{i,q-1}$), both measured at the end of the prior quarter q. Finally, we include three controls for a firm's past stock performance: past return ($PastRet_{i,t}$), idiosyncratic return volatility ($IVol_{i,t}$), and idiosyncratic return

smaller than the distance between $Keypoint_{i,l,k}$ and its second-closest neighbor $Keypoint_{i,j,m \neq k}$. Following prior research, we define a match as good if the distance between $Keypoint_{i,l,k}$ and its closest neighbor is 60% or less of the distance between $Keypoint_{i,l,k}$ and its second-closest neighbor. If no $Keypoint_{i,j,k}$ meets this criterion, then $Keypoint_{i,l,k}$ is not matched. The resulting similarity measure is the percentage of all good matches across all keypoints k in $Ad_{i,l}$.

[6] These cutoff thresholds seem 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 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 technique produces a similarity measure between 5 and 15, results are not sensitive to using cutoff levels that are close to these thresholds.

skewness ($ISkew_{i,t}$), all measured over the past month and defined following Han and Kumar (2013). Detailed variable definitions are provided in Appendix A.

In terms of data sources, 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 daily returns are from CRSP daily stock files.

II.E Summary Statistics

[Insert Table 1 approximately here]

Our final sample consists of 138,534 trading days associated with 266 unique U.S. firms between April 2009 and October 2013. Table 1 reports summary statistics. As shown, 9,220 firm-trading days (6.65% of the sample) had a WSJ ad placed seven days earlier, which are associated with 10,225 individual ads (as some ad days feature multiple ads and non-trading ad days are aligned to the first subsequent trading day). To ease presentation of the regression outputs, we divide trade counts by one hundred and dollar trading volumes by one million, and multiply return volatility by one hundred, price impact by one thousand, and λ by one million.

Our sample firms are large, with an average market capitalization of $40.5 billion and a book-to-market ratio of 0.78. The average firm in our sample is associated with 1,355 retail trades and $11.7 million retail dollar volume measured over two-day rolling windows. The intraday stock return volatility, measured across five- (thirty-) minute intervals over two-day rolling windows, is on average 3.3 (18.1). The average two-day informed trading intensity is 0.267, and the average two-day price impact and λ are 32.15 and -0.594, respectively.

III Recurring Ads, Retail Trading, and Uninformed Volume

III.A Introducing the Ad-based Instrument for Uninformed Volume

Figure 2 reveals that retail trading spikes on ad days, lasts for two days, and repeats weekly. In Table IA1 of the Internet Appendix, we confirm this result in regression analysis.[7] This pattern, combined with prior evidence that firms frequently place ads at weekly intervals (Madsen and Niessner (2019)), suggests that the cyclical spike in retail trading is triggered by weekly recurring ads. To show that such spikes are more likely driven by attention than motivated by information, we examine the timing and content of WSJ ads in our sample.

[Insert Table 2 approximately here]

Table 2 Panel A shows that, conditional on firm i placing an ad in the WSJ on calendar day $t-7$, the probability of the firm placing an ad on calendar day t is 42.5%. In contrast, the probability that the firm places an ad any other day during the week is only 7.0–12.1%. More important, conditional on a firm placing WSJ ads on both day $t-7$ and day t, there is a 62% (i.e., 26.2%/(26.2%+16.3%)) probability that the ad on day t is a duplicate of another ad that appeared in the WSJ within the previous 60 days. This number is likely understated because, as noted earlier, the duplicate ads that we define are nearly identical images and thus exclude highly similar images with minor differences.

[7] To be consistent with Figure 2, we regress daily measures of retail trade count and volume on an indicator for WSJ ad days, controls discussed in Section II.D, and four additional indicators for the two days before and after an ad day. Results confirm that retail trading increases on ad days, lasts for one additional day, and then declines.

These patterns support our conjecture that ads placed in the WSJ every seven days contain minimal information content.

Table 2 Panel B reports the distribution of the 10,225 ads in our sample by day of the week. Weekday ads are spread evenly between Mondays and Wednesdays (22.2%, 20.3%, and 22.2%, respectively), slightly decrease in frequency on Thursdays (17.5%), and further decrease on Fridays (12.4%). Only 5.4% of our sample ads appear in the WSJ's weekend issues. Duplicate and non-duplicate ads exhibit similar distributions, which suggests that neither type of ad concentrates on a specific day of the week. These observations increase confidence that the observed cyclical pattern in retail trading is driven by weekly recurring ads rather than confounding effects such as day-of-the week effects (e.g., French (1980), Lakonishok and Levi (1982)).

Based on the motivating evidence so far, we introduce an instrument for uninformed volume: $Ad_{i,t-7}$, an indicator of whether there exists a WSJ ad seven calendar days earlier. By design, this instrument aims to capture increases in uninformed retail trading triggered by weekly recurring ads. We verify the relevance of the instrument to retail trading by estimating the following ordinary least squares (OLS) model:

$$Retail\ Trading_{i,t} = \alpha + \beta \times Ad_{i,t-7} + \gamma \times Controls_{i,t} + \epsilon_{i,t}. \tag{1}$$

The sample is at the firm-trading day level, with subscript i indexing firm and t indexing day. The dependent variable is one of the two BJZZ measures of retail trading defined in Section II.B, and the key independent variable is the instrument, $Ad_{i,t-7}$. $Controls_{i,t}$ includes those discussed in Section II.D, firm fixed effects to control for firm-level heterogeneity, and date fixed effects to control for intertemporal variation in advertising and retail trading due to common shocks (such as market conditions). Results are robust throughout if we replace date fixed effects with day-of-the-week fixed effects (together with year-week and firm fixed effects). We cluster standard errors by date.

[Insert Table 3 approximately here]

Table 3 reports the results of estimating equation (1), with $\textit{Retail Trades}_{i,t}$ and $\textit{Retail Volume}_{i,t}$ as the dependent variable in columns 1 and 2, respectively. The coefficient estimate on $Ad_{i,t-7}$ is positive and significant at the 5% level in column 1 and 1% level in column 2, confirming the relevance of our instrument to retail trading. In terms of economic significance, the existence of an ad seven days earlier is associated with an increase in the two-day rolling average number of daily retail trades of 26.1 (1.9% of the sample mean) and an increase in the two-day rolling average retail dollar volume of $305,000 (2.6% of the sample mean). Table IA2 of the Internet Appendix shows consistent results if we use as alternative dependent variables off-exchange one-share orders (Panel A columns 1–2) or all orders of $5,000 or less (Panel B columns 1–2). Table IA3 of the Internet Appendix further shows robustness if we omit the control for non-duplicate ads (Panel A), measure retail trading over a one-day window (Panel B), cluster standard errors by firm and date (Panel C), or use Newey and West (1987) standard errors (Panel D); see column 1 of each panel.

Turning to the controls, the coefficient estimate on $\textit{Non-duplicate}\, Ad_{i,t}$, which aims to capture the information content of ads, is positive and significant at the 10% level in both columns. This result suggests that ads with non-duplicate images (such as the first ad in long campaigns) trigger additional retail trading. More important, including this control does not affect the positive relation between $Ad_{i,t-7}$ and retail trading. The coefficient estimates on controls for other information events, including the three indicators for earnings announcement days and the two days before and after announcement and the indicator for days with other news releases, are highly positive. These indicators provide useful benchmarks for $Ad_{i,t-7}$. The increase in the number of retail trades seven days after WSJ ad days is 49% of the increase on other news days (26.1 vs. 53.3) and 2.6% of the increase on earnings announcement days (26.1 vs. 968). The increase in retail dollar volume on ad days is comparable to the increase on other news days ($305,000 vs. $346,000) and 3.3% of the increase on earnings announcement days ($305,000 vs. $9.4 million). Thus, the increase in retail trading on recurring ad days is economically meaningful but also plausible.

Examining the remaining controls, we find that both measures of retail trading are positively associated with market capitalization but negatively associated with book-to-market, suggesting that larger firms and firms with higher market valuations tend to attract more retail investors. Both measures of retail trading are also greater for stocks with more volatile prices and less historical return skewness. Finally, retail dollar volume is greater for stocks with higher past returns.

III.B Further Validating the Ad-based Instrument for Uninformed Volume

We conduct two analyses to examine whether recurring ad-induced retail trades, which are arguably uninformed, share properties with uninformed volume as modeled by CF. First, we examine retail order imbalance on recurring ad days. If $Ad_{i,t-7}$ captures uninformed retail trades, then these trades should not exhibit systematic order imbalance (buy or sell) because pure noise trading is non-directional in theory. We find that the mean retail volume buy-sell imbalance is slightly negative (-0.008) on recurring ad days, but not statistically different from zero (p-value=0.25). We then estimate a modified version of equation (1) and separately regress aggregate retail buy trades and sell trades on $Ad_{i,t-7}$ and control variables. Results are reported in Table 4 columns 1 and 2. Although the coefficient estimates on $Ad_{i,t-7}$ are significantly positive in both columns, they are not statistically different from each other (p-value=0.80). In other words, both retail buy and sell trades increase seven days after ad days but these additional trades exhibit no significant order imbalance, which is consistent with the non-directional nature of uninformed volume.

[Insert Table 4 approximately here]

Interpreting this result at face value, the lack of an order imbalance would suggest that recurring WSJ ads direct attention to stocks, but are not powerful enough to induce a buying spree. Although this result may appear at odds with the perception that retail traders are typically net buyers, we note that Barber and Odean (2008) also find no retail order imbalance for stocks already owned following large positive returns and they attribute this finding to the disposition effect. This effect is likely heightened in this study because our sample coincides with a bull market. Additionally, as noted in Section II.B, the BJZZ measure of retail trades is subject to signing errors (Barber et al. (2024)), which may partly contribute to this null result. Nevertheless, Table IA2 of the Internet Appendix reports consistent results if we use as alternative dependent variables measures of buy-sell order imbalance based on signed off-exchange one-share orders (Panel A columns 3–4) or signed orders of $5,000 or less (Panel B columns 3–4).

Second, we assess whether recurring ad-induced retail trades fit CF's assumption of stochastic noise trading volatility. To do so, we examine the association between $Ad_{i,t-7}$ and measures of retail trading volatility. To capture retail trading volatility, we calculate the intraday variance of retail volume across five- and thirty-minute intervals, averaged over the two-day window $[t,\, t+1]$ for each firm-trading day i, t, and label the resulting measures $\textit{Retail Volatility}_{i,5,t}$ and $\textit{Retail Volatility}_{i,30,t}$, respectively.

In univariate analyses, we find that retail trading volatility is higher on days with ads placed seven days earlier than on days without (0.019 vs. 0.029 for $\textit{Retail Volatility}_{i,5,t}$ and 1.338 vs. 0.802 for $\textit{Retail Volatility}_{i,30,t}$, respectively, with the differences significant at the 1% level). We also test for differences in the distribution of these variables using Levene's test statistic for the equality of variances between groups (Brown and Forsythe (1974)) and find that the standard deviation of retail trading volatility is higher on days with ads placed seven days earlier than on days without (0.071 vs. 0.054 for $\textit{Retail Volatility}_{i,5,t}$ and 5.196 vs. 3.629 for $\textit{Retail Volatility}_{i,30,t}$, respectively, with the differences again significant at the 1% level). Finally, in Table 4 columns 3–4, we estimate a modified equation (1) and find a significant increase in the level of retail trading volatility seven days after ad days. In terms of economic significance, $\textit{Retail Volatility}_{i,5,t}$ ($\textit{Retail Volatility}_{i,30,t}$) is 5% (9.6%) higher relative to the respective sample mean seven days after ad days. An increase in both the level and volatility of retail trading volatility on recurring ad days is consistent with CF's assumption of stochastic noise trading volatility.

