Why do individual investors disregard accounting information?

The roles of information awareness and acquisition costs

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Abstract

We investigate the frictions that impede individual investors' use of accounting information and, in particular, their costs of monitoring and acquiring accounting disclosures. We do so using an archival setting in which individuals are presented with automated media articles that report both current earnings news and past stock returns. Although these investors have earnings information readily available, we find no evidence that their trades incorporate it. Instead we find that their trading responds to the trailing stock returns presented in the articles. Our study raises questions about the efficacy of regulations that aim to aid less sophisticated investors by increasing their awareness of and access to accounting information.

Keywords: Information Costs; Information Awareness; Information Acquisition; Individual Investors; Earnings Announcements; Trading Volume; Automation

JEL Codes: D83, G12, G14, M41

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1. Introduction

Individual investors often neglect value-relevant accounting information (e.g., Lee 1992; Hirshleifer et al. 2008; Maines & Hand 1996; Ayers et al. 2011; Taylor 2010), and their portfolios underperform because they chase attention-grabbing trends (Barber & Odean 2013). SEC regulations like FD and XBRL aim to help individuals make better trades by decreasing their costs of monitoring and accessing accounting information.[1] However, it is difficult to know whether these regulations are effective, without understanding the frictions that impede individuals' use of accounting information. We investigate this question.

Whatever information an investor uses, incorporating an incrementally informative signal will improve his or her valuations (Blackwell 1951; Vives 2008). Assuming accounting information is value-relevant (which we address below) and investors aim to maximize risk-adjusted returns, we expect investors to use accounting information in trading decisions. However, they may disregard accounting information if the cost of using it outweighs the benefit (Grossman & Stiglitz 1980; Bloomfield 2002). Figure 1 describes three sequential steps to using accounting information in trading and the costs of each. Two of these—awareness and acquisition costs—have been a particular focus of SEC regulations. Our study examines the extent to which awareness and acquisition costs impede individuals' use of accounting information in trading decisions.[2]

"Awareness costs" acknowledge that monitoring for the existence of firms' disclosure is costly, where "disclosure" could refer to a report or a specific piece of information within a report (Merton 1987; Hand 1990). Investors who are unaware of their informational disadvantage may continue to trade rather than withdrawing from the market (DellaVigna & Pollet 2009; Hirshleifer et al. 2009, 2011). Thus, one explanation for investors' neglect of accounting information is that, due to limited resources, they are unaware of a disclosure.

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[1] Further discussion of SEC regulations is provided in Section 2.

[2] We also discuss a third type of information cost—integration costs—and the possibility that behavioral biases prevent individual investors from using accounting information in trading decisions.

Once aware of an accounting disclosure, investors must expend resources to acquire information from the firm's financial reports and supplementary sources. Information is "acquired" once it is at hand and ready for use in a valuation model (Maines & McDaniel 2000; Bloomfield 2002). Examples of acquisition costs include the time and effort needed to obtain reports and convert raw data into statistics or the cost of outsourcing those efforts (e.g., analyst reports or a Dow Jones feed).[3] Even when investors are aware of a disclosure, acquisition costs could prevent them from trading on it (Bhattacharya 2001).

A challenge in disentangling awareness and acquisition costs from other frictions is that investors' information sets are typically unobservable. Our study uses an archival setting in which awareness and acquisition costs are reduced for a set of firms' earnings announcements, which we use to isolate and identify trading by individual investors with known information sets. Our empirical approach uses the Associated Press' (AP's) staggered rollout of nationally distributed "robo-journalism" articles of firms' earnings announcements (Blankespoor, deHaan, and Zhu 2018, BDZ hereafter). The existence and content of these algorithmically generated articles are largely exogenous to the firm and its earnings announcement; BDZ find the articles drive significant increases in trading by individual investors. Our study exploits the feature that all articles present both a firm's current earnings and trailing stock returns in a standardized way, allowing us to examine individuals' trading choices when both accounting information and technical trends are immediately at hand.

Our first prediction addresses awareness costs. Given that the automated headlines clearly identify the earnings announcement, we assume individual investors who trade in response to the articles are aware of the announcement. If awareness costs are typically the primary barrier to using earnings information, then investors who respond to the articles will incorporate the earnings news into their trades. Alternatively, if lowering awareness costs is insufficient to motivate the use of earnings news, these investors will disregard the news. Instead, they will likely trade in response to the trailing returns presented in the articles, consistent with evidence that individual investors trade on technical trends (Grinblatt & Keloharju 2000; Barber & Odean 2008; Kaniel et al. 2008).

Our second prediction examines the role of acquisition costs by exploiting variation across AP's automated articles: some articles provide the analyst consensus, while others do not. Investors responding to articles containing the analyst consensus can calculate a value-relevant earnings signal with minimal acquisition costs, while investors responding to the articles without a consensus must acquire some other benchmark to calculate the earnings innovation. If acquisition costs are primarily responsible for individual investors' neglect of earnings information, then investors who trade in response to AP articles will use earnings news when the analyst consensus is provided (i.e., because

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[3] Some papers use the term "acquisition costs" as a label for information costs more broadly (e.g., Verrecchia 1982; Larcker & Lys 1987), while others use it in a narrower context (Reis 2006; Sims 2010; Müller, Riedl, and Sellhorn 2015). We define acquisition more narrowly in order to best describe and differentiate between types of information costs.

acquisition costs are minimal). If reducing acquisition costs is insufficient to motivate the use of earnings news, these investors will continue to disregard the news and instead trade on the trailing returns presented in the articles.

Finding that individuals ignore earnings information even in the absence of awareness and acquisition costs indicates some other friction affects their trading. We see two likely candidates. First, individuals face a third type of information cost: integration costs, which include costs necessary to evaluate, combine, and incorporate accounting information into valuation models and trading decisions (Hodge et al. 2004).[4] Because integration follows awareness and acquisition, integration costs can cause investors to forgo fundamental analysis, even absent awareness and acquisition costs. Second, individuals may suffer from behavioral biases such as overconfidence in flawed trading strategies. In either of these cases, regulations designed to reduce awareness and acquisition costs are unlikely to motivate the use of accounting information.

Our sample consists of 29,776 earnings announcements relating to 2,264 firms that received no earnings media coverage from AP in the three years before automation began in October 2014. Of these firms, 66% begin receiving automated earnings articles on a staggered basis through the end of our sample in November 2015. We use a generalized difference-in-differences (DID) model to isolate the increase in trading volume generated by automated AP articles, which BDZ find is likely driven by individual investors.

Our tests of Prediction 1 examine the extent to which the trading generated by the AP articles is correlated with the firm's earnings news versus trailing returns. We use the absolute earnings surprise to measure the firm's earnings news. Consistent with the articles, we measure the firm's trailing raw stock returns excluding dividends. Our analyses fail to find that the incremental trading generated by the AP articles is associated with the firm's earnings news, even for large earnings surprises. We instead find a strong association between the incremental trading and trailing returns presented in the articles, consistent with individuals using technical analysis trading strategies. Analyses of Prediction 2 continue to find no evidence of investors trading on earnings surprises even when the articles include the analyst consensus. In sum, our results do not support predictions that awareness and acquisition costs are primarily responsible for individual investors' neglect of accounting information. Instead, the individuals who trade in response to AP's articles trade on technical trends even though earnings information is immediately at hand.[5]

Our setting has strengths and limitations. One strength is that earnings news is highly value-

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[4] For example, an individual unfamiliar with financial statements or the idea that earnings are value relevant would find it extremely costly to use accounting information. Integration costs are relevant in papers including Miller (2010), Lawrence (2013), Maines & McDaniel (2000), Chapman et al. (2018), Drake et al. (2017), and Blankespoor (2018).

[5] Tests in Section 6 ensure that, consistent with a large body of accounting research, earnings surprises are highly value-relevant within our sample and predict returns in the days and weeks following an earnings announcement.

relevant and relatively low cost to integrate. Though we cannot guarantee our findings generalize, they suggest that reducing awareness and acquisition costs is even less likely to matter for disclosures that are less value-relevant or more complex. A caveat is that our research design assumes that the association between abnormal trading volume and earnings surprises captures the extent to which investors use earnings in trading decisions. This design has extensive precedent (see Section 3.2), but we acknowledge its imperfections. Finally, individuals who trade in response to AP's articles do not represent all individual investors but instead likely characterize less sophisticated investors who trade on attention-grabbing trends. Even so, the population of investors examined here is sizable given that AP's articles drive a roughly 11% increase in trading volume (BDZ 2018).

Our first contribution is to bring together a framework of distinct frictions that impact investors' use of accounting information. Our framework entails three steps—awareness, acquisition, and integration—each of which is costly (see Figure 1). While information costs are central to the accounting and finance literatures, they are described with heterogeneous labels and without decomposing specific types of costs.[6] Our framework can facilitate research on the specific mechanisms that affect the usage and pricing of accounting information.