[Insert Table 5 approximately here]

We further study the intraday patterns of retail and non-retail trades and their interaction on recurring ad days to understand how noise trading and its volatility evolve during a trading day. We first divide a trading day into six one-hour and one thirty-minute intervals. For each interval, we then reestimate equation (1) with retail and non-retail trading volume as the dependent variable in Panels A and B of Table 5, respectively. Results indicate that both types of trades rise on recurring ad days compared to other days. However, the increase in retail trades is evenly spread throughout the day, while the increase in non-retail trades is more concentrated during the opening hour. Finally, we repeat the analysis using the correlation in the order imbalance between retail and non-retail orders as the dependent variable. Intuitively, market clearance implies a negative correlation and we expect an increase in noise trading volatility to amplify this negative correlation.[8] Indeed, results in Panel C of Table 5 indicate a negative correlation in five trading intervals, statistically significant during the opening hour.

Evidence reported in this section suggests that the uninformed retail trading induced by weekly recurring ads is non-directional and varying in volatility both interday and intraday (with a notable amplification during the opening hour), and thus closely resembles CF's construct of uninformed volume. In the following section, we use $Ad_{i,t-7}$, our ad-based instrument, to test three main predictions from CF regarding the microstructure implications of uninformed volume.

[8] To see this, let x denote uninformed retail trades and $-x$ denote all other trades. Our empirical proxies of retail and non-retail trades are noisy measures of x and $-x$ so we denote them as $x+\epsilon_1$ and $-x+\epsilon_2$, with ϵ_1 and ϵ_2 independent from x and from each other. We can write $\text{corr}(x+\epsilon_1, -x+\epsilon_2)$ as $\frac{-1}{\sqrt{1+\frac{\text{Var}(\epsilon_1)}{\text{Var}(x)}}\sqrt{1+\frac{\text{Var}(\epsilon_2)}{\text{Var}(x)}}}$ so the correlation monotonically decreases to -1 as $\text{Var}(x)$ becomes much larger than $\text{Var}(\epsilon_1)$ and $\text{Var}(\epsilon_2)$.

IV Microstructure Implications of Noise Trading

IV.A Uninformed Volume and Stock Price Volatility

We first examine CF's prediction that stock prices are more volatile in periods of higher uninformed volume, which they label the "positive volume-volatility relation" (CF, p. 1442). Given stochastic noise trading volatility, informed investors trade more aggressively when uninformed volume is higher and the market maker rationally anticipates such trading. Therefore, stock price volatility rises. In contrast, models assuming constant noise trading volatility (e.g., Kyle (1985)) do not generate this prediction.

To test this prediction, we use $Ad_{i,t-7}$ as an instrument for retail trading and measure stock price volatility using intraday return volatility. As Section III.A shows, $Ad_{i,t-7}$ is positively correlated with retail trading, likely satisfying the relevance criteria. Furthermore, the limited information content of weekly recurring ads (given their repetitive nature and the lack of significant retail order imbalance) suggests that $Ad_{i,t-7}$ is unlikely correlated with stock return volatility except through its correlation with retail trading (i.e., the exclusion restriction). While we focus on reduced form regressions in our main analyses for brevity, we elaborate on the exclusion restriction for our instrument and present robustness results using more formal 2SLS analyses and simultaneous equations in Section V.

We estimate the reduced form regression specified below as:

$$Return\ Volatility_{i,t} = \alpha + \beta \times Ad_{i,t-7} + \gamma \times Controls_{i,t} + \epsilon_{i,t}. \tag{2}$$

The sample is again at the firm-trading day level. The dependent variable is either *Return Volatility*$_{i,5,t}$ or *Return Volatility*$_{i,30,t}$, the two intraday stock return measures defined in Section II.C, and all other variables are defined previously. We continue to include firm and date fixed effects and cluster standard errors by date.

[Insert Table 6 approximately here]

Table 6 presents the results of estimating equation (2). The coefficient estimate on $Ad_{i,t-7}$ is positive and significant at the 1% level in both columns. In terms of economic significance, $Ad_{i,t-7}$ is associated with an increase of 1.4% (2%) in *Return Volatility*$_{i,5,t}$ (*Return Volatility*$_{i,30,t}$) relative to the respective sample mean. Benchmarked against news releases, the increase in *Return Volatility*$_{i,5,t}$ is 55.2% of the corresponding increase on other news days (0.048 vs. 0.087) and 2.4% of the increase on earnings announcement days (0.048 vs. 2.02), and the increase in *Return Volatility*$_{i,30,t}$ is 66.7% of the corresponding increase on other news days (0.354 vs. 0.531) and 3% of the increase on earnings announcement days (0.354 vs. 11.667). Thus, the increase in intraday stock return volatility following recurring ad days is economically meaningful but also plausible. As robustness checks, Table IA3 of the Internet Appendix reports comparable results with *Return Volatility*$_{i,30,t}$ if we omit the control for non-duplicate ads (Panel A), measure return volatility over a one-day window (Panel B), cluster standard errors by firm and date (Panel C), or use Newey and West (1987) standard errors (Panel D); see column 2 of each panel. In untabulated analyses, we find similar results for these checks with *Return Volatility*$_{i,5,t}$.

In terms of controls, the coefficient estimates on the indicators for days surrounding quarterly earnings announcements and days with other news are all highly positive, suggesting that returns become more volatile upon information release. Moreover, return volatility is negatively associated with market capitalization and book-to-market, suggesting more volatile returns for small and growth firms, and positively associated with past volatility, suggesting a positive autocorrelation.

Although results thus far support a "positive volume-volatility relation," it is noteworthy that this prediction is not unique to CF as other models of trading costs make a similar prediction (e.g., Ho and Stoll (1980), Grossman and Miller (1988), De Long et al. (1990), and Hendershott and Menkveld (2014)), albeit through a different mechanism. In these models, market makers demand greater price concessions when there is more noise trading, so stock price volatility is higher as a result. To shed light on which mechanism more likely explains the observed relation (i.e., trading costs in these models or adverse selection in CF), we check whether the relation is stronger for stocks with greater price impact, which presumably suggests higher adverse selection risk.

We first calculate the average price impact (defined in Section II.C) during the past four weeks. We then define an indicator, $High\ Past\ Adv_{i,t}$, to denote whether this average is above the sample median and reestimate an augmented version of equation (2) using both intraday return volatility measures, including this indicator and its interaction with the ad-based instrument, $Ad_{i,t-7}$. Results, reported in Table IA4 of the Internet Appendix, show that the interaction term is significantly positive in both columns, while the instrument itself is statistically insignificant, suggesting that the positive effect of ad-instrumented retail trading on stock return volatility is only evident among firms with higher adverse selection risk. Combined, results in this section support CF's prediction of a positive relation between uninformed volume and price volatility and, more important, highlight the role of adverse selection in driving this relation. We further differentiate these models in Section IV.C.

IV.B Uninformed Volume and Informed Trading

We next examine CF's prediction that informed investors strategically trade at times when uninformed volume is high. As in our tests of CF's first prediction, we continue to use $Ad_{i,t-7}$ as an instrument for retail trading. Our approach thus requires informed traders to form expectations about increases in uninformed retail trading on recurring ad days and trade accordingly. To that end, we assume that informed traders are rational and that the difference between expected and actual uninformed retail trading on recurring ad days is minimal on average.

We estimate the reduced form regression specified below as:

$$Informed\ Trading_{i,t} = \alpha + \beta \times Ad_{i,t-7} + \gamma \times Controls_{i,t} + \epsilon_{i,t}. \tag{3}$$

The dependent variable is the informed trading intensity measure defined in Section II.C and all other variables are defined previously. As before, we include firm and date fixed effects and cluster standard errors by date.

[Insert Table 7 approximately here]

Column 1 of Table 7 reports the results of estimating equation (3). The coefficient estimate on $Ad_{i,t-7}$ is positive and significant at the 10% level, which suggests that informed trading increases seven days after WSJ ad days. In terms of economic significance, the existence of an ad seven days earlier is associated with an increase of 0.7% in informed trading intensity relative to the sample mean. Benchmarked against news releases, the increase in informed trading intensity seven days after ad days is 25% of the corresponding increase on other news days (0.002 vs. 0.008) and 1.9% of the increase on earnings announcement days (0.002 vs. 0.103). As robustness checks, Table IA3 of the Internet Appendix reports comparable results if we omit the control for non-duplicate ads (Panel A), measure informed trading intensity over a one-day window (Panel B), or use Newey and West (1987) standard errors (Panel D) but weaker results if we cluster standard errors by firm and date (Panel C); see column 3 of each panel. Among the controls, indicators for news releases are highly positive, suggesting that new information arrival is accompanied by increased informed trading. Additionally, informed trading intensity is positively associated with past idiosyncratic volatility but negatively associated with firm size, past return, and idiosyncratic return skewness.

As a robustness check, we consider option trades as an alternative measure of informed trading, although it is arguably less refined than the informed trading intensity measure used in our main analyses. Option trades are sensitive to changes in stock price volatility and have been shown to predict future stock price movements (Pan and Poteshman (2006)). Using data from Option Metrics, we calculate two measures of option trades, similarly averaged over the two-day window $[t,\, t+1]$ for each firm-trading day i, t: the number of all and out-of-the-money (OTM) option contracts. Columns 2–3 of Table 7 repeat the analysis in Table 7 column 1 using these two measures as the dependent variables and similarly find that option trading (including trading of OTM options) increases seven days after WSJ ad days.

For completeness, we also study insider trades. Ex ante, we expect weaker results with this type of informed trading due to their regulatory constraints and relative infrequency during our sample period.[9] Nevertheless, using data from the Thomson Financial Insider Trading database, we calculate two measures of insider trades following Cohen et al. (2012), again averaged over the two-day window for each firm-trading day: the number of opportunistic and routine insider trades. Table IA5 of the Internet Appendix repeats the analysis with these two measures. Column 1 of Panel A shows that $Ad_{i,t-7}$ is positively related to opportunistic insider trades but its coefficient estimate is marginally insignificant (p-value=0.112). The coefficient estimate is, however, larger than the corresponding coefficient estimate in column 2 of Panel A, with the difference significant at the 10% level. This result suggests that firm insiders are more likely to execute their opportunistic trades than routine trades on recurring ad days compared to other trading days. Panel B shows that conditional on the firm having at least one opportunistic insider trade in a quarter, the likelihood of observing such a trade is 1.6% higher on recurring ad days, a 16.8% increase relative to other trading days; these numbers become 1.3% and 8.2%, respectively, if we extend the measurement window to two days.

IV.C Uninformed Volume and Price Impact

The results thus far suggest that stock price volatility rises with retail volume on recurring ad days and that informed investors also trade more actively. However, how price impact evolves on such days is unclear. Microstructure theories make mixed predictions regarding the relation between uninformed volume and price impact and whether the

[9] We note that informed firm insiders are not always at discretion to trade freely; trading at weekly intervals could raise red flags and prompt internal or external monitoring (Edmans, Fang, and Lewellen (2017)). In addition, our testing power may be lower as only 8.27% of our sample firm-day observations have opportunistic insider trades and only 1.97% have routine insider trades, consistent with Guettler, Hable, Launhardt, and Miebs's (2023) finding that insider trading volume in the U.S. dips after the 2008 financial crisis and stays low through our sample period.

resulting price impact exhibits reversals: CF show that positive shocks to time-varying noise trading volatility lead to both lower price impact and higher informed trading, and that any price impact that does result from increased informed trading is unlikely to exhibit reversals. In contrast, models like De Long et al. (1990) and Foucault et al. (2011) show that an increase in an exogenously specified noise trading volatility increases price impact. Grossman and Miller (1988) and other models of inventory holding costs similarly predict a positive effect of noise trader risk on price impact and such price impact is followed by reversals.

To assess the relation between uninformed volume and price impact, we estimate the reduced form regression specified below as:

$$Price\ Impact_{i,t} = \alpha + \beta \times Ad_{i,t-7} + \gamma \times Controls_{i,t} + \epsilon_{i,t}. \tag{4}$$

The dependent variable is either $Price\ Impact_{i,t}$ or $\lambda_{i,t}$ defined in Section II.C and all other variables are defined previously. We continue to include firm and date fixed effects and cluster standard errors by date.