Second, our framework and findings can contribute to evidence-based policymaking (Leuz 2018). Understanding the behavior of individual investors is critical to designing and evaluating investor protections (SEC 2017c).[7] The SEC has a mandate to aid individual investors and works to improve their access to accounting information (SEC 2017a). However, our results indicate that regulations designed to reduce awareness and acquisition costs are unlikely to help a sizable population of investors. As such, alternative regulatory strategies might i) limit the scope of regulations to exclude less sophisticated investors, ii) focus on reducing integration costs or mitigating behavioral biases, or iii) educate investors about the benefits of diversified index funds.[8]

Our third contribution is to help reconcile inconsistent results in the media literature.

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[6] For example, information costs are central to the literatures on investor attention (e.g., Gilbert et al. 2012; deHaan et al. 2015; Lawrence et al. 2016; Drake et al. 2016; Chapman 2018; Koester et al. 2016; deHaan et al. 2017), dissemination (e.g., Bushee et al. 2010; Tetlock 2011; Blankespoor et al. 2014), information overload (e.g., Dyer et al. 2017; Chapman et al. 2018; Drake et al. 2017), and recognition versus disclosure (e.g., Michels 2017), but these studies typically do not specify which types of information costs drive their hypotheses. Differentiating between types of costs is important not only to improve understanding of market frictions but also because different costs likely affect market outcomes differently.

[7] Understanding individual investors' trading also contributes to academic literatures. Many studies find that individuals trade on past returns (see Barber & Odean 2013). Our study advances toward explaining *why* individuals favor technical trading over fundamental analysis.

[8] We are unaware of any scope limitations for the types of individual investors that the SEC currently aims to aid. This contrasts with the FASB, which states that it designs standards for "users who have a reasonable knowledge of business and economic activities and who review and analyze [financial reports] diligently" (FASB Concept Statement No. 8, QC32). To be clear, our results do not indicate that the SEC *should* reduce the scope of its regulatory efforts. Such a conclusion would require comprehensive welfare analyses.

Several studies find that coverage by business newswires induces trading that speeds the pricing of accounting information (e.g., Twedt 2016; Rogers et al. 2016). Other studies find that media coverage by general interest outlets spurs capital market responses but does *not* help impound accounting information into price (BDZ 2018, Lawrence et al. 2018). Our study helps reconcile these results by finding that mainstream media coverage of earnings announcements motivates trading on non-accounting signals, increasing volume and liquidity without speeding the pricing of accounting news. These findings respond to Miller and Skinner's (2015) question of how different types of media outlets affect different stakeholders.

2. SEC regulations targeting awareness and acquisition costs

Protecting individual investors has long been an SEC priority and was reinforced by the Dodd-Frank Act in 2010. Former Chairperson Mary Jo White has said: "The retail investor must be a constant focus of the SEC—if we fail to serve and safeguard the retail investor, we have not fulfilled our mission."[9] While our study does not comprehensively analyze the SEC's efforts to help individual investors, we aim to provide evidence for policymaking discussions (Leuz 2018). To that end, this section provides examples of regulations designed in part to aid individual investors by reducing information awareness and acquisition costs, as described using language drawn from the cost-benefit analyses within those regulations.

First, Regulation FD aims to reduce awareness and acquisition costs by prohibiting firms from disclosing information to professional investors before the public (SEC 2000). The primary intended beneficiary is individual investors because selective disclosure "puts them at a severe disadvantage in the market" (SEC 2000, p. 3).[10] As another example, XBRL requires firms to electronically tag filings so that data can be extracted using computer code. XBRL was intended to create "greater investor awareness" of disclosures and reduce acquisition costs by eliminating the need to hand collect or purchase data (SEC 2009, p. 127). Again, a primary motivation was to aid individual investors.

More recently, the SEC has required firms to hyperlink exhibits to help "access a particular exhibit more efficiently as they will not need to search within the filing or through different filings [...] to locate the exhibit" (SEC 2017b, p. 24). Expected benefits of hyperlinking include "more effective monitoring" and "more informed investment and voting decisions" (p. 25). Another rule eliminates redundant disclosures in an attempt to reduce awareness and acquisition costs without significantly altering the total mix of information provided (SEC 2016). Finally, the SEC's emphasis on plain language disclosures attempts to reduce investors' costs of accessing information from filings,

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[9] https://www.sec.gov/news/speech/mjw-speech-032114-protecting-retail-investor. The use of the term "retail investor" in this quote is synonymous with our use of "individual investor."

[10] FD had many intended benefits, including some aimed at professional investors. This section only discusses regulations as they pertain to reducing awareness and acquisition costs of individual investors.

especially for individual investors who are “neither lawyers, accountants, nor investment bankers” (SEC 1998, p. 3; SEC 2007).

3. Empirical Setting and Predictions

3.1. Empirical Setting

In October 2014, the Associated Press (AP) began using automated “robo-journalism” technology to create articles about firms’ earnings releases. Zacks provides the data used in these articles, including information from firms’ earnings announcements, analyst reports, and stock returns. Algorithms convert the data into an article that resembles a simple human-written article. AP distributes these articles to nearly all U.S. media outlets, which then republish them in print and online.

By the end of 2015, AP provided automated articles for over 4,000 U.S. public companies per quarter. Automated coverage required a one-time algorithm setup for each firm, and AP focused on the largest firms first. Thus, while the roll-out order is largely exogenous to the contents of firms’ earnings announcements, it is correlated with firm size. Also, the initial implementation for industries with atypical data (e.g., banks) was delayed to allow for customized algorithms. Once set up, the algorithm automatically produced an article quarterly. Thus the existence and structure of the articles are largely unaffected by firm earnings news, stock returns, fundamentals, and other confounds typically arising from selective media coverage.

Appendix A presents a typical article for the firms in our sample. The article includes the firm’s reported earnings (GAAP and adjusted), the pre-announcement analyst consensus, and raw stock returns over the prior 12 months and year-to-date. AP distributed the article 90 minutes after the earnings announcement. Like all of AP’s earnings articles, it was immediately republished on Yahoo Finance. We do not have complete data on outlets that republished AP’s articles, but RavenPack shows articles frequently republished on outlets including CNBC, NBCNews.com, *The Huffington Post*, and *Investor’s Business Daily*.

BDZ use AP’s staggered introduction of automated articles to examine the capital market effects of the media’s synthesis and dissemination of purely public earnings information. They find significant increases in trading volume following the implementation of the articles. Given that AP’s articles are geared toward general interest readers and are released with a delay, the increase in trading observed by BDZ is likely driven by individual investors. Sophisticated investors, in contrast, can obtain the information more quickly from the original sources and data providers such as Zacks and Dow Jones. Three findings in BDZ further support this inference. First, volume does not spike in the minutes immediately after article release but instead persists for several days, which is inconsistent with professional investors or algorithms trading on AP's broadcasts.[11] Second, BDZ find increased volume in a sample of individuals' trades. Third, the volume is accompanied by an increase in depth, which indicates that depth-setting market participants are not concerned that the trading is driven by sophisticated investors with private information.

Several features of AP's automated articles are helpful for our investigation. First, the existence and structure of the articles are largely exogenous to the firm and its earnings announcement. Second, the articles induce an identifiable increase in individual investor trading. Third, they present both current earnings news and trailing returns, which allows us to compare investors' use of accounting information to their use of technical trends. Finally, a subset of articles includes the analyst consensus to calculate the earnings surprise, while others provide only current earnings. This variation allows us to distinguish acquisition and awareness costs.

3.2. Empirical predictions

Our predictions examine the extent to which individuals use earnings, technical trends, or both in trading decisions. Many papers find that trading volume at earnings announcements increases with the size of the earnings surprise (e.g., Bamber 1986; Bamber 1987; Kross et al. 1994; Drake et al. 2012).[12] Analytical models provide several reasons why larger earnings surprises drive more trading (e.g., Karpoff 1986; Holthausen & Verrecchia 1990; Kim & Verrecchia 1991; Bamber et al. 2011). Following these studies, we use the correlation between the earnings surprise and the trading volume of investors responding to AP articles as a proxy for the extent to which those investors use earnings information (e.g., Woodruff & Senchack 1988; Bhattacharya 2001; Battalio & Mendenhall 2005; Cready & Hurtt 2002; Bhattacharya et al. 2007; Hirshleifer et al. 2008). We depict our predictions in Figure 2.

Our first prediction examines awareness costs. We assume that investors who observe an AP article are aware of the earnings announcement. If awareness costs are typically a binding constraint, then investors who trade in response to an AP article will incorporate earnings news into their trading; i.e., they will invest the resources necessary to acquire and integrate the earnings information. If lowering awareness costs is insufficient, they will either refrain from trading or will trade using an information set that excludes earnings.

Conveniently, AP's automated articles provide a common focal point for investors following a trading strategy that excludes earnings: the firm's trailing stock returns. Individuals often trade either with or against trailing returns (e.g., Grinblatt & Keloharju 2000; Kaniel et al. 2008; Barber & Odean 2008). In addition, they likely understand what a return represents, so trailing returns may elicit a response from resource-constrained investors searching for trends. Thus, if investors

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[11] In contrast, Rogers et al. (2016) find that Dow Jones news flashes that are directed toward professional traders spur trading within seconds of being released.

[12] Holthausen & Verrecchia (1990) note: "The [empirical] evidence clearly indicates that trading volume increases at the time of earnings announcements and that trading volume is positively correlated with the absolute value of the unexpected component of earnings announcements" (p. 192).

disregard earnings news, we predict they instead focus on the trailing returns presented in the AP articles.

Prediction 1: If awareness costs are primarily responsible for individual investors' neglect of earnings information, then incremental trading generated by automated articles ***will*** *correlate with the size of the earnings surprise. If lowering awareness costs is insufficient to motivate the use of earnings information, then incremental trading generated by automated articles* ***will not*** *correlate with the size of the earnings surprise, and instead will correlate with the size of the trailing returns stated in the articles.*

Our second prediction addresses acquisition costs. While all articles provide current EPS, AP's algorithm only includes the pre-announcement analyst consensus when Zacks has at least three analyst forecasts.[13] In these cases, investors responding to the articles could trade on value-relevant analyst-based earnings surprises without additional acquisition costs. When the article does not include the consensus, the investor must incur costs to acquire a benchmark to calculate the earnings innovation or acquire supplementary information from other sources.

Prediction 2: If acquisition costs are a primary barrier to individual investors using earnings information, then incremental trading generated by automated articles ***will*** *correlate with the size of the earnings surprise when the analyst consensus is in the article. If lowering acquisition costs is insufficient to motivate the use of earnings information, then incremental trading generated by automated articles* ***will not*** *correlate with the size of the earnings surprise even when the analyst consensus is in the article, and instead will correlate with the size of the trailing returns stated in the articles.*

4. Sample

Our sample construction mirrors that of BDZ. The primary dataset is an index of earnings articles by AP between Jan. 1, 2012, and Nov. 12, 2015.[14] We use data listed in Appendix B to construct a sample of quarterly earnings announcements. We require data to identify the earnings announcement date, earnings surprise, past returns, and trading volume over days [0, 2] relative to the earnings announcement. We exclude trusts, closed-end funds, and REITs. To minimize sample noise, we require that each earnings date per Compustat is the same as the date provided by Zacks, IBES, or Wall Street Horizon (deHaan et al. 2015). For after-hours announcements, we set day 0 to the next trading day for market tests. We also require that each firm has at least one observation

[13] Within our data, 94% of articles comply with this rule. We could not confirm why there is not 100% compliance, but a likely explanation is that Zacks' data has been updated since what was available at the time of the article. Dropping the 6% of noncompliant articles produces qualitatively unchanged results. We define "qualitatively unchanged" as meaning that significant results remain significant at 10% and insignificant results remain insignificant for the test variables of interest. Note, too, that pre-announcement analyst coverage is not exogenous. Section S8 of the Supplementary Materials discusses potential concerns due to nonrandom analyst coverage and why we do not view these concerns as threats to our conclusions.

[14] We refer readers to BDZ for details on how AP's data are cleaned, quality-controlled, and matched to Compustat.

both before and after AP began distributing automated articles.

We retain only firms that received zero earnings-related articles from AP before the beginning of automation in October 2014. These firms experience the biggest relative increase in investor attention upon the introduction of automated AP articles. Also, retaining only firms without pre-automation AP articles facilitates a sharp DID design in which firms receive AP media coverage in 0% (100%) of quarters before (after) automation.

Although firms should receive automated articles in all quarters following initiation, algorithm warnings and errors occasionally delay article creation long enough that AP chooses not to distribute it. To maintain our sharp DID design, we drop firms without articles in more than one quarter following their robo-journalism initiation. For the firms with one missed quarter, we keep the firm but drop the quarter missing coverage. Our final sample includes 2,264 firms (56% of the original sample) and 29,776 earnings announcements.

Panel A of Table 1 shows the number of firms that begin receiving automated articles in each calendar quarter. We use “treatment firms” to refer to the 1,487 firms that receive automated coverage, while 777 “nontreatment firms” do not yet receive automated articles by the end of our sample. The median treatment firm size tends to decrease each quarter, which is consistent with AP implementing large firms first. Panel B of Table 1 provides summary statistics. The mean (median) firm-quarter has a market value of $1.3 billion ($253 million), analyst coverage of 3.5 (2), and institutional ownership of 40% (38%). Variable definitions are provided in Appendix B.

5. Research Design and Results

Our analyses use three main variables: (i) abnormal trading volume, (ii) unexpected earnings, and (iii) the trailing stock returns presented in the AP articles. As discussed above, we use the correlations between trading volume and unexpected earnings and trailing returns to gauge the extent to which investors use each signal.

We measure abnormal trading volume, *Abn_Vol*, as the firm’s average shares traded over days [0, 2] divided by total shares outstanding, minus the firm’s trailing average over days [-41, -11], and less the market abnormal turnover. We use days [0, 2] to allow several days for individuals to respond to the AP articles, and because BDZ (2018) find evidence of heightened trading through two days after the announcement.

In firm-quarters in which analyst forecast data are available in IBES or Zacks, we calculate unexpected earnings as the firm’s realized earnings less the most recently available consensus. In firm-quarters lacking forecast data, we calculate unexpected earnings based on a seasonal random walk. In both cases, the earnings innovations are scaled by price, and the absolute values are sorted into deciles to form the variable *UE_Abs*.

AP’s articles present raw stock returns over the trailing 12 months as well as year-to-date. It is not obvious which return matters more to investors, so we measure stock performance as the average of the two. We then sort the absolute values into deciles to form the variable *Ret_Abs*. The correlation between *UE_Abs* and *Ret_Abs* is 0.176.[15]

5.1. Descriptive visual evidence

Panel A of Figure 3 provides visual evidence of the effect of automated articles on *Abn_Vol*. Consistent with our DID models below, the "benchmark" observations in the left bar include non-treatment firms as well as treatment firms that have not yet begun receiving articles. The "treatment" observations in the right bar include firms after they begin receiving articles. *Abn_Vol* increases by 0.20, from 0.34 to 0.54, between the benchmark and treatment observations, consistent with the AP articles generating greater trading volume.

We next examine which articles drive this effect. We disaggregate the treatment observations on two dimensions: small versus large UE and small versus large trailing returns. "Extreme" earnings (returns) observations have signed *UE (Ret)* in the top or bottom decile, and "non-extreme" observations have *UE (Ret)* in the inner eight deciles. If investors responding to articles are primarily motivated by earnings (returns), the treatment effect should be concentrated in observations with larger earnings surprises (trailing returns).

The left two bars of Panel B show that the treatment effect for articles with non-extreme versus extreme UE is roughly 0.21 and 0.17, respectively. These effects both resemble the average effect of 0.20 in Panel A, providing no indication that the treatment effect is driven by articles reporting large earnings surprises. In fact, the treatment effect for extreme UE observations appears slightly smaller than that for non-extreme UE, but our tests below find that this difference is far from statistically significant.

The right two bars of Panel B show that the treatment effect for articles with non-extreme returns is 0.167, while the effect for articles with extreme returns is 0.356. Compared to normal announcement-window turnover of 0.98 (untabulated), trading volume increases by roughly (0.167/0.98=) 17% for articles with non-extreme trailing returns, while the effect is 36% for articles with extreme returns.[16] Observing that the treatment effect is concentrated in the articles reporting extreme returns is consistent with individual investors using trailing returns to inform their trades. We formally test these descriptive findings below.

5.2. Initial model setup—isolating trading volume driven by automated articles

We first use a generalized DID model from BDZ to isolate the incremental trading volume generated by the AP articles around earnings announcements:

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[15] Analyses in the Supplementary Materials find qualitatively unchanged results using shorter and longer trading windows and using different specifications of *UE_Abs* and *Ret_Abs.*

[16] These point estimates shrink to 10%–14% and 34%, respectively, in our regression tests in the following sections.

$$Abn\_Vol = \beta_1 Post + \Sigma\beta_n Group_n + \Sigma\beta_q YearQtr_q + \varepsilon. \quad \textbf{(1)}$$

Group are fixed effects for each group of staggered treatment and nontreatment firms (e.g., 2014 fourth-quarter firms, 2015 first-quarter firms) and eliminate average differences in *Abn_Vol* across the groups.[17] *YearQtr* are fixed effects for each calendar year-quarter and eliminate the temporal trend in *Abn_Vol* for benchmark observations. *Post* is an indicator equal to one for all earnings announcements after a firm begins automated coverage. The β_1 coefficient on *Post* is a DID measure of the average within-*Group* increase in *Abn_Vol* after a firm begins receiving AP articles, as compared to other firms in the same quarter that have not begun receiving articles. Assuming parallel trends in *Abn_Vol* between *Groups* in the absence of AP articles, β_1 estimates the incremental trading volume generated by these articles.[18] Column (i) of Table 2 presents results of estimating model (1). The *Post* coefficient is positive and significant, consistent with automated AP articles driving increased trading volume.