[Insert Table 8 approximately here]

Table 8 presents the results of estimating equation (4). The coefficient estimate on $Ad_{i,t-7}$ is negative and significant at the 5% level in both columns, which suggests that despite the documented increase in informed trading, price impact is lower seven days after WSJ ad days. In terms of economic significance, the existence of an ad seven days earlier is associated with a decreased price impact of 2.3% relative to the sample mean and a decreased $\lambda_{i,t}$ of 1.8% relative to the sample standard deviation. As robustness checks, Table IA3 the Internet Appendix reports comparable results if we omit the control for non-duplicate ads (Panel A), measure price impact measures over a one-day window (Panel B), cluster standard errors by firm and date (Panel C), or use Newey and West (1987) standard errors (Panel D); see columns 4–5 of each panel.

To further distinguish CF from other trading cost models, we examine price reversals on recurring ad days relative to other trading days. Specifically, we analyze firms' return autocorrelation by regressing their weekly abnormal return ($\textit{Weekly AbRet}_{i,t}$) on the corresponding return of the previous week ($\textit{Past Weekly AbRet}_{i,t}$), the indicator for days with an ad placed seven calendar days earlier ($Ad_{i,t-7}$), the interaction between the two, and controls. We define $\textit{Weekly AbRet}_{i,t}$ and $\textit{Past Weekly AbRet}_{i,t}$ as the market-adjusted buy-and-hold returns for firm i over the five trading days starting from day t and the five trading days preceding day t, respectively. Results, reported in Panel A of Table IA6 in the Internet Appendix, reveal no evidence of increased price reversals on recurring ad days relative to other trading days. In Panel B of Table IA6 in the Internet Appendix, we further check for any intraday price reversal. For each intraday trading interval defined in Table 5, we first compute the 5-minute return based on the midpoint of the bid-ask spread, denoted as $Ret_{i,t,k,5}$. We then measure the $\textit{Price Reversal}_{i,t,k}$ as the return autocorrelation over trading interval k for firm-trading day i, t. We find no evidence of increased price reversals on recurring ad days compared to other trading days in all seven trading intervals, including the opening hour.

A conventional prediction suggested by most models of trading costs is that price impact should rise with informed trading. Our evidence that price impact is lower on recurring ad days despite an increase in informed trading is at odds with this prediction. This result, however, is consistent with CF's prediction of a negative volume-price impact relation, which arises because informed investors with relatively long-lived information optimally time liquidity and trade only when uninformed volume is high and price impact is low. This evidence, combined with evidence of no increased price reversals on recurring ad days, provides further support to CF.

V 2SLS Analyses and Simultaneous Equations

In this section, we conduct additional analyses that formally use the indicator for recurring ads on the WSJ as an instrument for uninformed volume in both 2SLS and simultaneous equation models. We first estimate a 2SLS system, with the first- and second-stage regressions specified below as:

$$Retail\ Volume_{i,t} = \alpha + \beta_1 \times Ad_{i,t-7} + \beta_2 \times Ad_{i,t-14} + \gamma \times Controls_{i,t} + \epsilon_{i,t}. \tag{5}$$

$$Outcome_{i,t} = \alpha + \beta \times Fitted\ Retail\ Volume_{i,t} + \gamma \times Controls_{i,t} + \epsilon_{i,t}, \tag{6}$$

$Fitted\ Retail\ Volume_{i,t}$ is the fitted value from the first-stage regression, and $Outcome_{i,t}$ represents an outcome variable of interest. All other variables are defined previously. We include firm and date fixed effects and cluster standard errors by date.

In this 2SLS system, we include a second instrument $Ad_{i,t-14}$, an indicator for the existence of a WSJ ad fourteen calendar days earlier, in addition to $Ad_{i,t-7}$. The inclusion of $Ad_{i,t-14}$ is motivated by Madsen and Niessner's (2019) finding that some firms advertise at bi-weekly intervals. Including two instruments allows us to test for the overidentifying restrictions assuming that at least one of them is valid. The exclusion restriction for both instruments is that they are uncorrelated with our outcomes of interest (return volatility, informed trading, and price impact) except through their effects on uninformed trading. Although not directly testable, we argue that the exclusion restriction is likely satisfied because retail trading in response to weekly recurring ads is more likely driven by attention rather than information due to these ads' rigid timing and tendency to contain duplicate images.

Table IA7 of the Internet Appendix presents the 2SLS results. Column 1 reports the first-stage regression results, and columns 2–5 report the second-stage regression results for our main measures of return volatility, informed trading, and price impact. The weak instrument test reasonably rejects the null of no correlation between the two instruments and $\textit{Retail Volume}_{i,t}$ as the Cragg-Donald F-statistic in all models is well above 10 as a rule of thumb suggested by Staiger and Stock (1997), with one exception.[10] The p-value for an F-test of the joint significance of the two instruments is also well below 1%. More important, the second-stage results are consistent with the reduced form regression results reported in Tables 6, 7, and 8, as the fitted value of $\textit{Retail Volume}_{i,t}$ exhibits the predicted sign significant at the 10% level or better in all columns.[11] Hansen's J-statistic is insignificant with p-values well above 0.1. Although IV exogeneity cannot be conclusively tested, this statistic provides some comfort that, assuming that one of the two instruments is valid, we cannot reject the null of no correlation between the other instrument and the 2SLS residuals.

[10] The Cragg-Donald F-statistic is slightly lower at 9.66 in column 3 of Table IA7, likely due to a smaller sample restricted by data availability of the informed trading intensity measure.

[11] We note that the 2SLS estimates are larger than the respective OLS estimates. This pattern is common in prior studies as discussed by Jiang (2017) and is consistent with heterogeneous effects in the underlying population (see Angrist and Pischke (2009)). In our setting, the 2SLS estimates uncover a "local average treatment effect" for investors whose behavior is more likely to be shifted by the presence of a recurring ad, whereas OLS estimates capture the population "average treatment effect." Thus, although the 2SLS estimates may be farther away from the true population average treatment effect, this need not imply that the model is misspecified.

With the use of two instruments, $Ad_{i,t-7}$ and $Ad_{i,t-14}$, we are able to estimate a simultaneous equation system using three-stage-least-squares (3SLS) on the relation between uninformed trading, informed trading, and price impact. We employ both $Ad_{i,t-7}$ and $Ad_{i,t-14}$ as exogenous variables in the simultaneous equation system, and *Retail Volume*$_{i,t}$ as the endogenous regressor. Specifically, we estimate the following system of equations:

$$Retail\ Volume_{i,t} = \alpha + \beta_1 \times Ad_{i,t-7} + \beta_2 \times Ad_{i,t-14} + \gamma \times Controls_{i,t} + \epsilon_{i,t}, \tag{7}$$

$$Informed\ Trading_{i,t} = \alpha + \phi \times Fitted\ Retail\ Volume_{i,t} + \chi \times Controls_{i,t} + \epsilon_{i,t}, \tag{8}$$

$$\begin{aligned} Price\ Impact_{i,t} = \alpha + \psi \times Informed\ Trading_{i,t} + \kappa \times Fitted\ Retail\ Volume_{i,t} + \\ \delta \times Controls_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{9}$$

For brevity, we focus on the informed trading intensity measure of Bogousslavsky et al. (2024) and λ as the measure of price impact in this analysis.

Table IA8 of the Internet Appendix reports the results. As predicted by CF, we observe a positive association between recurring ad-instrumented retail trading and informed trading intensity in column 1 and a negative association between instrumented retail trading and λ in column 2. Thus, using a jointly determined system to estimate the relation between uninformed trading, informed trading, and price impact, we corroborate the reduced form evidence that an exogenous increase in uninformed volume is positively associated with informed trading and negatively associated with price impact.

VI Conclusion

Retail trading has substantially increased in recent years as trading innovations (such as mobile trading platforms studied in Eaton, Green, Roseman, and Wu (2022) and fractional trading studied in Da et al. (2024)) and COVID-19 disruption and policy response (Ozik, Sadka, and Shen (2021)) have attracted a large number of amateur retail investors to financial markets. Because small retail trading is often linked to uninformed volume, understanding its implications for financial markets becomes particularly timely.

Motivated by evidence that firms regularly place duplicate ads at weekly intervals and that retail trading spikes on recurring ad days, we introduce an instrument for uninformed volume: an indicator of whether the firm placed an ad in the WSJ seven calendar days earlier. We use this instrument to test three predictions of CF, an important microstructure theory. Our results support CF's theoretical predictions and provide three insights. First, an increase in uninformed retail trading amplifies stock price volatility, consistent with a positive volume-volatility relation. Second, an increase in uninformed retail trading stimulates informed trading, consistent with informed traders taking advantage of increases in uninformed retail trading and price volatility to trade more aggressively. Third, despite the observed increases in price volatility and informed trading, measured price impact is actually lower on recurring ad days, consistent with informed investors strategically timing liquidity to trade.

Although our identification strategy limits our sample to earlier years when print ads were more frequent, we believe the insights drawn from our analyses remain highly relevant. Consistent with the first insight, we note that a growing number of amateur retail traders are using Fintech trading apps like Robinhood to day trade popular stocks and their trading noticeably amplifies price volatility. Although the extreme price movements in meme stocks are difficult to justify based on changes in firm fundamentals, increased price volatility in some retail-favored stocks may not be entirely behavioral as CF theoretically prove and our results empirically show. Consistent with the second and third insights, we note that institutional investors are reportedly chasing these retail investors for liquidity (Ro (2020)). The fact that hedge funds are willing to pay for data on retail order flow from brokers like Robinhood also adds evidence that informed investors actively gather information on uninformed retail volume and time liquidity conditions in the market. Given the rapid growth in retail trading (particularly by young and budget-constrained individual investors who are likely to be less informed and particularly exposed to social media chatter as shown in Da et al. (2024)), we expect our results continue to be relevant in today's markets.

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Appendix A: Definition of Variables

This appendix describes the calculation of variables used in the main analyses. Underlined variables refer to variable names within Compustat. i indexes firm, t indexes day, and q indexes the quarter to which day t belongs. 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 to the first subsequent trading day.

Variable	Definition
Measures of advertising	
$Ad_{i,t-7}$	An indicator that equals one if day $t-7$ (i.e., seven calendar days before trading day t) is a WSJ ad day of firm i and zero otherwise.
Non-duplicate $Ad_{i,t}$	An indicator that equals one if trading day t is a WSJ ad day of firm i and the ad contains a non-duplicate image, and zero otherwise. We identify duplicate images by comparing the ad to all ads placed in the WSJ by the firm for the same brand within the previous 60 days. See Section II.D for a detailed description of the image analysis.
Measures of retail and non-retail trading	
Retail $Trades_{i,t}$	The daily number of retail trades of \$50,000 or less for firm i averaged between days t and $t+1$, calculated following the method of Boehmer et al. (2021) and divided by one hundred. To identify retail trades, we first retrieve trades and quotes marked with exchange code "D" in TAQ and then sort these transactions into retail seller-initiated trades if they are recorded at a price higher than a round penny by (0, 0.4) cents and retail buyer-initiated trades if they are recorded at a price higher than a round penny by (0.6, 1) cent(s).
Retail $Volume_{i,t}$	The daily dollar volume of retail trades for firm i averaged between days t and $t+1$, divided by one million.
Retail $Buy_{i,t}$ (*Retail* $Sell_{i,t}$)	The daily dollar volume of retail buyer- (seller-) initiated trades for firm i averaged between days t and $t+1$, divided by one million.
Retail $Volatility_{i,5,t}$ (*Retail* $Volatility_{i,30,t}$)	The intraday variance of retail dollar volume for firm i averaged across all five- (thirty-) minute intervals on days t and $t+1$.
Retail $Volume_{i,t,k}$ (*Non-Retail* $Volume_{i,t,k}$)	The dollar volume of retail (non-retail) trades aggregated for firm i's trading interval k on day t (with k denoting [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), or [15:00 to 16:00] ET), divided by one million.
Corr(Retail, NonRetail)$_{i,t,k}$	The correlation between *Retail* $OIB_{i,t,k,5}$ and *Non-Retail* $OIB_{i,t,k,5}$ for firm i's trading interval k on day t (with k defined above). *Retail* $OIB_{i,t,k,5}$ (*Non-Retail* $OIB_{i,t,k,5}$) is the five-minute retail (non-retail) order imbalance calculated within trading interval k as the difference between the retail (non-retail) buy and sell dollar volume scaled by the sum of the retail (non-retail) buy and sell dollar volume.
Measures of outcome variables	
Return $Volatility_{i,5,t}$ (*Return* $Volatility_{i,30,t}$)	The intraday variance of stock return for firm i averaged across all five- (thirty-) minute intervals on days t and $t+1$, multiplied by one hundred. Stock return for each interval is calculated as the midpoint of the National Best Bid and Ask at the end of the interval divided by the corresponding number at the end of the previous interval minus one.
Informed Trading $Intensity_{i,t}$	The daily informed trading intensity measure of Bogousslavsky et al.'s (2024) for firm i averaged between days t and $t+1$.
Option $Volume_{i,t}$ (*OTM Option* $Volume_{i,t}$)	The daily number of total (out-of-the-money) option contracts for firm i averaged between days t and $t+1$, divided by one hundred.