5.3. Analyses of Prediction 1

We next incorporate *UE_Abs* and *Ret_Abs* to examine whether the incremental trading generated by the articles correlates with earnings news or trailing returns.

$$\begin{aligned} Abn\_Vol &= \beta_1 Post + \beta_2(UE\_Abs *Post) + \beta_3(Ret\_Abs *Post) \quad \textbf{(2)} \\ &+ \Sigma\beta_n Group_n + \Sigma\beta_n(UE\_Abs *Group_n) + \Sigma\beta_n(Ret\_Abs *Group_n) \\ &+ \Sigma\beta_q YearQtr_q + \Sigma\beta_q(UE\_Abs *YearQtr_q) + \Sigma\beta_q(Ret\_Abs *YearQtr_q) + \varepsilon. \end{aligned}$$

The *UE_Abs* $*Group_n$ interactions estimate the group-specific relations between *Abn_Vol* and earnings surprises. The *UE_Abs* $*YearQtr_q$ interactions allow the relation between *Abn_Vol* and earnings surprises to vary by quarter. Interactions between *Ret_Abs* and each of $Group_n$ and $YearQtr_q$ perform similar functions.[19] *UE_Abs* and *Ret_Abs* are de-meaned so that main effects of

[17] The generalized DID model requires group and time fixed effects. Like Gipper, Leuz, and Maffett (2017), we do not use firm fixed effects because our model extensions require interacting regressors with each fixed effect. Thus using firm fixed effects requires 2,264 interactions for each regressor other than *Post*, creating an extremely restrictive model. However, using group fixed effects in model (1) produces *Post* coefficient estimates that are within 0.01 of those using firm fixed effects, although results using group fixed effects have slightly larger standard errors (i.e., our models produce weaker results).

[18] Although the treatment group order was a function of firm size, BDZ find no differences in trends in *Abn_Vol* between treatment and nontreatment groups prior to the beginning of automated AP articles, which supports the parallel trends assumption. Analyses of pre-treatment trends for our model extensions below can be found in Section S5 of the Supplementary Materials.

[19] The main effects of *UE_Abs* and *Ret_Abs* are absorbed by the fixed effect interactions.

interacted variables can be interpreted at the sample averages.

β_1 now estimates the average increase in trading volume generated by the articles, *conditional* on average values of *UE_Abs* and *Ret_Abs*. The interaction *UE_Abs *Post* is a DID coefficient that estimates the extent to which the incremental trading generated by AP articles correlates with unexpected earnings. If incremental traders use earnings information, we expect $\beta_2 > 0$. We expect $\beta_2 = 0$ if they disregard earnings.[20] Similarly, the interaction *Ret_Abs *Post* estimates the extent to which the incremental trading generated by the articles correlates with the firm's trailing returns. If incremental traders are motivated to trade by prior returns, we expect $\beta_3 > 0$.

Column (ii) of Table 2 presents results of estimating model (2). β_2 differs insignificantly from zero, which is inconsistent with investors responding to the AP articles using earnings news. β_3 is significantly positive, consistent with investors trading in response to trailing returns. These findings indicate that reducing awareness costs is insufficient to motivate individual investors to incorporate earnings information into their trading. Rather, the investors appear to rely on returns-based technical strategies.

Model (2) imposes a linear relation between *Abn_Vol* and *UE_Abs*, but extreme earnings surprises may generate a disproportionate amount of trading.[21] Thus we modify (2) to examine whether extreme earnings surprises motivate investors to use earnings news. Following Hirshleifer et al. (2008), the variable *Extreme UE_Abs* equals *UE_Abs* for quarters with signed *UE* in the top or bottom decile. *Non-Extreme UE_Abs* equals *UE_Abs* for other firm-quarters. We similarly define *Extreme Ret_Abs* and *Non-Extreme Ret_Abs* based on signed *Ret*.

$$\begin{aligned}
Abn_Vol = \;& \beta_1 Post \\
&+ \beta_2(Non\text{-}Extreme\ UE_Abs *Post) + \beta_3(Extreme\ UE_Abs *Post) \\
&+ \beta_4(Non\text{-}Extreme\ Ret_Abs *Post) + \beta_5(Extreme\ Ret_Abs *Post) \\
&+ \Sigma\beta_n Group_n \\
&+\Sigma\beta_n(Non\text{-}Extreme\ UE_Abs *Group_n)+\Sigma\beta_n(Extreme\ UE_Abs *Group_n) +\Sigma\beta_n(Non\text{-}Extreme\ Ret_Abs *Group_n)+\Sigma\beta_n(Extreme\ Ret_Abs *Group_n) \\
&+ \Sigma\beta_q YearQtr_q \\
&+\Sigma\beta_q(Non\text{-}Extreme\ UE_Abs *YearQtr_q) +\Sigma\beta_q(Extreme\ UE_Abs *YearQtr_q)
\end{aligned} \tag{3}$$

[20] Finding $\beta_2 < 0$ would suggest that investors use the signal not to update their beliefs about firm value but rather that large earnings surprises deter them from making trades they otherwise would have.

[21] Individual investors likely respond more to larger earnings surprises because these surprises cause more belief revision or are more salient (Hirshleifer et al. 2008; Koester et al. 2016). Bordalo et al. (2012, 2013a, 2013b) operationalize salience by focusing on magnitudes, with more extreme magnitudes being more salient.

$$+\Sigma\beta_q(\text{Non-Extreme Ret\_Abs} * YearQtr_q) + \Sigma\beta_q(\text{Extreme Ret\_Abs} * YearQtr_q) + \varepsilon.$$

Each information variable (*Extreme*, *Non-Extreme UE_Abs*, *etc.*) is interacted with *Group* and *YearQtr*. If investors responding to articles are motivated to trade by large earnings surprises, we expect a significantly positive coefficient on *Extreme UE_Abs * Post*.

Column (iii) of Table 2 provides the results of estimating model (3). The coefficients on *Post * Extreme UE_Abs* and *Post * Non-Extreme UE_Abs* are both insignificant, indicating that individual investors continue to disregard earnings information, even when the signal is extreme. The β_5 coefficient on *Post * Extreme Ret_Abs* is positive and significant, indicating that investors respond to extreme trailing returns.[22]

5.3.1. Additional analyses: positive news, negative news, buys and sells

Results in Table 3 extend model (3) along two dimensions. First, we disaggregate *UE* and *Ret* into positive and negative values, for a total of eight signals: non-extreme positive UE and returns, non-extreme negative UE and returns, extreme positive UE and returns, and extreme negative UE and returns. All eight are interacted with the fixed effects. Second, we separate absolute trading volume from TAQ into buy- and sell-initiated trades, using the Lee and Ready (1991) tick test. A caveat is that identifying buy- and sell-initiated trades based on the tick test is problematic in recent years, so results of buys and sells should be interpreted with caution (Easley et al., 2012; Johnson & So 2017).

Results in columns (i) and (ii) of Table 3 analyze *Abn_Vol* buy- and sell-initiated trades, respectively. Both models fail to find associations between trading volume and any type of earnings news.[23] At the same time, the models find significantly positive associations between trading volume and extreme positive trailing returns for both buy- and sell-initiated trades. These results indicate that either these individual investors include both momentum and contrarian traders or that the tick test incorrectly identifies trade direction in our sample.

5.3.2. Additional analyses: individual investor trading data

We also examine a second proxy for abnormal volume that more specifically measures trading by individual investors. We isolate a subset of individual investor trades in TAQ following the

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[22] Section S4 of the Supplementary Materials discusses our rationale for excluding control variables from our primary tests, and also investigates extensions of models (3) and (4) with control variables. All results are qualitatively unchanged except that one *Ret_Abs* coefficient becomes insignificant in one iteration of model (4).

[23] Failing to find an association for both positive and negative earnings news also provides comfort that our results are not confounded by asymmetric incentives to preempt negative earnings surprises with manager forecasts.

method of Boehmer, Jones, & Zhang (2017). These trades do not include nonmarketable limit orders or any orders fulfilled on an exchange, so they have a low type I error rate but a high type II rate (i.e., many individuals' trades are unidentified). We calculate abnormal individual investor trading volume (*Abn_IndivVol*) as the firm's average shares traded by individuals over days [0, 2] divided by total shares outstanding, minus the firm's trailing average over days [-41, -11]. Table 4 presents results of model (3) using *Abn_IndivVol*. The results are consistent with those in column (iii) of Table 2.

5.4. Analysis of Prediction 2

Prediction 2 examines acquisition costs. Articles that contain the pre-announcement analyst consensus are designated as low acquisition cost (*LowAcqCost*), while others are designated as high acquisition cost (*HighAcqCost*). We partition the nontreatment observations into low versus high acquisition costs using the algorithm's rule that articles contain the consensus when Zacks has at least three analyst forecasts (see Section 3.2). Finding that investors respond to earnings news in the lower acquisition-cost treatment sample would indicate that acquisition costs are a primary barrier to investors' use of earnings information. In contrast, finding no response to earnings would indicate that reducing acquisition costs is insufficient to motivate the use of earnings information.

Our tests are based on an extension of model (3) that partitions each of our UE and returns measures depending on whether the observation has higher or lower acquisition cost; e.g., *LowAcqCost Extreme UE_Abs*Post, HighAcqCost Extreme UE_Abs *Post*. The model, labeled (4), therefore includes 16 UE and returns measures, each of which is interacted with the fixed effects. For brevity, we do not present the specification for model (4).

The left (right) side of column (i) in Table 5 presents coefficient estimates for the *LowAcqCost* (*HighAcqCost*) UE and returns measures in model (4). Column (ii) repeats (i) but uses *Abn_IndivVol* as the dependent variable. Across the two columns, there is little evidence that investors respond to earnings, regardless of whether the components of earnings news are readily available. The coefficient on *HighAcqCost Non-Extreme UE_Abs*Post* is significantly positive at 10% in column (i) but insignificant in column (ii). These results indicate that reducing information acquisition costs is not enough to motivate these investors to use earnings news.[24] Turning to returns, our models find that the association between trading volume and extreme trailing returns is concentrated in the *HighAcqCost* firms.[25]

5.5. Analysis of Stock Return Volatility

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[24] Given that the analyses in Section 5.3.1 find little difference in trading between buys/sells and positive/negative UE, we do not tabulate similar partitions of those models using high versus low acquisition costs. However, untabulated results again find no consistent associations between UE and volume across any partition.

[25] Although not the focus of our paper, this finding could have two plausible explanations. First, the individuals in our sample might prefer to trade in the types of firms that have less analyst following. Second, the automated articles might have a bigger relative impact on firms with less analyst coverage.

This section investigates a logical follow-on question: does the observed increase in trading on technical trends around earnings announcements affect short-term stock return volatility? The predicted effect is not obvious. The increase in buying and selling following extreme trailing returns could induce greater volatility as the market adjusts to the post-earnings announcement equilibrium (e.g., Black 1986; De Long et al. 1990; Foucault et al. 2011). Alternatively, more sophisticated investors may realize that the increased trading is naïve and thus absorb the additional liquidity without affecting stock price (e.g., Kyle 1985).

For brevity, detailed discussion of our analysis of abnormal returns volatility is provided in Section S1 of the Supplementary Materials. In short, we find some evidence that the increase in trading on technical trends is associated with increased volatility around earnings announcements, although only in one of two common volatility variable specifications.

6. Profits to Trading on UE and Past Returns

This section investigates returns to trading strategies based on earnings surprises and trailing returns. These analyses have two objectives. First, they investigate whether investors gain by trading on trailing returns. Second, they investigate our assumption that earnings surprises are value-relevant. If so, in the absence of information costs, rational investors who already incur transaction costs to trade would be better off trading on earnings information.[26]

Calculating abnormal returns to a strategy of trading on trailing returns requires us to assume that momentum is not a risk factor. Thus, we calculate abnormal returns as the firm's return (including dividends) minus the return of a 5x5 portfolio of firms matched on size and book-to-market, similar to Daniel et al. (1997) but without momentum.

Panel A of Table 6 presents the unconditional average post-earnings announcement abnormal returns for holding windows of a few days through one quarter. We present multiple windows because we do not know the holding patterns of the individuals in our sample. Panel B presents returns for portfolios based on the trailing returns in the AP articles: extreme positive, non-extreme positive, etc., as previously defined. A long-short strategy based on extreme positive versus negative trailing returns generates insignificant abnormal returns over all windows except [2, 60]. Interestingly, a long-short strategy based on non-extreme trailing returns performs slightly better over [2, 40], but our earlier analyses provide no indication that our sample investors trade on non-extreme returns. In short, the analyses in Panel B provide little indication that investors in our sample generate abnormal profits or losses by trading on extreme trailing returns, whether they take a momentum or contrarian strategy. Because of transaction costs, these results are consistent with findings that individuals trade "too much" (Odean 1999).

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[26] Finding that *UE_Abs* predicts returns incremental to *Ret_Abs* further eliminates concerns that the information in the earnings surprise is subsumed by trailing returns.

Panel C of Table 6 presents a similar analysis for portfolios based on UE. Consistent with the PEAD literature, long-short strategies generate significant profits over all windows, for extreme and non-extreme UE. Untabulated results confirm that a long-short strategy based simply on the sign of UE also generates significant profits. Panels B and C indicate that, in the absence of information costs, investors already trading at the earnings announcement would be better off following a UE-based strategy, rather than a momentum strategy.

Finally, investors do not have to choose between a UE- versus momentum-based trading strategy but can layer both signals into a single strategy. In our final analysis, we investigate whether investors could generate abnormal returns from a UE-based strategy after conditioning on a momentum strategy. We replace our measure of abnormal future stock returns with the firm's raw return minus the return of a 5x5x5 portfolio matched on size, book-to-market, and 12-month momentum. By matching on momentum, abnormal returns are incremental to what investors could earn from simple strategies based on trailing returns. Results in Panel D continue to find highly significant abnormal returns to UE strategies over all windows.

In sum, these analyses (1) provide no evidence that trading on extreme trailing returns generates abnormal profits within our sample over windows up to 60 days, (2) provide strong evidence that UE-based strategies generate significant profits, and (3) provide strong evidence that UE-based strategies generate significant returns, even after conditioning on momentum.

7. Conclusion

Prior literature finds that individual investors do not fully incorporate accounting information into their trading decisions, potentially due to the high cost of doing so. We disaggregate the broad construct of "information costs" into three types—awareness costs, acquisition costs, and integration costs—and investigate the extent to which awareness costs and acquisition costs drive individual investors' under-use of earnings information.

Our tests are based on an archival setting in which individual investors are presented with both earnings news and trailing returns. Our findings indicate that the type of individual investors in our sample—likely on the lower end of the sophistication spectrum—do not use value-relevant earnings information, even when it is readily at hand, and instead trade on technical trends. These findings suggest awareness and acquisition costs are not the primary barriers to these investors' use of accounting information. Rather, the likely obstacles are high integration costs (e.g., they do not understand earnings or its use in valuation), behavioral biases, or both.

Accepted Article

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Appendix A: Example Article

Below is the automated AP article following A10 Networks' 2015 second quarter earnings announcement at approximately 4:03 pm EST on July 3, 2015.

A10 Networks reports 2Q loss

A10 Networks reports second-quarter loss but tops expectations

July 30, 2015 5:33 pm

SAN JOSE, Calif. (AP) _ A10 Networks Inc. (ATEN) on Thursday reported a loss of $10 million in its second quarter.

The San Jose, California-based company said it had a loss of 16 cents per share. Losses, adjusted for stock option expense and non-recurring costs, were 9 cents per share.

The results beat Wall Street expectations. The average estimate of eight analysts surveyed by Zacks Investment Research was for a loss of 15 cents per share.

The provider of networking technologies posted revenue of $47.5 million in the period, also surpassing Street forecasts. Four analysts surveyed by Zacks expected $45.9 million.

A10 Networks shares have risen 25 percent since the beginning of the year. In the final minutes of trading on Thursday, shares hit $5.43, a decline of 58 percent in the last 12 months.

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This story was generated by Automated Insights using data from Zacks Investment Research.

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Appendix B: Variable Definitions

Variable	Description	Source
Abn_IndivVol	Abnormal individual investor turnover: the firm's daily average percentage of shares traded by individual investors during days [0, 2] relative to the earnings announcement, minus the equivalent amount over days [-41, -11], multiplied by 100. TAQ trades are defined as individual trades if they have transaction code "D" and the transaction price is not at the round penny or the half penny (between 0.4 and 0.6, inclusive). Transaction code "D" trades are off-exchange trades reported to a FINRA Trade Reporting Facility. Most brokers tend to route retail trades off-exchange for only small price improvements, while any off-exchange institutional trades are transacted at the penny or half-penny.	TAQ, CRSP
Abn_BuyVol	Abnormal buy turnover: the firm's market-adjusted daily average percentage of shares bought during days [0, 2] relative to the earnings announcement, minus the equivalent amount over days [-41, -11], multiplied by 100. Trades are classified as buys or sells based on the Lee and Ready (1991) convention, which classifies a trade as a liquidity-demander "buy" when the trade price is greater than the midpoint of	TAQ, CRSP

Variable	Description	Source
	NBBO quotes and uses the tick test when the trade price is equal to the midpoint. The market adjustment is based on the equal-weighted average percentage of shares that are buys for all CRSP firms.	
Abn_SellVol	Abnormal sell turnover: the firm's market-adjusted daily average percentage of shares sold during days [0, 2] relative to the earnings announcement, minus the equivalent amount over days [-41, -11], multiplied by 100. Trades are classified as buys or sells based on the Lee and Ready (1991) convention, which classifies a trade as a liquidity-demander "sell" when the trade price is less than the midpoint of NBBO quotes and uses the tick test when the trade price is equal to the midpoint. The market adjustment is based on the equal-weighted average percentage of shares that are sells for all CRSP firms.	TAQ, CRSP
Abn_Vol	Abnormal turnover: the firm's market-adjusted daily average percentage of shares traded during days [0, 2] relative to the earnings announcement, minus the equivalent amount over days [-41, -11], multiplied by 100. The market adjustment is based on the equal-weighted average percentage of shares traded for all CRSP firms.	CRSP
Analysts	Log of 1 plus the maximum of the number of Zacks or IBES analysts.	Zacks, IBES
BTM	Book to market: calculated as Compustat CEQQ divided by market value. If missing CEQQ, then use Compustat ATQ less LTQ.	Compustat, CRSP
Dow_Article	Indicator variable set to 1 if the earnings announcement has a Dow Jones Newswire media article.	Ravenpack
Extreme Ret_Abs	Equal to *Ret_Abs* for observations with signed *Ret* in the top or bottom decile	CRSP
Extreme UE_Abs	Equal to *UE_Abs* for observations with signed *UE* in the top or bottom decile	Zacks, IBES, Compustat, CRSP
Firm_Size	Log of quarter end market cap in millions, calculated as Compustat PRCCQ*CSHOQ. If missing Compustat variables, set to CRSP abs(PRC)*SHROUT/1000.	Compustat, CRSP
Future_Abn_Ret [2,x]	Buy-and-hold portfolio-adjusted return measured over trading days [2, x] relative to the earnings announcement. Calculated as the firm's return (CRSP RET) less the equal-weighted return of a benchmark portfolio. Benchmark portfolios are determined based on (size and book-to-market) or (size, book-to-market, and momentum). All common stocks on NYSE, AMEX, and NASDAQ are sorted into nested quintiles on market value, industry-adjusted book-to-market ratio using FF49 industries, and trailing twelve-month return (momentum), all measured as of the month prior to the earnings announcement. We require at least six months of trailing returns when matching on momentum. Multiplied by 100 to be in percentage points.	CRSP, Compustat