Price Impact$_{i,t}$	The value-weighted average price impact for firm i, defined as $\frac{2D_{i,q}(M_{i,q+5}-M_{i,q})}{M_{i,q}}$, where $M_{i,q}$ is the midpoint at the time of the *qth* trade and $M_{i,q+5}$ is the consolidated best bid and ask offer (BBO) midpoint prevailing five minutes after the *qth* trade, and $D_{i,q}$ equals 1 (-1) if the *qth* trade is a buy (sell) order for firm i, and then averaged between days t and $t+1$ and multiplied by a thousand.
$\lambda_{i,t}$	The estimated coefficient from the regression model for firm i–trading day t: $Ln\frac{M_{i,k}}{M_{i,k-5}} = \alpha + \lambda \times Sgn(\sum_{k-5}^{k} BuyShare_i - \sum_{k-5}^{k} SellShare_i) \times \sqrt{\lvert \sum_{k-5}^{k} BuyShare_i - \sum_{k-5}^{k} SellShare_i \rvert}$, where $M_{i,k}$ is the firm's prevailing bid-ask midpoint at second k of day t, $M_{i,k-5}$ is the prevailing bid-ask midpoint five minutes earlier, and *BuyShare (SellShare)* indicates the firm's number of shares bought (sold) during the five-minute window. averaged between days t and $t+1$ and multiplied by a million.
Controls	
$QEA_{i,[t-2,t-1]}$	An indicator that equals one if day t is the first or second trading day before a quarterly earnings announcement day of firm i and zero otherwise.
$QEA_{i,t}$	An indicator that equals one if day t is a quarterly earnings announcement day of firm i and zero otherwise.
$QEA_{i,[t+1,t+2]}$	An indicator that equals one if day t is the first or second trading day after a quarterly earnings announcement day of firm i and zero otherwise.
$Other\ News_{i,t}$	An indicator that equals one if day t is a news release day (excluding earnings announcements) of firm i and zero otherwise.
ln(Market Cap)$_{i,q-1}$	Natural logarithm of market capitalization (abs(PRC) $\times$ SHROUT) for firm i at the end of quarter $q-1$.
$Book/Market_{i,q-1}$	The ratio of book value of assets to market value of assets for firm i, calculated as total assets (ATQ) divided by [market capitalization plus total liability (LTQ)], both at the end of quarter $q-1$.
$PastRet_{i,t}$	The cumulative sum of daily stock returns for firm i over the month preceding day t, standardized to a mean of zero and a standard deviation of one.
$IVol_{i,t}$	Idiosyncratic volatility for firm i, defined as the variance of the residuals from a four-factor model (Fama-French three factors and momentum factor) over the month preceding day t, standardized to a mean of zero and a standard deviation of one.
$ISkew_{i,t}$	Idiosyncratic skewness for firm i, defined as the skewness of the residuals from a factor model that includes the market excess return ($RMRF$) and market excess return squared ($RMRF^2$) over the month preceding day t, standardized to a mean of zero and a standard deviation of one.

Figure 1
WSJ Ads Example

This figure displays images of the WSJ ads placed by Oracle Corporation on ten consecutive Thursdays between August 29, 2013 and October 31, 2013.

Figure 1A
08/29/2013

Figure 1B
09/05/2013

Figure 1C
09/12/2013

Figure 1D
09/19/2013

Figure 1E
09/26/2013

Figure 1F
10/03/2013

Figure 1G
10/10/2013

Figure 1H
10/17/2013

Figure 1I
10/24/2013

Figure 1J
10/31/2013

Figure 2
Retail Trading Surrounding Ad Days

This figure plots the average number of retail trades (solid line) and dollar volume of retail trades (dashed line), from seven trading days before to seven trading days after ad days, with day 0 indicating ad days. Retail trades are defined following the method of Boehmer et al. (2021). The sample comprises 10,225 ads of 266 firms in the WSJ between April 2009 and October 2013; ads placed on non-trading day are aligned to the next trading day.

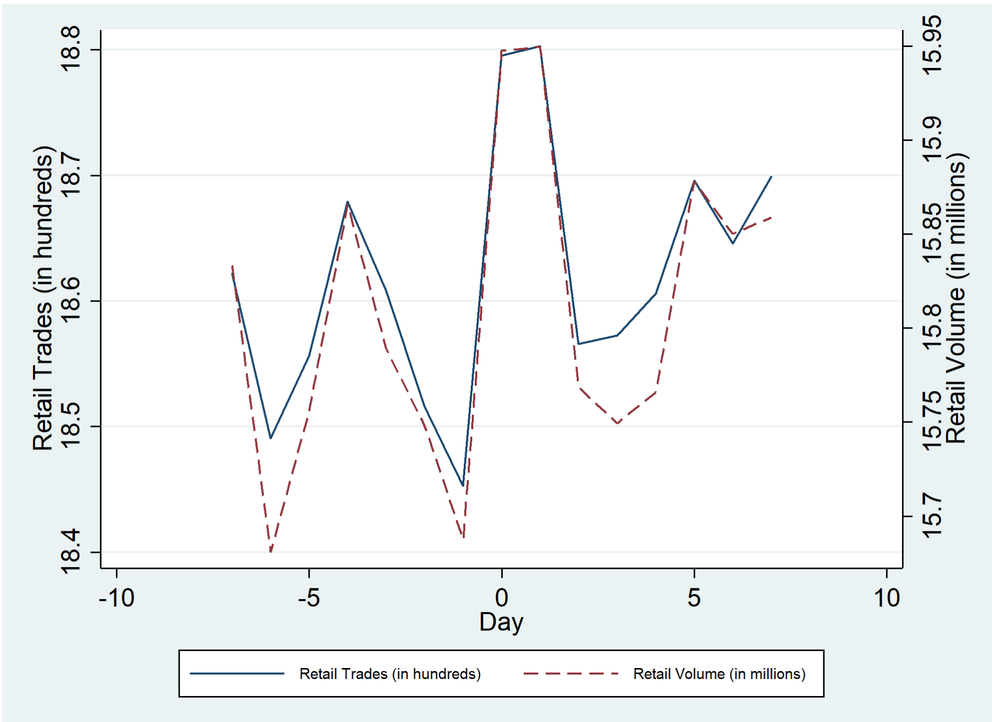

Figure 3
Image Analysis Example

This figure presents a sample SIFT analysis of two WSJ ads placed by Oracle Corporation on October 10, 2013 and October 17, 2013. Keypoints are denoted using circles and good matches between keypoints are denoted using lines.

SIFT Similarity = 42.31

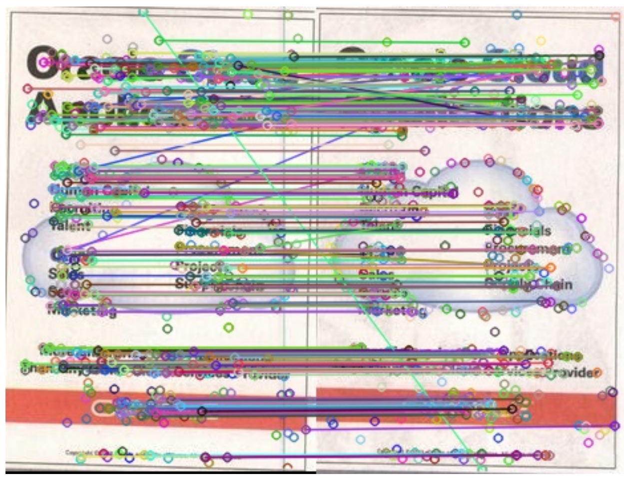

Table 1
Summary Statistics

This table reports summary statistics of the main variables used in the regression analyses. $Ad_{i,t-7}$ indicates days with an ad placed seven calendar days earlier in the WSJ. *Non-duplicate* $Ad_{i,t}$ indicates ad days with at least one non-duplicate image. *Retail Trades*$_{i,t}$ and *Retail Volume*$_{i,t}$ are the number (in hundreds) and dollar volume (in millions) of retail trades, respectively. *Retail Volatility*$_{i,5,t}$ and *Retail Volatility*$_{i,30,t}$ are the intraday variance of retail volume, measured across five- and thirty-minutes intervals, respectively. *Return Volatility*$_{i,5,t}$ and *Return Volatility*$_{i,30,t}$ are the intraday stock return volatility, measured across five- and thirty-minute intervals, respectively. *Informed Trading Intensity*$_{i,t}$ is the informed trading intensity measure of Bogousslavsky et al. (2024). *Price Impact*$_{i,t}$ is the value-weighted average price impact (multiplied by a thousand). $\lambda_{i,t}$ is the standard estimate of adverse selection (multiplied by a million). $QEA_{i,t}$ indicates days with quarterly earnings announcements; $QEA_{i,[t-2,t-1]}$ ($QEA_{i,[t+1,t+2]}$) indicates the two days before (after) quarterly earnings announcements; and *Other News*$_{i,t}$ indicates days with news other than earnings announcements. *ln(Market Cap)*$_{i,t}$ is the natural algorithm of market capitalization (in thousands) and *Book/Market*$_{i,t}$ is the book-to-market ratio, both measured at the end of prior quarter. *PastRet*$_{i,t}$ is the firm's cumulative stock return over the previous month, *IVol*$_{i,t}$ is idiosyncratic volatility, and *ISkew*$_{i,t}$ is idiosyncratic skewness; all three market-based controls are standardized to a mean of zero and a standard deviation of one. 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.

	Obs	Mean	SD	P25	P50	P75
$Ad_{i,t-7}$	138,534	0.067	0.249	0.000	0.000	0.000
Non-duplicate $Ad_{i,t}$	138,534	0.036	0.187	0.000	0.000	0.000
Retail Trades$_{i,t}$	138,534	13.551	20.328	2.115	6.340	15.075
Retail Volume$_{i,t}$	138,534	11.699	17.162	1.514	4.942	13.534
Retail Volatility$_{i,5,t}$	138,534	0.020	0.055	0.001	0.003	0.012
Retail Volatility$_{i,30,t}$	138,534	0.838	3.785	0.007	0.051	0.308
Return Volatility$_{i,5,t}$	138,534	3.338	3.132	1.336	2.303	4.138
Return Volatility$_{i,30,t}$	138,534	18.097	18.339	6.322	11.971	22.655
Informed Trading Intensity$_{i,t}$	130,903	0.267	0.127	0.173	0.247	0.341
Price Impact$_{i,t}$	138,534	32.150	45.197	9.671	21.681	40.969
$\lambda_{i,t}$	138,534	-0.594	1.699	-0.833	-0.255	0.067
Non-duplicate $Ad_{i,t}$	138,534	0.036	0.187	0.000	0.000	0.000
$QEA_{i,[t-2,t-1]}$	138,534	0.025	0.155	0.000	0.000	0.000
$QEA_{i,t}$	138,534	0.016	0.124	0.000	0.000	0.000
$QEA_{i,[t+1,t+2]}$	138,534	0.023	0.151	0.000	0.000	0.000
Other News$_{i,t}$	138,534	0.455	0.498	0.000	0.000	1.000
$ln(Market\,Cap)_{i,q-1}$	138,534	16.447	1.657	15.416	16.513	17.601
$Book/Market_{i,q-1}$	138,534	0.782	0.263	0.587	0.823	0.990
$PastRet_{i,t}$	138,534	-0.001	1.001	-0.563	0.010	0.551
$IVol_{i,t}$	138,534	0.000	1.004	-0.516	-0.342	0.058
ISkew$_{i,t}$	138,534	-0.003	1.001	-0.512	-0.015	0.511

Table 2
Patterns of WSJ Ads

Panel A reports the percentage of firms advertising in the WSJ on calendar days t through $t-6$ conditional on the firm placing an ad in the WSJ on day $t-7$. Panel B reports the number and percentage of ads placed on each weekday and on weekends. The sample comprises 10,225 individual ads of 266 firms in the WSJ between April 2009 and October 2013.