Variable	Description	Source
HighAcqCost	Indicator variable set to 1 for (1) treatment firm-quarters with AP articles that do not include the analyst consensus earnings or (2) non-treatment firm-quarters with fewer than three Zacks analysts.	AP, Zacks
InstOwn	Fraction of shares held by institutional investors, calculated at the most recent file date between 100 days prior to the earnings announcement date and the earnings announcement date.	WhaleWisdom
Loss	Indicator variable set to 1 if EPS is negative. EPS is defined as actual EPS from Zacks if available, actual EPS from IBES if Zacks EPS is unavailable, and Compustat EPSFXQ if Zacks and IBES EPS are unavailable.	Compustat, Zacks, IBES
LowAcqCost	Indicator variable set to 1 for (1) treatment firm-quarters with AP articles that do include the analyst consensus earnings or (2) non-treatment firm-quarters with three or more Zacks analysts.	AP, Zacks
News_Flashes	Log of 1 plus the number of Dow Jones news flashes for the earnings announcement.	Ravenpack
Non-Extreme Ret_Abs	Equal to *Ret_Abs* for observations signed *Ret* not in the top or bottom decile	CRSP
Non-Extreme UE_Abs	Equal to *UE_Abs* for observations signed *UE* not in the top or bottom decile	Zacks, IBES, Compustat, CRSP
Post	Indicator variable set to 1 for quarters after the firm begins receiving automated articles.	AP, Compustat
Price	Firm's share price as of the most recent fiscal quarter end.	CRSP
Ret_Abs	Decile ranking (0=low, 9=high) of the absolute average of the buy and hold raw return for the firm for the trailing twelve months ending the day before the earnings announcement and the buy and hold raw return from the beginning of the calendar year through the day before the earnings announcement, exclusive of dividends.	CRSP
UE_Abs	Decile ranking (0=low, 9=high) of the absolute value of the mean of Zacks and IBES unexpected earnings (UE). UE is the difference between actual EPS and consensus EPS reported by Zacks or IBES, scaled by the quarter-end CRSP price (adjusted for stock splits). If neither Zacks nor IBES UE are available, this variable is the decile ranking of the absolute value of seasonal random walk UE. Decile rankings are performed separately for UE based on analyst consensus versus seasonal random walk.	Zacks, IBES, Compustat, CRSP
Volatility_Pre	Pre-period stock return volatility: annualized standard deviation of stock returns, calculated as the standard deviation of log of 1 plus daily stock returns over the prior quarter, multiplied by $\sqrt{252}$.	CRSP
YearQtr	Calendar year-quarter of the firm's earnings announcement date.	Compustat

Figure 1: Sequential Framework of Information Usage

This Figure depicts the three sequential steps to using an accounting disclosure in trading decisions. The lower portion provides examples of the costs of accomplishing each step, any of which could prevent investors from using accounting information in trading decisions.

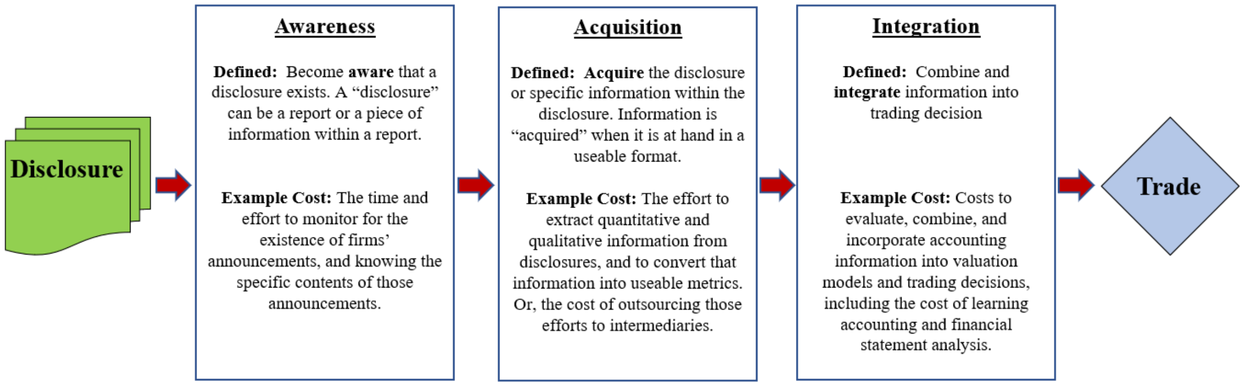


Figure 2: Predictions Based on the Information Costs Framework

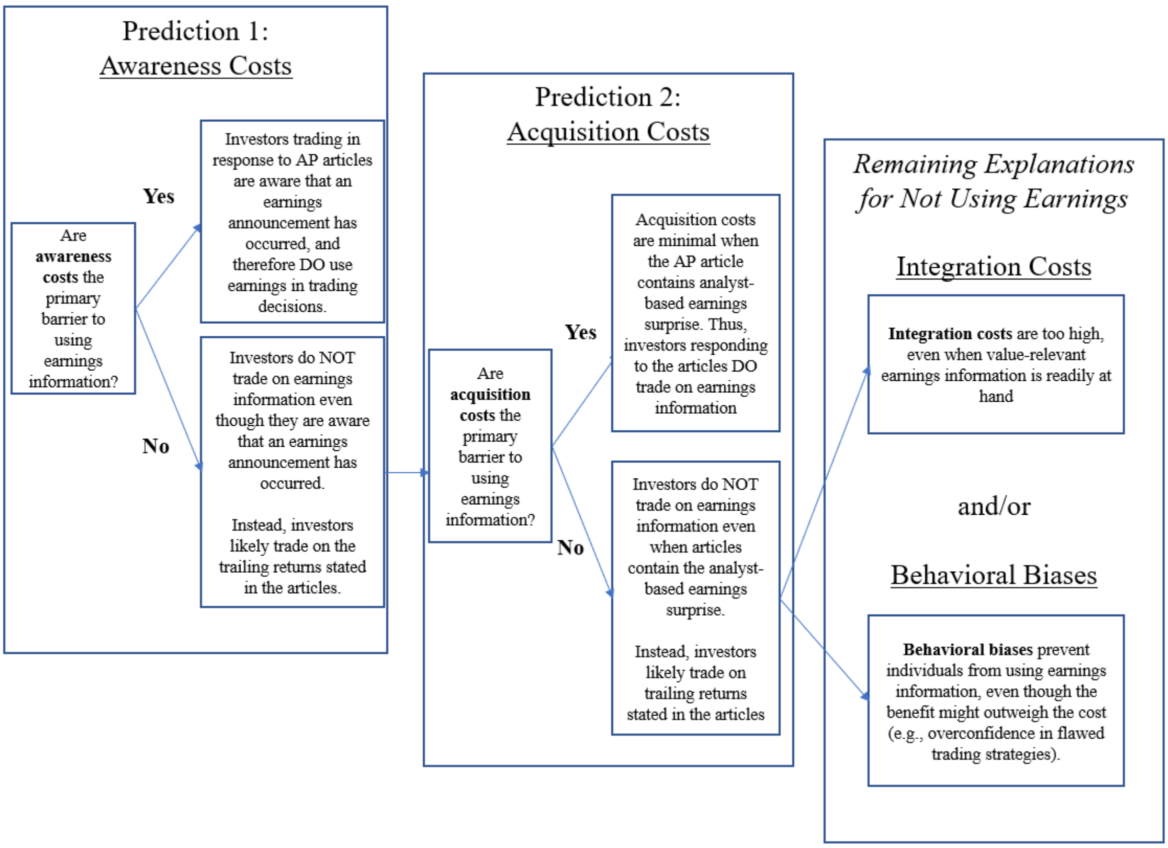
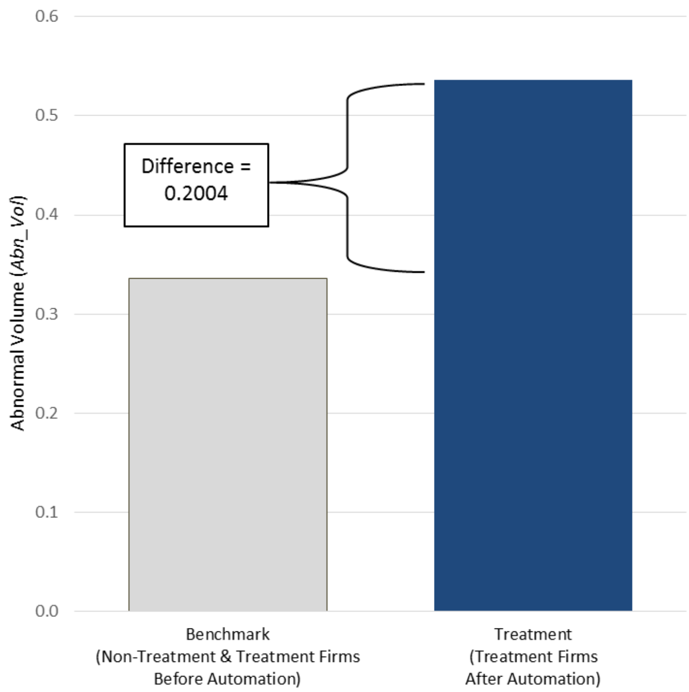


Figure 3: Visual Representation of Univariate Treatment Effect

Panel A displays the average *Abn_Vol* for benchmark and treatment firms to highlight the univariate average treatment effect across the full sample. Panel B then displays the average treatment effect separately for treatment observations with non-extreme or extreme *UE_Abs* and non-extreme or extreme *Ret_Abs*. See Appendix B for variable definitions.

Panel A: Average treatment effect for all firms



Panel B: Treatment effect – disaggregated by automated article contents

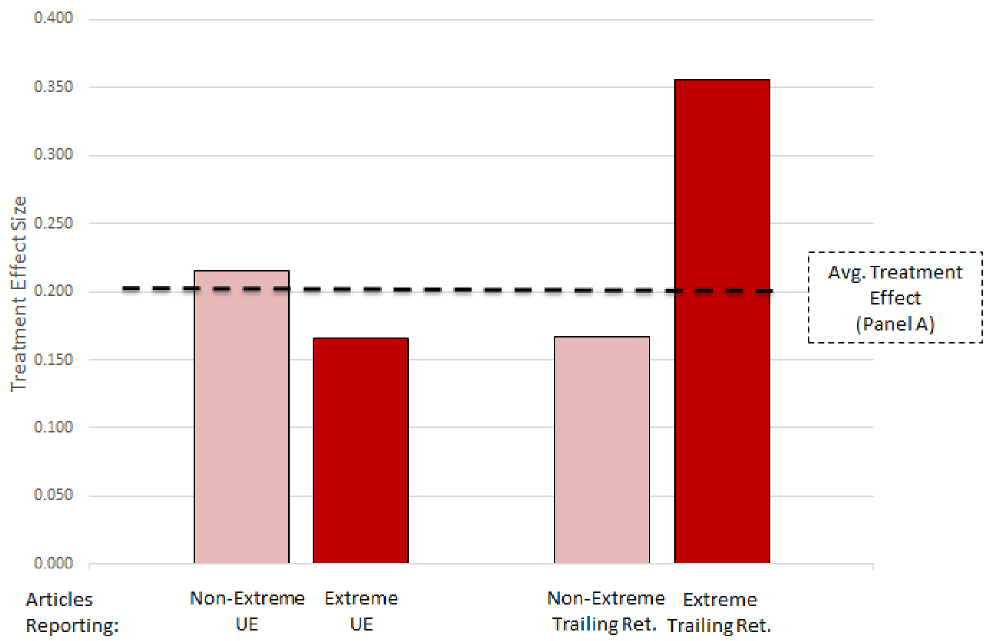


Table 1: Sample Summary Information

The sample includes 29,776 earnings announcements for 2,264 firms spanning January 1, 2012 through November 12, 2015. None of our sample firms received earnings media coverage from AP during the sample period preceding the beginning of automated articles on October 14, 2014. Panel A details our six groups of sample firms. Five groups correspond with the quarter in which they begin receiving automated AP earnings articles. The sixth group had not yet begun receiving automated articles by the end of the sample. Panel B presents summary statistics. All variables are defined in Appendix B. *Indicates that a decile ranking or logged specification is used in our analyses (as per Appendix B), but for descriptive purposes the summary statistics are presented using untransformed values.

Panel A: Groups of treatment and non-treatment firms

	Firms			**Market Value Equity**	
	N	**%**		**Mean**	**Median**
2014Q4 treatment firms	727	32.11%		1,401.17	631.10

2015Q1 treatment firms	457	20.19%		905.22	297.70
2015Q2 treatment firms	214	9.45%		581.35	166.35
2015Q3 treatment firms	65	2.87%		1,136.31	95.97
2015Q4 treatment firms	24	1.06%		2,504.00	162.19
Non-treatment firms	777	34.32%		1,718.77	51.83
Total	**2,264**			**1,333.93**	**252.71**

Panel B: Sample summary statistics

	N	Mean	Std. Dev.	P25	Median	P75
Abn_Vol	29,776	0.37	1.03	-0.05	0.11	0.45
Firm_Size	29,776	5.61	1.74	4.29	5.54	6.76
*UE_Abs**	29,776	0.022	0.063	0.001	0.004	0.015
*Ret_Abs**	29,776	0.26	0.28	0.07	0.17	0.33
Loss	29,776	0.34	0.47	0	0	1
BTM	29,776	0.75	0.72	0.31	0.61	0.98
*Analysts**	29,776	3.5	4.0	0	2	5
InstOwn	29,776	0.40	0.26	0.17	0.38	0.62
Volatility_Pre	29,776	0.43	0.26	0.25	0.36	0.53
Price	29,776	18.0	21.1	4.0	11.1	23.3
Dow_Article	29,776	0.02	0.16	0	0	0
*News_Flashes**	29,776	2.20	1.71	0	3	3

Table 2: Analysis of Awareness Costs

This table presents results of estimating models (1), (2), and (3), where *Abn_Vol* is the dependent variable. All variables are defined in Appendix B. Standard errors are clustered by firm and year-month. T-statistics are in parentheses. *** indicates significance at 1%; ** at 5%; and * at 10%.

	(i)	(ii)	(iii)
Dependent Variable	*Abn_Vol*	*Abn_Vol*	*Abn_Vol*
	Model 1	Model 2	Model 3
Post	0.134**	0.140**	0.096
	(2.69)	(2.57)	(1.33)
Post * UE_Abs		-0.002	
		(-0.21)	
Post * Ret_Abs		0.039***	
		(3.21)	
Post * Non-Extreme UE_Abs			0.001
			(0.09)
Post * Extreme UE_Abs			-0.018
			(-0.99)
Post * Non-Extreme Ret_Abs			0.013
			(0.95)
Post * Extreme Ret_Abs			0.084**
			(2.62)
Group & YearQtr fixed effects included?	Yes	Yes	Yes
UE and Ret Measures interacted with Group and YearQtr?	No	Yes	Yes
Observations	29,776	29,776	29,776
Adjusted R^2	0.026	0.042	0.045

Table 3: Analysis of Awareness Costs – Positive News, Negative News, Buys, and Sells

This table presents results of estimating an extension of model (3), where *Abn_BuyVol* and *Abn_SellVol* are the dependent variables and the earnings and returns signals are split based on sign. All variables are defined in Appendix B. Standard errors are clustered by firm and year-month. T-statistics are in parentheses. *** indicates significance at 1%; ** at 5%; and * at 10%.

	(i)	**(ii)**
Dependent Variable	*Abn_BuyVol*	*Abn_SellVol*
Post	0.050	0.047
	(1.42)	(1.46)
Post * Non-Extreme Positive UE_Abs	-0.000	0.001
	(-0.05)	(0.09)
Post * Non-Extreme Negative UE_Abs	-0.001	-0.004
	(-0.15)	(-0.44)
Post * Extreme Positive UE_Abs	-0.008	-0.010
	(-0.49)	(-0.71)
Post * Extreme Negative UE_Abs	-0.012	-0.014
	(-1.27)	(-1.13)
Post * Non-Extreme Positive Ret_Abs	0.006	0.009
	(0.73)	(0.96)

Post * Non-Extreme Negative Ret_Abs	0.007	0.008
	(1.09)	(1.10)
Post * Extreme Positive Ret_Abs	0.041**	0.039**
	(2.30)	(2.18)
Post * Extreme Negative Ret_Abs	0.024	0.021
	(1.22)	(1.07)
Group & YearQtr fixed effects included?	Yes	Yes
(Ret measures * Group) & (UE measures * Group) included?	Yes	Yes
(Ret measures * YearQtr) & (UE measures * YearQtr) included?	Yes	Yes
Observations	29,776	29,776
Adjusted R^2	0.053	0.050

Table 4: Analysis of Awareness Costs – Individual Traders Data

This table presents results of estimating model (3), where *Abn_IndivVol* is the dependent variable. All variables are defined in Appendix B. Standard errors are clustered by firm and year-month. T-statistics are in parentheses. *** indicates significance at 1%; ** at 5%; and * at 10%.

	(i)
Dependent Variable	*Abn_IndivVol*

	Model 3
Post	0.004
	(0.55)
Post * Non-Extreme UE_Abs	0.002
	(1.15)
Post * Extreme UE_Abs	-0.003
	(-0.97)
Post * Non-Extreme Ret_Abs	0.000
	(0.15)
Post * Extreme Ret_Abs	0.017***
	(4.10)
Group & YearQtr fixed effects included?	Yes
(Ret measures * Group) & (UE measures * Group) included?	Yes
(Ret measures * YearQtr) & (UE measures * YearQtr) included?	Yes
Observations	29,776
Adjusted R^2	0.035

Table 5: Analysis of Acquisition Costs

This table presents results of estimating model (4), where *Abn_Vol* and *Abn_IndivVol* are the dependent variables and the primary explanatory variables are partitioned by whether the costs of acquiring components of earnings news are low (*Low Acq Cost*) or high (*High Acq Cost*). Cost of acquiring information is low (high) when a pre-announcement analyst consensus is (is not) provided in the AP article. All variables are defined in Appendix B. Standard errors are clustered by firm and year-month. T-statistics are in parentheses. *** indicates significance at 1%; ** at 5%; and * at 10%.

	(i)			(ii)	
Dependent Variable	*Abn_Vol*			*Abn_IndivVol*	
	Model 4			Model 4	
	Low Acq Cost	*High Acq Cost*		*Low Acq Cost*	*High Acq Cost*
Post	0.091			0.004	
	(1.25)			(0.50)	
Post * Non-Extreme UE_Abs	-0.008	0.019*		0.002	0.002
	(-0.25)	(1.79)		(0.51)	(1.62)
Post * Extreme UE_Abs	-0.043	-0.010		0.001	-0.003
	(-0.80)	(-0.56)		(0.14)	(-1.04)
Post * Non-Extreme Ret_Abs	-0.003	0.015		-0.004	0.001
	(-0.09)	(0.97)		(-1.07)	(0.30)
Post * Extreme Ret_Abs	0.018	0.064**		0.008	0.015***
	(0.22)	(2.04)		(0.66)	(3.62)
Group & YearQtr fixed effects included?	Yes			Yes	
(Ret Measures * Group) & (UE Measures * Group) included?	Yes			Yes	
(Ret Measures * YearQtr) & (UE Measures * YearQtr) included?	Yes			Yes	
Observations	29,776			29,776	
Adjusted R^2	0.050			0.036	

Table 6: Implications of UE- and Momentum-Based Trading Strategies for Future Returns

This table presents future returns to UE- and momentum-based trading strategies. Abnormal returns (*Future_Abn_Ret [2, x]*) are calculated as the firm's return minus the mean return of a matched portfolio, as defined in Appendix B. Panel A presents unconditional average abnormal returns matching on (size and BTM) and (size, BTM, and momentum), measured over post-earnings holding windows ranging from [2, 3] to [2, 60]. Panels B and C examine abnormal returns based on size and book-to market matched benchmark portfolios. Panel D uses benchmark portfolios matched on size, book-to-market, and momentum. Standard errors are clustered by firm and year-week. T-statistics are in parentheses. *** indicates significance at 1%; ** at 5%; and * at 10%.

Panel A: Unconditional average abnormal returns

	Post-Earnings Holding Window						
	[2, 3]	**[2, 4]**	**[2, 5]**	**[2, 10]**	**[2, 20]**	**[2, 40]**	**[2, 60]**
Size and BTM adjusted	-0.134***	-0.099***	-0.069	0.005	0.069	0.173	0.189
	(-4.39)	(-2.59)	(-1.49)	(0.07)	(0.64)	(1.02)	(0.87)
Size, BTM, and Momentum adjusted	-0.123***	-0.090**	-0.064	0.009	0.065	0.129	0.103
	(-4.33)	(-2.54)	(-1.50)	(0.14)	(0.70)	(0.90)	(0.60)

Panel B: Momentum-Based Trading Strategy Returns – Abnormal returns based on firm size and BTM

	Post-Earnings Holding Window						
	[2, 3]	**[2, 4]**	**[2, 5]**	**[2, 10]**	**[2, 20]**	**[2, 40]**	**[2, 60]**
Portfolio							
Extreme Positive Returns	-0.319***	-0.380***	-0.522***	-0.262	0.340	0.153	0.192
	(-2.85)	(-3.11)	(-3.70)	(-1.32)	(1.04)	(0.26)	(0.28)
Non-Extreme Positive Returns	-0.064	-0.050	-0.017	0.087	0.166	0.592***	0.933***
	(-1.62)	(-0.98)	(-0.30)	(1.00)	(1.13)	(3.12)	(3.63)
Non-Extreme Negative Returns	-0.056	-0.011	0.069	0.049	0.005	-0.151	-0.266
	(-1.22)	(-0.20)	(1.00)	(0.47	(0.03	(-0.67)	(-0.87)

				)	)		
Extreme Negative Returns	-0.538***	-0.333	-0.306	-0.262	-0.461	-0.770	-1.916**
	(-3.25)	(-1.39)	(-1.13)	(-0.64)	(-0.78)	(-0.85)	(-1.99)
Long-Short Strategy Returns							
Extreme (Positive – Negative)	0.220	-0.047	-0.216	-0.001	0.801	0.923	2.108**
Test Statistic	(1.14)	(-0.18)	(-0.73)	(-0.00)	(1.16)	(0.96)	(1.99)
Non-Extreme (Positive – Negative)	-0.007	-0.039	-0.086	0.038	0.161	0.742***	1.199***
Test Statistic	(-0.14)	(-0.57)	(-1.01)	(0.33)	(0.80)	(2.71)	(3.32)

Panel C: UE-Based Trading Strategy Returns – Abnormal returns based on firm size and BTM

	Post-Earnings Holding Window						
	[2, 3]	**[2, 4]**	**[2, 5]**	**[2, 10]**	**[2, 20]**	**[2, 40]**	**[2, 60]**
Portfolio							
Extreme Positive UE	-0.033	0.085	0.368*	0.726**	1.388***	1.441**	1.242*
	(-0.29)	(0.58)	(1.93)	(2.56)	(2.98)	(2.30)	(1.66)
Non-Extreme Positive UE	-0.012	0.049	0.089*	0.141*	0.336***	0.590***	0.876***
	(-0.36)	(1.13)	(1.71)	(1.72)	(3.04)	(3.54)	(3.66)
Non-Extreme Negative UE	-0.208***	-0.193***	-0.212***	-0.134	-0.308**	-0.413*	-0.580**
	(-4.71)	(-3.25)	(-3.07)	(-1.23)	(-2.03)	(-1.88)	(-2.01)
Extreme Negative UE	-0.595***	-0.702***	-0.821***	-0.938***	-1.355***	-1.263**	-1.768**

	(-5.40)	(-5.41)	(-5.93)	(-4.10)	(-4.15)	(-2.05)	(-2.51)
Long-Short Strategy Returns							
Extreme (Positive – Negative)	0.562***	0.786***	1.189***	1.665***	2.744***	2.703***	3.010***
Test Statistic	(4.00)	(4.45)	(5.62)	(5.00)	(5.69)	(3.55)	(3.37)
Non-Extreme (Positive – Negative)	0.196***	0.242***	0.301***	0.275**	0.644***	1.002***	1.456***
Test Statistic	(4.03)	(3.59)	(3.93)	(2.58)	(4.04)	(4.18)	(4.49)

Panel D: UE-Based Trading Strategy Returns – Abnormal returns based on firm size, BTM, and pre-earnings momentum

	Post-Earnings Holding Window						
	[2, 3]	**[2, 4]**	**[2, 5]**	**[2, 10]**	**[2, 20]**	**[2, 40]**	**[2, 60]**
Portfolio							
Extreme Positive UE	0.015	0.138	0.432**	0.833***	1.456***	1.608***	1.494**
	(0.14)	(0.98)	(2.35)	(2.91)	(3.20)	(2.72)	(2.17)
Non-Extreme Positive UE	-0.019	0.037	0.070	0.093	0.242***	0.391***	0.555***
	(-0.59)	(0.90)	(1.45)	(1.30)	(2.77)	(2.61)	(2.81)
Non-Extreme Negative UE	-0.207***	-0.203***	-0.225***	-0.144	-0.284**	-0.441**	-0.676***
	(-4.87)	(-3.44)	(-3.31)	(-1.34)	(-1.99)	(-2.21)	(-2.67)
Extreme Negative UE	-0.505***	-0.583***	-0.705***	-0.748***	-1.100***	-0.829*	-1.038*

	(-4.57)	(-4.78)	(-5.29)	(-3.51)	(-3.43)	(-1.65)	(-1.65)
Long-Short Strategy Returns							
Extreme (Positive – Negative)	0.519***	0.721***	1.138***	1.581***	2.556***	2.437***	2.531***
Test Statistic	(3.78)	(4.12)	(5.33)	(4.54)	(5.13)	(3.27)	(2.76)
Non-Extreme (Positive – Negative)	0.188***	0.240***	0.295***	0.237**	0.526***	0.832***	1.231***
Test Statistic	(3.90)	(3.63)	(3.96)	(2.19)	(3.36)	(3.78)	(4.03)