Panel A: Advertising Probability Conditional on Ad Seven Calendar Days Earlier

	All Ads	Duplicate Ads	Non-Duplicate Ads
Day_t	42.5%	26.2%	16.3%
Day_{t-1}	12.1%	5.9%	6.2%
Day_{t-2}	9.9 %	4.6%	5.3%
Day_{t-3}	7.4 %	3.2%	4.2%
Day_{t-4}	7.0 %	3.4%	3.6%
Day_{t-5}	9.8 %	4.5%	5.3%
Day_{t-6}	11.5 %	5.8%	5.7%

Panel B: Distribution of WSJ Ads 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%

Table 3
Recurring Ad Days and Retail Trading

This table reports the regression results on the relation between recurring ad days and retail trading. $Ad_{i,t-7}$ indicates days with an ad placed seven calendar days earlier in the WSJ. Retail trading is measured using $Retail\ Trades_{i,t}$ in column 1 and $Retail\ Volume_{i,t}$ 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 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.

	1 $Retail\ Trades_{i,t}$	2 $Retail\ Volume_{i,t}$
$Ad_{i,t-7}$	0.261**	0.305***
	(2.54)	(3.57)
$Non\text{-}duplicate\ Ad_{i,t}$	0.244*	0.193*
	(1.81)	(1.77)
$QEA_{i,[t-2,t-1]}$	3.631***	3.563***
	(20.03)	(22.42)
$QEA_{i,t}$	9.680***	9.355***
	(31.61)	(31.40)
$QEA_{i,[t+1,t+2]}$	4.391***	4.508***
	(20.46)	(22.30)
$Other\ News_{i,t}$	0.533***	0.346***
	(11.93)	(9.39)
$ln(Market\ Cap)_{i,q-1}$	0.423**	2.874***
	(2.07)	(18.23)
$Book/Market_{i,q-1}$	-5.035***	-3.775***
	(-10.87)	(-9.77)
$PastRet_{i,t}$	-0.052	0.404***
	(-1.16)	(10.93)
$IVol_{i,t}$	2.183***	1.603***
	(41.22)	(40.54)
$ISkew_{i,t}$	-0.434***	-0.358***
	(-15.04)	(-15.12)
Observations	138,534	138,534
Adj R-Squared	0.84	0.84
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Table 4
Properties of Retail Trades on Recurring Ad Days

This table reports the regression results on the relation between recurring ad days and retail buy and sell volume as well as the relation between recurring ad days and retail trading volatility. $Ad_{i,t-7}$ indicates days with an ad placed seven calendar days earlier in the WSJ. $Retail\ Buy_{i,t}$ and $Retail\ Sell_{i,t}$ measure the aggregate dollar volume (in millions) of retail buyer-initiated and seller-initiated trades, respectively. Retail trading volatility is measured using $Retail\ Volatility_{i,5,t}$ in column 3 and $Retail\ Volatility_{i,30,t}$ in column 4, 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.

	1 $Retail\ Buy_{i,t}$	2 $Retail\ Sell_{i,t}$	3 $Retail\ Volatility_{i,5,t}$	4 $Retail\ Volatility_{i,30,t}$
$Ad_{i,t-7}$	0.148***	0.156***	0.001***	0.081**
	(3.08)	(3.68)	(3.13)	(2.28)
$Non\text{-}duplicate\ Ad_{i,t}$	0.069	0.124**	0.001*	0.105**
	(1.10)	(2.30)	(1.77)	(2.02)
$QEA_{i,[t-2,t-1]}$	2.094***	1.468***	0.010***	0.409***
	(22.36)	(20.23)	(14.40)	(7.45)
$QEA_{i,t}$	5.040***	4.332***	0.022***	1.486***
	(30.47)	(30.78)	(20.65)	(11.58)
$QEA_{i,[t+1,t+2]}$	2.256***	2.257***	0.009***	0.555***
	(21.38)	(22.04)	(14.15)	(8.70)
$Other\ News_{i,t}$	0.200***	0.144***	0.000**	0.006
	(9.76)	(7.98)	(2.32)	(0.65)
$ln(Market\ Cap)_{i,q-1}$	1.524***	1.365***	0.005***	0.201***
	(17.11)	(18.92)	(7.14)	(2.70)
$Book/Market_{i,q-1}$	-1.783***	-1.993***	-0.014***	-1.129***
	(-8.48)	(-10.53)	(-8.05)	(-7.47)
$PastRet_{i,t}$	0.096***	0.314***	0.002***	0.162***
	(4.54)	(17.92)	(11.48)	(10.20)
$IVol_{i,t}$	0.841***	0.764***	0.003***	0.231***
	(38.54)	(40.98)	(29.66)	(19.89)
$ISkew_{i,t}$	-0.184***	-0.176***	-0.001***	-0.099***
	(-13.73)	(-15.39)	(-12.66)	(-12.73)
Observations	138,534	138,534	138,534	138,534
Adj R-Squared	0.81	0.85	0.76	0.55
Date Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes

Table 5
Retail and Non-Retail Trading: Intraday Analyses

This table examines intraday patterns of retail trading (Panel A), non-retail trading (Panel B), and the correlation between retail and non-retail trading (Panel C) on recurring ad days. Each trading day is divided into six one-hour and one thirty-minute intervals (with trading intervals denoted with subscript k), 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] ET. $Ad_{i,t-7}$ indicates days with an ad placed seven calendar days earlier in the WSJ. Retail trading is measured using $Retail\ Volume_{i,t,k}$ (in millions) and non-tetail trading is measured using $Non\text{-}Retail\ Volume_{i,t,k}$ (in millions), and correlation between retail and non-retail trading is measured using $Corr(Retail,\ NonRetail)_{i,t,k}$, calculated for each interval. 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.

Panel A: Retail Trading

	$Retail\ Volume_{i,t,k}$						
	1	2	3	4	5	6	7
	[9:30,10:30)	*[10:30,11:30)*	*[11:30,12:30)*	*[12:30,13:00)*	*[13:00,14:00)*	*[14:00,15:00)*	*[15:00,16:00]*
$Ad_{i,t-7}$	0.125**	0.206***	0.189***	0.146***	0.197***	0.127**	0.151***
	(2.17)	(3.53)	(3.30)	(3.14)	(3.53)	(2.40)	(3.27)
Observations	75,680	65,144	59,293	43,545	56,389	62,126	87,533
Adj R-Squared	0.75	0.68	0.63	0.45	0.60	0.63	0.76
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Non-Retail Trading

	$Non\text{-}Retail\ Volume_{i,t,k}$						
	1	2	3	4	5	6	7
	[9:30,10:30)	*[10:30,11:30)*	*[11:30,12:30)*	*[12:30,13:00)*	*[13:00,14:00)*	*[14:00,15:00)*	*[15:00,16:00]*
$Ad_{i,t-7}$	1.024***	0.405	0.690***	0.470**	0.643**	0.457*	0.409
	(3.33)	(1.60)	(2.67)	(2.18)	(2.54)	(1.87)	(1.52)
Observations	75,680	65,144	59,293	43,545	56,389	62,126	87,533
Adj R-Squared	0.68	0.59	0.53	0.36	0.50	0.54	0.72
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Correlation Between Retail and Non-Retail Trading

	$Corr(Retail,\ NonRetail)_{i,t,k}$						
	1	2	3	4	5	6	7
	[9:30,10:30)	*[10:30,11:30)*	*[11:30,12:30)*	*[12:30,13:00)*	*[13:00,14:00)*	*[14:00,15:00)*	*[15:00,16:00]*
$Ad_{i,t-7}$	-0.016**	-0.005	-0.013	0.006	-0.001	-0.007	0.004
	(-1.99)	(-0.52)	(-1.32)	(0.48)	(-0.10)	(-0.70)	(0.51)
Observations	75,680	65,144	59,293	43,545	56,389	62,126	87,533
Adj R-Squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6
Uninformed Volume and Stock Price Volatility

This table reports the regression results on the relation between recurring ad-instrumented uninformed volume and stock price volatility. The instrument is $Ad_{i,t-7}$, which indicates days with an ad placed seven calendar days earlier in the WSJ. Stock price volatility is measured using $Return\ Volatility_{i,5,t}$ in column 1 and $Return\ Volatility_{i,30,t}$ in column 2. 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.

	1 $Return\ Volatility_{i,5,t}$	2 $Return\ Volatility_{i,30,t}$
$Ad_{i,t-7}$	0.048***	0.354***
	(2.74)	(2.84)
$Non\text{-}duplicate\ Ad_{i,t}$	0.008	-0.066
	(0.33)	(-0.40)
$QEA_{i,[t-2,t-1]}$	1.015***	5.576***
	(27.71)	(23.20)
$QEA_{i,t}$	2.020***	11.667***
	(42.50)	(34.94)
$QEA_{i,[t+1,t+2]}$	0.635***	3.731***
	(18.92)	(16.15)
$Other\ News_{i,t}$	0.087***	0.531***
	(8.92)	(7.64)
$ln(Market\ Cap)_{i,q-1}$	-1.310***	-7.856***
	(-23.21)	(-22.21)
$Book/Market_{i,q-1}$	-1.511***	-9.399***
	(-12.53)	(-11.30)
$PastRet_{i,t}$	-0.129***	-0.812***
	(-7.67)	(-7.76)
$IVol_{i,t}$	0.700***	3.827***
	(52.70)	(48.47)
$ISkew_{i,t}$	-0.003	0.034
	(-0.44)	(0.83)
Observations	138,534	138,534
Adj R-Squared	0.78	0.68
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Table 7
Uninformed Volume and Informed Trading

This table reports the regression results on the relation between ad-instrumented uninformed volume and informed trading. The instrument is $Ad_{i,t-7}$, which indicates days with an ad placed seven calendar days earlier in the WSJ. Informed trading is measured using *Informed Trading Intensity*$_{i,t}$ in column 1, *Option Volume*$_{i,t}$ in column 2, and *OTM Option Volume*$_{i,t}$ in column 3. Option volumes are in hundreds. 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.

	1 *Informed Trading Intensity*$_{i,t}$	2 *Option Volume*$_{i,t}$	3 *OTM Option Volume*$_{i,t}$
$Ad_{i,t-7}$	0.002*	5.821***	4.153***
	(1.67)	(3.47)	(3.29)
Non-duplicate $Ad_{i,t}$	0.002	3.625*	2.747*
	(1.38)	(1.67)	(1.74)
$QEA_{i,[t-2,t-1]}$	0.053***	92.138***	71.064***
	(19.72)	(22.97)	(23.59)
$QEA_{i,t}$	0.103***	145.153***	106.519***
	(31.54)	(24.87)	(24.49)
$QEA_{i,[t+1,t+2]}$	0.061***	55.472***	39.643***
	(23.78)	(15.86)	(15.71)
$Other\ News_{i,t}$	0.008***	2.372***	1.526***
	(9.94)	(3.24)	(2.79)
$ln(Market\ Cap)_{i,q-1}$	-0.019***	34.141***	25.646***
	(-8.42)	(10.29)	(10.68)
$Book/Market_{i,q-1}$	-0.006	42.231***	38.429***
	(-0.87)	(4.94)	(6.01)
$PastRet_{i,t}$	-0.006***	8.765***	4.752***
	(-9.59)	(12.43)	(9.00)
$IVol_{i,t}$	0.023***	15.175***	11.578***
	(39.14)	(21.82)	(22.42)
$ISkew_{i,t}$	-0.004***	-3.176***	-2.528***
	(-8.80)	(-7.31)	(-7.71)
Observations	130,903	138,534	138,534
Adj R-Squared	0.17	0.75	0.73
Date Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes

Table 8
Uninformed Volume and Price Impact

This table reports the regression results on the relation between ad-instrumented uninformed volume and price impact. The instrument is $Ad_{i,t-7}$, which indicates days with an ad placed seven calendar days earlier in the WSJ. Price impact is measured using *Price Impact*$_{i,t}$ (multiplied by a hundred) in column 1 and $\lambda_{i,t}$ (multiplied by a million) in column 2. 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.

	1 *Price Impact*$_{i,t}$	2 $\lambda_{i,t}$
$Ad_{i,t-7}$	-0.763**	-0.031**
	(-2.09)	(-2.42)
Non-duplicate Ad$_{i,t}$	-0.673	0.010
	(-1.38)	(0.59)
$QEA_{i,[t-2,t-1]}$	1.339**	-0.105***
	(2.52)	(-3.86)
$QEA_{i,t}$	3.576***	-0.070*
	(4.19)	(-1.95)
$QEA_{i,[t+1,t+2]}$	0.636	0.085***
	(0.91)	(3.42)
$Other\ News_{i,t}$	0.291	0.010
	(1.41)	(1.15)
$ln(Market\ Cap)_{i,q-1}$	-23.042***	0.108***
	(-23.50)	(3.47)
$Book/Market_{i,q-1}$	-32.875***	-0.041
	(-12.09)	(-0.34)
$PastRet_{i,t}$	-2.874***	0.025***
	(-16.86)	(3.62)
$IVol_{i,t}$	3.677***	0.083***
	(19.18)	(10.85)
$ISkew_{i,t}$	0.194**	-0.012***
	(2.03)	(-3.15)
Observations	138,534	138,534
Adj R-Squared	0.49	0.29
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Appendix IA:
Definition of Additional Variables Used in the Internet Appendix

This appendix describes the calculation of variables used only in this Internet Appendix. i indexes firm and t indexes day. 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 to the first subsequent trading day.

Variable	Definition
n Days Before Ad$_{i,t}$	An indicator that equals one if day t is the n^{th} trading day before a subsequent WSJ ad day of firm i and zero otherwise, $n = 1, 2$.
n Days After Ad$_{i,t}$	An indicator that equals one if day t is the n^{th} trading day after a previous WSJ ad day of firm i and zero otherwise, $n = 1, 2$.
OneShr Trades$_{i,t}$	The daily number of off-exchange one-share trades for firm i averaged between days t and $t+1$. One share trades are identified using trades with size of one in TAQ.
OneShr Vol$_{i,t}$	The daily dollar volume of one share trades for firm i averaged between days t and $t+1$.
OneShr Trades Buy-Sell$_{i,t}$ (*OneShr Vol Buy-Sell*$_{i,t}$)	The daily buy-sell imbalance of *OneShr Trades*$_{i,t}$ (*OneShr Vol*$_{i,t}$) for firm i averaged between days t and $t+1$.
Small Trades(5k)$_{i,t}$	The daily number of small trades for firm i averaged between days t and $t+1$. Small trades are identified using trades of $5,000 or less in TAQ.
Small Vol(5k)$_{i,t}$	The daily dollar volume of small trades for firm i averaged between days t and $t+1$.
Small Trades(5k) Buy-Sell$_{i,t}$ (*Small Vol(5k) Buy-Sell*$_{i,t}$)	The daily buy-sell imbalance of *Small Trades(5k)*$_{i,t}$ (*Small Vol(5k)*$_{i,t}$) for firm i averaged between days t and $t+1$.
High Past Adv$_{i,t}$	An indicator that equals one if firm i's average value-weighted average price impact over four weeks before day t is above the sample median and zero otherwise.
Opportunistic Trade$_{i,t}$ (*Routine Trade*$_{i,t}$)	The daily dollar volume of opportunistic (routine) insider trades for firm i averaged between days t and $t+1$, calculated following the method of Cohen et al. (2012).
Weekly AbRet$_{i,t}$ (*Past Weekly AbRet*$_{i,t}$)	The market-adjusted buy-and-hold return for firm i over the measurement window of [t, t+4] ([t-5, t-1]).
Price Reversal$_{i,t,k}$	The intraday price reversal for firm i, measured as the firm's return autocorrelation over its trading interval k of day t. k is defined in Table 5 of the paper.
$Ad_{i,t-14}$	An indicator that equals one if day $t-14$ (i.e., fourteen calendar days before trading day t) is a WSJ ad day of firm i and zero otherwise.

Table IA1
Ad Days and Retail Trading

This table reports the regression results on the relation between ad days and retail trading. $Ad_{i,t}$ indicates days with an ad in the WSJ, and $n\,Day(s)\,Before\,Ad_{i,t}$ and $n\,Day(s)\,After\,Ad_{i,t}$ indicate n days before and after ad days, $n = 1, 2$. Retail trading is measured using daily *Retail Trades*$_{i,t}$ in column 1 and daily *Retail Volume*$_{i,t}$ in column 2, respectively. 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 and Appendix IA. 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.

	1 *Retail Trades*$_{i,t}$	2 *Retail Volume*$_{i,t}$
$2\,Days\,Before\,Ad_{i,t}$	0.077	0.147
	(0.67)	(1.60)
$1\,Day\,Before\,Ad_{i,t}$	0.046	0.122
	(0.40)	(1.28)
$Ad_{i,t}$	0.306***	0.304***
	(2.66)	(3.24)
$1\,Day\,After\,Ad_{i,t}$	0.221**	0.225**
	(2.02)	(2.57)
$2\,Days\,After\,Ad_{i,t}$	0.106	0.149
	(0.93)	(1.59)
$QEA_{i,[t-2,t-1]}$	0.929***	0.924***
	(5.88)	(7.07)
$QEA_{i,t}$	9.827***	9.522***
	(30.34)	(31.11)
$QEA_{i,[t+1,t+2]}$	6.612***	6.608***
	(22.88)	(23.60)
$Other\,News_{i,t}$	0.679***	0.468***
	(13.86)	(11.48)
$ln(Market\,Cap)_{i,q-1}$	0.663***	3.071***
	(3.06)	(17.93)
$Book/Market_{i,q-1}$	-4.676***	-3.487***
	(-9.16)	(-8.12)
$PastRet_{i,t}$	-0.022	0.434***
	(-0.45)	(10.73)
$IVol_{i,t}$	2.417***	1.783***
	(40.96)	(39.89)
$ISkew_{i,t}$	-0.483***	-0.393***
	(-14.94)	(-14.58)
Observations	138,534	138,534
Adj R-Squared	0.82	0.82
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
P($Ad_{i,t}$ > *2 Days Before* $Ad_{i,t}$)	0.07	0.11
P($Ad_{i,t}$ > *1 Day Before* $Ad_{i,t}$)	0.05	0.08
P($Ad_{i,t}$ > *1 Day After* $Ad_{i,t}$)	0.30	0.27
P($Ad_{i,t}$ > *2 Days After* $Ad_{i,t}$)	0.10	0.12

Table IA2
Alternative Measures of Retail Trading

This table reports the regression results on the relation between recurring ad days and alternative retail trading measures. $Ad_{i,t-7}$ indicates days with an ad placed seven calendar days earlier in the WSJ. In Panel A, retail trading is measured using *OneShr Trades*$_{i,t}$ in column 1 and *OneShr Vol*$_{i,t}$ in column 2. Columns 3 and 4 report the regression results on the relation between recurring ad days and *OneShr Trades Buy-Sell*$_{i,t}$ and *OneShr Vol Buy-Sell*$_{i,t}$, the trading imbalance measures based on *OneShr Trades*$_{i,t}$ and *OneShr Vol*$_{i,t}$. In Panel B, retail trading is measured using *Small Trades(5k)*$_{i,t}$ in column 1 and *Small Vol(5k)*$_{i,t}$ in column 2. Columns 3 and 4 report the regression results on the relation between recurring ad days and *Small Trades Buy-sell(5k)*$_{i,t}$ and *Small Vol Buy-sell(5k)*$_{i,t}$, the trading imbalance measures based on *Small Trades(5k)*$_{i,t}$ and *Small Vol(5k)*$_{i,t}$. 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 and Appendix IA. 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.

Panel A: Off-Exchange One-Share Trades

	1 *OneShr Trades*$_{i,t}$	2 *OneShr Vol*$_{i,t}$	3 *OneShr Trades Buy-Sell*$_{i,t}$	4 *OneShr Vol Buy-Sell*$_{i,t}$
$Ad_{i,t-7}$	0.224*	0.032*	0.010	-0.001
	(1.86)	(1.65)	(0.13)	(-0.04)
$Non\text{-}duplicate\ Ad_{i,t}$	-0.167	-0.024	0.134	0.024
	(-1.30)	(-1.14)	(1.16)	(1.07)
$QEA_{i,[t-2,t-1]}$	0.281**	0.042**	0.129	0.052
	(2.45)	(2.22)	(0.80)	(1.34)
$QEA_{i,t}$	0.264**	0.035*	-0.117	-0.036
	(2.29)	(1.89)	(-0.60)	(-1.08)
$QEA_{i,[t+1,t+2]}$	0.119***	0.010**	0.322**	0.034
	(2.73)	(2.10)	(2.09)	(1.12)
$Other\ News_{i,t}$	-0.004	-0.000	-0.035	0.010
	(-0.13)	(-0.09)	(-0.57)	(0.87)
$ln(Market\,Cap)_{i,q-1}$	-0.248***	-0.001	0.094	-0.027
	(-4.41)	(-0.28)	(0.49)	(-0.83)
$Book/Market_{i,q-1}$	-0.714***	0.009	1.183**	-0.154
	(-3.55)	(0.66)	(2.06)	(-1.49)
$PastRet_{i,t}$	0.040***	0.002**	0.020	-0.012
	(3.63)	(2.15)	(0.52)	(-1.59)
$PastVol_{i,t}$	0.059***	0.002**	0.022	0.004
	(3.86)	(2.01)	(0.59)	(0.60)
$PastRetSkew_{i,t}$	0.011	0.001	-0.043	0.017**
	(1.01)	(0.78)	(-1.36)	(2.52)
Observations	89,425	89,425	2,113	2,113
Adj R-Squared	0.94	0.95	0.02	0.00
Date Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes

Table IA2 (continued)

Panel B: Small Trades of $5,000 or Less

	1 *Small Trades(5k)*$_{i,t}$	2 *Small Vol(5k)*$_{i,t}$	3 *Small Trades Buy-sell(5k)*$_{i,t}$	4 *Small Vol Buy-sell(5k)*$_{i,t}$
$Ad_{i,t-7}$	7.403***	2.740***	-0.001	-0.001
	(5.11)	(6.56)	(-0.20)	(-0.20)
$Non\text{-}duplicate\ Ad_{i,t}$	6.364***	2.168***	0.001	0.002
	(3.42)	(3.92)	(0.19)	(0.39)
$QEA_{i,[t-2,t-1]}$	13.542***	3.835***	-0.007	-0.007
	(6.03)	(5.66)	(-1.45)	(-1.47)
$QEA_{i,t}$	110.200***	29.939***	-0.021***	-0.021***
	(25.92)	(24.70)	(-3.50)	(-3.49)
$QEA_{i,[t+1,t+2]}$	74.128***	20.360***	-0.002	-0.001
	(20.71)	(19.12)	(-0.35)	(-0.11)
$Other\ News_{i,t}$	6.564***	1.430***	-0.001	-0.001
	(9.10)	(6.68)	(-0.44)	(-0.41)
$ln(Market\,Cap)_{i,q-1}$	-13.203***	8.542***	0.003	0.004
	(-4.70)	(12.32)	(0.71)	(0.96)
$Book/Market_{i,q-1}$	-31.759***	-7.805***	-0.005	0.002
	(-4.38)	(-4.40)	(-0.42)	(0.17)
$PastRet_{i,t}$	2.608***	2.616***	0.004***	0.004***
	(4.00)	(14.82)	(5.50)	(5.33)
$PastVol_{i,t}$	24.775***	4.722***	0.001	0.001
	(37.52)	(27.08)	(1.10)	(1.61)
$PastRetSkew_{i,t}$	-5.864***	-1.739***	-0.001	-0.001
	(-14.38)	(-15.59)	(-1.15)	(-1.11)
Observations	138,534	138,534	100,275	100,275
Adj R-Squared	0.80	0.76	0.02	0.02
Date Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes

Table IA3
Microstructure Implications of Uninformed Volume: Robustness Checks

This table reports robustness checks of the main results reported in the paper. In Panel A, we drop the control variable *Non-duplicate* $Ad_{i,t}$; in Panel B, we measure all outcome variables over one-day windows. In Panels A and B, standard errors are clustered by date. In Panel C, we cluster standard errors by both firm and date; in Panel D, we use Newey and West (1987) standard errors. 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. t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

Panel A: Alternative Control Variables

	1 $Retail\ Volume_{i,t}$	2 $Return\ Volatility_{i,30,t}$	3 $Informed\ Trading\ Intensity_{i,t}$	4 $Price\ Impact_{i,t}$	5 $\lambda_{i,t}$
$Ad_{i,t-7}$	0.325***	0.346***	0.003*	-0.839**	-0.030**
	(3.82)	(2.81)	(1.88)	(-2.31)	(-2.37)
$QEA_{i,[t-2,t-1]}$	3.557***	5.577***	0.053***	1.345**	-0.105***
	(22.43)	(23.21)	(19.71)	(2.53)	(-3.87)
$QEA_{i,t}$	9.340***	11.666***	0.103***	3.574***	-0.070*
	(31.42)	(34.94)	(31.54)	(4.18)	(-1.95)
$QEA_{i,[t+1,t+2]}$	4.502***	3.731***	0.061***	0.637	0.085***
	(22.32)	(16.15)	(23.77)	(0.91)	(3.42)
$Other\ News_{i,t}$	0.347***	0.531***	0.008***	0.289	0.010
	(9.42)	(7.64)	(9.94)	(1.40)	(1.15)
$ln(Market\ Cap)_{i,q-1}$	2.871***	-7.857***	-0.019***	-23.045***	0.108***
	(18.26)	(-22.21)	(-8.42)	(-23.50)	(3.47)
$Book/Market_{i,q-1}$	-3.770***	-9.399***	-0.006	-32.875***	-0.041
	(-9.78)	(-11.30)	(-0.88)	(-12.09)	(-0.34)
$PastRet_{i,t}$	0.403***	-0.812***	-0.006***	-2.874***	0.025***
	(10.92)	(-7.76)	(-9.59)	(-16.86)	(3.62)
$IVol_{i,t}$	1.601***	3.827***	0.023***	3.678***	0.083***
	(40.56)	(48.47)	(39.15)	(19.18)	(10.85)
$ISkew_{i,t}$	-0.357***	0.034	-0.004***	0.193**	-0.012***
	(-15.12)	(0.83)	(-8.80)	(2.03)	(-3.15)
Observations	138,534	138,534	130,903	138,534	138,534
Adj R-Squared	0.84	0.68	0.17	0.49	0.29
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA3 (continued)

Panel B: One-Day Windows

	1	2	3	4	5
	Retail Volume$_{i,t}$	*Return Volatility*$_{i,30,t}$	*Informed Trading Intensity*$_{i,t}$	*Price Impact*$_{i,t}$	$\lambda_{i,t}$
$Ad_{i,t-7}$	0.348***	0.005***	0.003*	-0.001*	-0.036**
	(3.62)	(2.89)	(1.72)	(-1.77)	(-1.98)
Non-duplicate $Ad_{i,t}$	0.195	-0.001	0.002	-0.000	0.007
	(1.57)	(-0.54)	(0.86)	(-0.55)	(0.34)
$QEA_{i,[t-2,t-1]}$	0.925***	0.022***	0.075***	0.003***	-0.071**
	(7.07)	(9.17)	(19.99)	(3.59)	(-2.09)
$QEA_{i,t}$	9.520***	0.133***	0.106***	0.002	-0.143***
	(31.11)	(30.25)	(26.43)	(1.56)	(-2.84)
$QEA_{i,[t+1,t+2]}$	6.607***	0.063***	0.043***	-0.000	0.070*
	(23.58)	(19.16)	(13.45)	(-0.19)	(1.95)
Other News$_{i,t}$	0.469***	0.008***	0.005***	0.000	0.010
	(11.49)	(8.79)	(5.52)	(0.11)	(0.91)
$ln(Market\,Cap)_{i,q-1}$	3.076***	-0.075***	-0.021***	-0.023***	0.107***
	(17.94)	(-17.89)	(-7.52)	(-20.16)	(2.61)
$Book/Market_{i,q-1}$	-3.484***	-0.089***	-0.008	-0.034***	-0.048
	(-8.10)	(-8.53)	(-0.99)	(-9.56)	(-0.29)
$PastRet_{i,t}$	0.434***	-0.007***	-0.006***	-0.003***	0.023**
	(10.73)	(-5.84)	(-8.12)	(-13.60)	(2.44)
$IVol_{i,t}$	1.783***	0.042***	0.021***	0.004***	0.083***
	(39.90)	(43.38)	(29.63)	(14.74)	(8.35)
$ISkew_{i,t}$	-0.393***	-0.000	-0.003***	0.000	-0.012**
	(-14.58)	(-0.24)	(-5.28)	(1.61)	(-2.23)
Observations	138,534	138,534	130,665	138,268	138,534
Adj R-Squared	0.82	0.59	0.13	0.35	0.19
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA3 (continued)

Panel C: Two-Way Clustering

	1 $Retail\ Volume_{i,t}$	2 $Return\ Volatility_{30,t}$	3 $Informed\ Trading\ Intensity_{i,t}$	4 $Price\ Impact_{i,t}$	5 $\lambda_{i,t}$
$Ad_{i,t-7}$	0.305**	0.354*	0.002	-0.763**	-0.031*
	(2.12)	(1.85)	(1.33)	(-2.05)	(-1.71)
$Non\text{-}duplicate\ Ad_{i,t}$	0.193	-0.066	0.002	-0.673	0.010
	(1.33)	(-0.30)	(1.27)	(-0.88)	(0.43)
$QEA_{i,[t-2,t-1]}$	3.563***	5.576***	0.053***	1.339***	-0.105***
	(9.72)	(13.23)	(14.16)	(2.66)	(-3.66)
$QEA_{i,t}$	9.355***	11.667***	0.103***	3.576***	-0.070*
	(10.30)	(18.76)	(26.93)	(4.14)	(-1.97)
$QEA_{i,[t+1,t+2]}$	4.508***	3.731***	0.061***	0.636	0.085***
	(6.90)	(9.69)	(15.60)	(0.87)	(2.72)
$Other\ News_{i,t}$	0.346***	0.531***	0.008***	0.291	0.010
	(4.10)	(4.63)	(7.60)	(0.86)	(0.77)
$ln(Market\ Cap)_{i,q-1}$	2.874***	-7.856***	-0.019*	-23.042***	0.108
	(3.03)	(-4.93)	(-1.69)	(-4.08)	(0.69)
$Book/Market_{i,q-1}$	-3.775	-9.399**	-0.006	-32.875*	-0.041
	(-1.37)	(-2.00)	(-0.18)	(-1.96)	(-0.07)
$PastRet_{i,t}$	0.404***	-0.812***	-0.006***	-2.874***	0.025**
	(2.77)	(-4.71)	(-3.70)	(-5.06)	(2.12)
$IVol_{i,t}$	1.603***	3.827***	0.023***	3.677***	0.083***
	(6.87)	(15.83)	(12.61)	(3.04)	(3.84)
$ISkew_{i,t}$	-0.358***	0.034	-0.004***	0.194	-0.012
	(-4.58)	(0.34)	(-3.63)	(0.95)	(-1.36)
Observations	138,534	138,534	130,903	138,534	138,534
Adj R-Squared	0.84	0.68	0.17	0.49	0.29
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA3 (continued)

Panel D: Newey-West Standard Errors

	1 $Retail\ Volume_{i,t}$	2 $Return\ Volatility_{i,30,t}$	3 $Informed\ Trading\ Intensity_{i,t}$	4 $Price\ Impact_{i,t}$	5 $\lambda_{i,t}$
$Ad_{i,t-7}$	0.304***	0.354***	0.002*	-0.763**	-0.031**
	(3.57)	(2.88)	(1.66)	(-2.07)	(-2.30)
$Non\text{-}duplicate\ Ad_{i,t}$	0.192*	-0.066	0.002	-0.673	0.010
	(1.74)	(-0.41)	(1.38)	(-1.38)	(0.60)
$QEA_{i,[t-2,t-1]}$	3.558***	5.576***	0.053***	1.339**	-0.105***
	(21.70)	(21.94)	(20.17)	(2.23)	(-3.65)
$QEA_{i,t}$	9.340***	11.667***	0.103***	3.576***	-0.070*
	(32.92)	(35.59)	(32.86)	(4.09)	(-1.92)
$QEA_{i,[t+1,t+2]}$	4.502***	3.731***	0.061***	0.636	0.085***
	(20.61)	(14.78)	(22.65)	(0.84)	(3.08)
$Other\ News_{i,t}$	0.347***	0.531***	0.008***	0.291	0.010
	(9.08)	(7.67)	(9.70)	(1.39)	(1.11)
$ln(Market\ Cap)_{i,q-1}$	2.871***	-7.856***	-0.019*	-23.042***	0.108***
	(14.16)	(-23.59)	(-6.71)	(-22.02)	(3.00)
$Book/Market_{i,q-1}$	-3.770***	-9.399***	-0.006	-32.875***	-0.041
	(-7.81)	(-9.46)	(-0.67)	(-10.13)	(-0.29)
$PastRet_{i,t}$	0.403***	-0.812***	-0.006***	-2.874***	0.025***
	(10.33)	(-11.43)	(-9.40)	(-14.44)	(3.05)
$PastVol_{i,t}$	1.601***	3.827***	0.023***	3.677***	0.083***
	(34.04)	(42.95)	(34.55)	(16.07)	(9.10)
$PastRetSkew_{i,t}$	-0.357***	0.034	-0.004***	0.194	-0.012**
	(-12.42)	(0.82)	(-7.85)	(1.62)	(-2.51)
Observations	138,534	138,534	130,903	138,534	138,534
Adj R-Squared	0.84	0.69	0.17	0.53	0.20
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table IA4
Uninformed Volume and Stock Price Volatility: Adverse Selection Risk

This table examines the role of adverse selection risk in explaining the relation between ad-instrumented uninformed volume and stock price volatility in reduced form analyses. The instrument is $Ad_{i,t-7}$, which indicates days with an ad placed seven calendar days earlier in the WSJ. Stock price volatility is measured using $Return\ Volatility_{i,5,t}$ in column 1 and $Return\ Volatility_{i,30,t}$ in column 2. $High\,Past\,Adv_{i,t}$ is an indicator denoting firm-day observations for which the average price impact over the four weeks before day t is above the sample median. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A and Appendix IA. 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.

	1 $Return\ Volatility_{i,5,t}$	2 $Return\ Volatility_{i,30,t}$
$Ad_{i,t-7} \times$ $High\ Past\ Adv_{i,t}$	0.122***	0.715***
	(3.60)	(3.03)
$Ad_{i,t-7}$	-0.010	0.009
	(-0.59)	(0.08)
$High\ Past\ Adv_{i,t}$	0.140***	0.877***
	(12.21)	(11.40)
$Non\text{-}duplicate\ Ad_{i,t}$	0.009	-0.059
	(0.39)	(-0.36)
$QEA_{i,[t-2,t-1]}$	1.014***	5.571***
	(27.69)	(23.18)
$QEA_{i,t}$	2.018***	11.655***
	(42.54)	(34.94)
$QEA_{i,[t+1,t+2]}$	0.634***	3.724***
	(18.93)	(16.14)
$Other\ News_{i,t}$	0.088***	0.536***
	(9.02)	(7.73)
$ln(Market\,Cap)_{i,q-1}$	-1.289***	-7.726***
	(-22.75)	(-21.78)
$Book/Market_{i,q-1}$	-1.520***	-9.455***
	(-12.60)	(-11.37)
$PastRet_{i,t}$	-0.127***	-0.800***
	(-7.57)	(-7.67)
$IVol_{i,t}$	0.699***	3.819***
	(52.56)	(48.35)
$ISkew_{i,t}$	-0.003	0.035
	(-0.41)	(0.86)
Observations	138,534	138,534
Adj R-Squared	0.78	0.68
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Table IA5
Uninformed Volume and Informed Trading: Insider Trades

This table reports an unconditional reduced form analysis in Panel A and a conditional univariate analysis in Panel B that examine the relation between ad-instrumented uninformed volume and insider trading. In Panel A, the instrument is $Ad_{i,t-7}$, which indicates days with an ad placed seven calendar days earlier in the WSJ. Informed trading is measured using $Opportunistic\ Trade_{i,t}$ in column 1 and $Routine\ Trade_{i,t}$ in column 2. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A and Appendix IA. 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. In Panel B, we restrict the sample to firm-day observations with at least one opportunistic trade observed in the firm-quarter and then report the conditional probabilities of observing opportunistic and routine insider trades either for day t or over the two-day window $[t,\ t+1]$.

Panel A: Unconditional Analysis

	1 $Opportunistic\ Trade_{i,t}$	2 $Routine\ Trade_{i,t}$
$Ad_{i,t-7}$	0.809	-0.023
	(1.59)	(-1.63)
$Non\text{-}duplicate\ Ad_{i,t}$	1.442	-0.019
	(1.47)	(-1.03)
$QEA_{i,[t-2,t-1]}$	-0.572***	-0.092***
	(-8.38)	(-3.66)
$QEA_{i,t}$	-0.086	-0.014
	(-1.08)	(-0.59)
$QEA_{i,[t+1,t+2]}$	0.433***	0.052*
	(2.79)	(1.66)
$Other\ News_{i,t}$	0.486***	0.036***
	(3.73)	(3.64)
$ln(Market\ Cap)_{i,q-1}$	0.359	0.020
	(1.33)	(1.02)
$Book/Market_{i,q-1}$	1.961**	-0.251**
	(2.53)	(-2.30)
$PastRet_{i,t}$	0.031	0.012***
	(0.40)	(3.38)
$IVol_{i,t}$	0.186***	0.001
	(4.16)	(0.49)
$ISkew_{i,t}$	0.089***	-0.008*
	(2.88)	(-1.65)
Observations	138,534	138,534
Adj R-Squared	0.00	0.02
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes

Table IA5 (continued)

Panel B: Conditional Analysis

	1		2		3	
	$Ad_{i,t-7}$ = 0		***$Ad_{i,t-7}$ = 1***		***Difference***	
	Mean	Std.Dev.	Mean	Std.Dev.	Diff.	t-Statistics
Prob(Opp Insider Trade)$_{i,t}$	0.095	0.29	0.110	0.31	-0.016***	(-4.235)
Prob(Routine Insider Trade)$_{i,t}$	0.048	0.21	0.050	0.22	-0.002	(-0.411)
Prob(Opp Insider Trade)$_{i,[t,t+1]}$	0.159	0.37	0.173	0.38	-0.013**	(-3.038)
Prob(Routine Insider Trade)$_{i,[t,t+1]}$	0.084	0.28	0.085	0.28	-0.001	(-0.281)

Table IA6
Price Reversal

This table examines patterns of price reversals related to recurring ad days. In Panel A, we report the regression analysis on the association between recurring ad days and firms' weekly return autocorrelation. We regress the weekly abnormal return ($Weekly\ AbRet_{i,t}$) on past weekly abnormal return ($Past\ Weekly\ AbRet_{i,t}$), the indicator for days with an ad placed seven calendar days earlier in the WSJ ($Ad_{i,t-7}$), and their interaction term. In Panel B, we report the intraday price reversal patterns. Each trading day is divided into six one-hour and one thirty-minute intervals (with trading intervals denoted with subscript k), 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] ET. Price reversal is measured as the return autocorrelation calculated for each interval. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A and Appendix IA. 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.

Panel A: Weekly Reversal

	1 $Weekly\ AbRet_{i,t}$
$Ad_{i,t-7} \times Past\ Weekly\ AbRet_{i,t}$	-0.007 (-0.49)
$Ad_{i,t-7}$	-0.001* (-1.68)
$Past\ Weekly\ AbRet_{i,t}$	-0.075*** (-11.59)
$Non\text{-}duplicate\ Ad_{i,t}$	-0.000 (-0.83)
$QEA_{i,[t-2,t-1]}$	-0.001 (-0.67)
$QEA_{i,t}$	-0.002 (-1.49)
$QEA_{i,[t+1,t+2]}$	-0.001* (-1.90)
$Other\ News_{i,t}$	-0.000 (-1.20)
$ln(Market\ Cap)_{i,q-1}$	-0.009*** (-9.35)
$Book/Market_{i,q-1}$	0.002 (1.05)
$PastRet_{i,t}$	0.003*** (10.79)
$PastVol_{i,t}$	-0.000 (-0.52)
$PastRetSkew_{i,t}$	0.001*** (4.06)
Observations	138,534
Adj R-Squared	0.05
Date Fixed Effects	Yes
Firm Fixed Effects	Yes

Table IA6 (continued)

Panel B: Intraday Reversals

	Price Reversal$_{i,t,k}$						
	1	2	3	4	5	6	7
	[9:30,10:30)	*[10:30,11:30)*	*[11:30,12:30)*	*[12:30,13:00)*	*[13:00,14:00)*	*[14:00,15:00)*	*[15:00,16:00]*
$Ad_{i,t-7}$	0.004	-0.003	0.001	0.002	-0.001	-0.000	-0.004
	(1.26)	(-0.74)	(0.29)	(0.39)	(-0.15)	(-0.07)	(-1.26)
Observations	75,680	65,144	59,293	43,545	56,389	62,126	87,533
Adj R-Squared	0.05	0.09	0.09	0.09	0.11	0.15	0.19
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA7
Microstructure Implications of Uninformed Volume: Two-Stage Least Squares

This table reports the 2SLS regression results on the relation between ad-instrumented uninformed volume and market outcomes using $Ad_{i,t-7}$ and $Ad_{i,t-14}$ as instruments. Column 1 reports the first-stage regression results and columns 2–5 report the second-stage regression results with *Return Volatility*$_{i,30,t}$, *Informed Trading Intensity*$_{i,t}$, *Price Impact*$_{i,t}$, and $\lambda_{i,t}$ as the dependent variable, respectively. Controls include those described in Table 1 as well as date and firm fixed effects. Detailed variable definitions are in Appendix A and Appendix IA. 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.

	1 *Retail Volume*$_{i,t}$	2 *Return Volatility*$_{i,30,t}$	3 *Informed Trading Intensity*$_{i,t}$	4 *Price Impact*$_{i,t}$	5 $\lambda_{i,t}$
$Ad_{i,t-7}$	0.225**				
	(2.52)				
$Ad_{i,t-14}$	0.247***				
	(2.68)				
Fitted Retail Volume$_{i,t}$		0.864**	0.008*	-2.513**	-0.114***
		(2.33)	(1.72)	(-2.27)	(-2.74)
Non-duplicate Ad$_{i,t}$	0.157	-0.216	0.001	-0.186	0.033
	(1.43)	(-1.10)	(0.37)	(-0.31)	(1.45)
$QEA_{i,[t-2,t-1]}$	3.563***	2.497*	0.027*	10.293**	0.303**
	(22.43)	(1.86)	(1.81)	(2.56)	(2.01)
$QEA_{i,t}$	9.354***	3.584	0.036	27.090***	1.001**
	(31.40)	(1.04)	(0.91)	(2.61)	(2.57)
$QEA_{i,[t+1,t+2]}$	4.508***	-0.164	0.029	11.966**	0.601***
	(22.29)	(-0.10)	(1.59)	(2.36)	(3.16)
Other News$_{i,t}$	0.346***	0.232	0.005**	1.161***	0.050***
	(9.38)	(1.56)	(2.58)	(2.61)	(2.81)
$ln(Market\ Cap)_{i,q-1}$	2.873***	-10.339***	-0.033***	-15.818***	0.437***
	(18.23)	(-9.29)	(-3.91)	(-4.82)	(3.48)
$Book/Market_{i,q-1}$	-3.775***	-6.138***	0.036	-42.364***	-0.473**
	(-9.77)	(-3.74)	(1.46)	(-8.15)	(-2.30)
$PastRet_{i,t}$	0.405***	-1.161***	-0.008***	-1.858***	0.071***
	(10.93)	(-6.08)	(-5.62)	(-3.85)	(3.94)
$IVol_{i,t}$	1.603***	2.442***	0.011	7.707***	0.267***
	(40.53)	(4.08)	(1.58)	(4.31)	(3.96)
$ISkew_{i,t}$	-0.358***	0.343**	-0.001	-0.707*	-0.054***
	(-15.12)	(2.44)	(-0.82)	(-1.71)	(-3.46)
Observations	138,534	138,534	130,903	138,534	138,534
Adj R-Squared	0.84	-0.02	0.02	-0.22	-0.29
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic		12.33	9.66	12.33	12.33

Table IA8
Uninformed Volume, Informed Trading, and Price Impact: Simultaneous Equations

This table reports the results for a system of simultaneous equations to examine the effect of uninformed volume on informed trading intensity and price impact measured using $\lambda_{i,t}$, with $Retail\ Volume_{i,t}$ as the endogenous regressor, and $Ad_{i,t-7}$ and $Ad_{i,t-14}$ as the exogenous instruments. Column 1 reports the regression results on the relationship between uninformed volume and informed trading; Column 2 reports the regression results on the relationship between uninformed volume, informed trading, and price impact. 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. t-statistics are in parentheses, and ***,**, and * indicate significance at the 1%, 5%, and 10% two-tailed levels, respectively.

	1 $Informed\ Trading\ Intensity_{i,t}$	2 $\lambda_{i,t}$
$Fitted\ Retail\ Volume_{i,t}$	0.007*	-0.726*
	(1.77)	(-1.87)
$Informed\ Trading\ Intensity_{i,t}$		69.690
		(1.62)
$Non\text{-}duplicate\ Ad_{i,t}$	0.001	-0.007
	(0.37)	(-0.07)
$QEA_{i,[t-2,t-1]}$	0.028*	-1.315
	(1.92)	(-1.09)
$QEA_{i,t}$	0.036	-0.745
	(0.97)	(-0.39)
$QEA_{i,[t+1,t+2]}$	0.030*	-1.107
	(1.68)	(-0.85)
$Other\ News_{i,t}$	0.005***	-0.262
	(2.69)	(-1.24)
$ln(Market\ Cap)_{i,q-1}$	-0.029***	0.514**
	(-4.68)	(2.01)
$Book/Market_{i,q-1}$	0.042	-8.747*
	(1.50)	(-1.82)
$PastRet_{i,t}$	-0.008***	0.586*
	(-6.04)	(1.83)
$PastVol_{i,t}$	0.011*	-0.482
	(1.72)	(-0.89)
$PastRetSkew_{i,t}$	-0.001	0.009
	(-0.88)	(0.13)
Observations	130,903	130,903
R-Squared	0.16	0.18
Date Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes