Why do individual investors disregard accounting information?

The roles of information awareness and acquisition costs

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Abstract

Individual investors often fail to incorporate value-relevant accounting information into trading decisions, and they instead tend to underperform by trading on attention-grabbing technical trends. Many SEC regulations attempt to help individuals make better-informed trading decisions by decreasing their costs of monitoring and acquiring firms' accounting disclosures. We examine whether information awareness and acquisition costs are responsible for individual investors' neglect of accounting information. We do so using a unique archival setting where individual investors are presented with automated media articles that report both current earnings announcement news and past stock returns. Although these investors have value-relevant earnings surprise information readily at hand, we find no evidence that their trades incorporate earnings news. Instead we find that they trade in response to the trailing stock returns presented in the articles. Our study raises questions about the likely efficacy of regulations that aim to aid less sophisticated individual investors by increasing their awareness of, and access to, accounting information.

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1. Introduction

Prior literature finds that individual investors often fail to incorporate value-relevant accounting information into trading decisions (e.g., Lee 1992; Hirshleifer et al. 2008; Maines & Hand 1996; Ayers et al. 2011) and instead tend to underperform by trading on attention-grabbing trends and events (Barber & Odean 2013). Part of the motivation for SEC regulations such as FD and XBRL has been to help individuals make better-informed trading decisions by decreasing their costs of monitoring and accessing accounting information from firms' disclosures.[1] However, without understanding the specific frictions that prevent individuals from using accounting information in trading decisions, it is difficult to know whether regulations like these are likely to be effective in helping individuals. Our study provides evidence for this question by investigating why individual investors fail to incorporate earnings news into trades made around earnings announcements.

Whatever information set an investor is using, incorporating an incrementally informative signal improves the accuracy or precision of their valuations (Blackwell 1951; Vives 2008). Thus, assuming that accounting information is incrementally value-relevant (which we address below) and that investors aim to maximize risk-adjusted returns, we would typically expect investors to use accounting information in trading decisions. However, investors may disregard accounting information if the cost of using it outweighs the benefit (Grossman & Stiglitz 1980; Bloomfield 2002). As depicted in Figure 1, we describe three sequential steps to using accounting information in trading decisions, each of which involves distinct costs. Two of these

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[1] The SEC's Final Rules on FD and XBRL explicitly state that a primary motivation is to aid individual investors by reducing the cost of monitoring and accessing firms' disclosures. We do not argue these regulations were enacted *only* to reduce awareness and acquisition costs, or that their intended benefits are limited to individuals. Further discussion of SEC regulations is provided in Section 2.

types of information costs – awareness costs and acquisition costs – have been a particular focus of SEC regulations designed to aid individual investors. Our study examines the extent to which awareness and acquisition costs are binding constraints that prevent individuals from using accounting information in trading decisions.[2]

Awareness is a binary construct: an investor is either aware or unaware that information exists. "Awareness costs" acknowledge that monitoring for the existence of firms' disclosures is costly, where "disclosure" could refer to an entire report or a specific item within a report (Merton 1987; Hand 1990). Thus, one explanation for individual investors' neglect of accounting information is that, due to high awareness costs and limited resources, they are unaware that an accounting disclosure exists. Inattentive investors who are unaware of their informational disadvantage will continue to trade rather than withdrawing from the market (DellaVigna & Pollet 2009; Hirshleifer et al. 2011).

Once aware that an accounting disclosure exists, investors must expend resources to acquire information from the firm's report and supplementary sources such as analyst reports. Information is "acquired" once an investor has the information readily at hand in a useable format (Maines & McDaniel 2000; Bloomfield 2002). Examples of "acquisition costs" include the opportunity cost of the investor's time and mental capacity to obtain and read reports, or direct costs such as purchasing access to information (e.g., analyst reports or a Dow Jones feed).[3] In the presence of high acquisition costs, some investors refrain from trading while others continue trading using incomplete information or heuristics (Tversky & Kahneman 1974; Easley

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

[3] Some prior papers use the term "acquisition costs" as a label for information costs more broadly (e.g., Verrecchia 1982; Larcker & Lys 1987), which is different from the more specific definition we provide.

& O'Hara 2004). Thus, even when investors are aware that an accounting disclosure exists, high acquisition costs could prevent them from fully incorporating accounting information into their trading decisions.

Existing empirical research provides extensive evidence that awareness and acquisition costs are material frictions in the market pricing of accounting news. Several papers find that awareness costs prevent some investors from being aware of an accounting release, which delays the pricing of earnings news (DellaVigna & Pollet 2009; Hirshleifer et al. 2009; deHaan et al. 2015; Lawrence et al. 2016; Drake et al. 2016; Chapman 2017; Koester et al. 2016). Acquisition costs play a specific role in the literature examining differences in how small versus large investors respond to earnings announcements (e.g., Bhattacharya 2001; Battalio & Mendenhall 2005; Malmendier & Shanthikumar 2007). However, the majority of empirical papers examine outcomes that could be driven by either or both awareness and acquisition costs, without distinguishing between the two. For example, several papers conclude that the media's dissemination of public accounting information affects price responses (e.g., Twedt 2016; Rogers et al. 2016; Bushee et al. 2010; Tetlock 2011; Lawrence et al. 2018). Given that the media coverage in these papers is thought to provide no private information, the media's effect is likely through some combination of reducing awareness and acquisition costs. Similarly, Blankespoor et al. (2014) find that increased dissemination via Twitter improves liquidity, likely by reducing awareness and/or acquisition costs. The "information overload" literature finds that awareness and acquisition costs are material and have potentially increased in recent years (Eppler & Mengis 2004; Dyer et al. 2017; Chapman et al. 2017; Drake et al. 2017).

While awareness and acquisition costs have been found to affect price-setting market participants, it is less clear whether these costs are responsible for individual investors' under-use of accounting information. There are at least two other reasons why individuals might disregard value-relevant accounting information in favor of trading on technical trends, even in the absence of awareness and acquisition costs. The first is that individuals are constrained by a third type of information cost – "integration costs" – which include any costs necessary to evaluate, combine, and incorporate accounting information into valuation models and trading decisions (Hodge et al. 2004). For example, an individual who is unfamiliar with financial statements and their value relevance would find it extraordinarily costly to use accounting information. Because integration is "downstream" from awareness and acquisition, high integration costs may cause investors to forgo fundamental analysis even in the absence of awareness and acquisition costs.[4] A second, psychology-based explanation is that individual investors suffer from behavioral biases such as overconfidence in technical trading strategies, which lead them to incorrectly disregard accounting information even though the benefit of using it would outweigh the cost. In either case, regulations designed to reduce awareness and acquisition costs are unlikely to motivate these investors to use accounting information.

The primary challenge in disentangling the effects of awareness and acquisition costs from other frictions is that individual investors' information sets are typically unobservable. Our study uses a unique archival setting in which awareness and acquisition costs are reduced for a set of firms' earnings announcements. We isolate trading around those earnings announcements to capture trading by individual investors with known minimum information sets.

Our empirical approach uses the setting from Blankespoor, deHaan, and Zhu (2018, BDZ

[4] We do not discuss integration costs in detail for brevity, although integration costs have been the focus of many prior papers. For example: Hirshleifer et al. (2011); Cohen & Lou (2012); Miller (2010); Lawrence (2013); Hodge et al. (2004); Maines & Hand (1996); Maines & McDaniel (2000), Eppler & Mengis (2004); Chapman et al. (2017); Drake et al. (2017).

hereafter) of the Associated Press' (AP's) staggered rollout of nationally-distributed "robo-journalism" news articles of firms' earnings announcements. The existence and contents of these algorithmically-generated articles are largely exogenous to a firm's earnings announcement, and BDZ find evidence that these articles drive significant increases in trading by individual investors. Our study exploits the feature that all articles simultaneously present both the firm's current earnings news and trailing stock returns on a highly-standardized basis, which provides us the opportunity to examine individuals' choices of whether to trade on accounting information or technical trends when both are readily at hand.

Our first prediction addresses the role of awareness costs. We assume that the individual investors who trade in response to AP's automated articles are aware that an earnings announcement has taken place, thereby eliminating awareness costs as a friction for these traders. This assumption is supported by the fact that the headlines and bodies of all articles clearly identify that an earnings announcement has occurred. Therefore, if awareness costs are a primary barrier to using earnings information, we predict that investors who trade in response to AP articles will incorporate earnings news into their trading decisions (because awareness costs are eliminated). Alternatively, if lowering awareness costs is insufficient to motivate the use of earnings news, these investors will disregard earnings news in their trading decisions. Instead, consistent with extensive evidence that individual investors trade on technical trends (Grinblatt & Keloharju 2000; Barber & Odean 2008; Kaniel et al. 2008), we predict that these investors likely trade in response to the trailing returns presented in the articles.

Our second prediction examines the role of acquisition costs by exploiting variation across AP's automated articles: some articles provide information to easily calculate analyst-based earnings surprises, while others provide the current quarter's earnings without any benchmark. Investors responding to articles containing the analyst-based earnings surprise have a value-relevant earnings signal with minimal acquisition costs, while investors responding to the articles without analyst consensus must acquire some other benchmark or supplementary data. If acquisition costs are primarily responsible for individual investors' neglect of earnings information, we predict that investors who trade in response to AP articles will incorporate earnings news into their trading decisions when the analyst consensus is presented in the article (because acquisition costs are minimal). If reducing acquisition costs is insufficient to motivate the use of earnings news, these investors will continue to disregard earnings news and instead trade on the trailing returns presented in the article.

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 follow BDZ in using a generalized difference-in-differences (DID) model to isolate the abnormal 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 driven by the firm's earnings news versus trailing returns. We use the absolute earnings surprise as our measure of the firm's earnings news. Consistent with the information presented in the articles, we measure the firm's trailing stock returns excluding dividends and without a market adjustment. Our analyses fail to find any evidence that the incremental trading generated by the AP articles is associated with the firm's earnings news, even for large earnings surprises. Instead our tests find a strong association between the incremental trading and the trailing returns presented in the AP articles, consistent with individuals responding to the articles using technical analysis trading strategies. Together, these results provide no support for the idea that eliminating awareness costs will increase individual investors' use of earnings information. Analyses of Prediction 2 still find no evidence of investors trading on earnings surprises even when the analyst consensus is presented in the articles, which provides no support for the idea that reducing acquisition costs will increase individuals' use of earnings information. Meanwhile, we continue to find evidence of trading on trailing returns. Together, our results indicate that the individuals who trade in response to AP's articles choose to trade on technical trends and disregard value-relevant earnings news, even though awareness and acquisition costs are minimal.[5]

Our empirical setting has both strengths and limitations for investigating whether awareness and acquisition costs prevent individuals from using accounting information. One strength is that earnings news is highly value-relevant and relatively low-cost to integrate into trading decisions. Thus, our finding that individuals disregard earnings news suggests that reducing awareness and acquisition costs is even less likely to be effective for accounting disclosures that are less value-relevant or more complex. Still, we cannot be sure that our findings would generalize to other accounting disclosures. Another caveat is that our research design relies on the assumption that the strength of the empirical association between abnormal trading volume and earnings surprises captures the extent to which investors use earnings in trading decisions. This assumption and research design have extensive precedent (e.g., Woodruff and Senchack 1988; Bhattacharya 2001; Battalio & Mendenhall 2005; Cready & Hurtt 2002; Bhattacharya et al. 2007; Hirshleifer et al. 2008), but we acknowledge that they are imperfect.

[5] Tests in Section 6 ensure that, consistent with a large body of accounting research, earnings surprises are highly value-relevant within our sample.

Finally, the individual investors who trade in response to AP's articles are unlikely to represent all individual investors, but instead likely characterize less sophisticated investors who trade on attention-grabbing trends and events. While our results likely do not generalize to more sophisticated investors, the population of investors examined in this paper is not de minimis given that AP's automated articles drive a roughly 11% increase in trading volume (BDZ 2018).

Our first contribution is to inform discussions of whether and to what extent certain types of accounting regulations would affect individual investors' behavior. Understanding the trading behavior of individual investors is critical to designing, implementing, and evaluating effective investor protections (Leuz et al. 2017; SEC 2017c).[6] The SEC has a mandate to aid individual investors and often works to improve their awareness of, and access to, accounting information (SEC 2017a). However, the type of individual investor in our sample does not use accounting information even when it is readily available, indicating that regulations designed to reduce awareness and acquisition costs are unlikely to help a sizable population of individual investors. Given these results, possible alternative regulatory strategies might be: i) limit the intended scope of regulations to exclude individual investors who lack a minimum threshold of financial sophistication; ii) focus more efforts on reducing integration costs or mitigating behavioral biases; and/or iii) focus more efforts on education about the benefits of low-cost, buy-and-hold investment strategies in diversified index funds.[7]

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[6] Understanding individual investors' trading also contributes to academic literatures. Many studies find that individuals trade on past returns (e.g. Barberis et al. 2015; Hong & Stein 1999; Cutler et al. 1990; Barber & Odean 2013; Greenwood & Shleifer 2014). Our study takes a step toward explaining *why* individuals favor technical trading over fundamental analysis.

[7] We are unaware of any scope limitations for the types of individual investors that the SEC currently aims to aid. This is in contrast to the FASB, which states that they design 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.

Our second contribution is to propose a unified framework based on prior literature for thinking about how types of information costs affect investors' use of accounting information in decision-making. Our framework involves three sequential steps to using accounting information - awareness, acquisition, and integration - each of which involves distinct costs (see Figure 1). While information costs as a broad construct play a central role in the accounting and finance literatures, they are often described with heterogeneous labels and without differentiating types of costs. Our framework on specific frictions that affect accounting usage should facilitate future research and help regulators devise interventions to mitigate those frictions.

Our third contribution is to help reconcile inconsistent results in the existing media literature. Several studies find that media coverage by specialized business newswires such as Dow Jones 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 incorporate accounting information into price (BDZ 2018, Lawrence et al. 2018). Our study helps explain these inconsistent results by finding that mainstream media coverage of earnings announcements motivates trading on non-accounting signals, which therefore increases volume and liquidity without speeding the pricing of accounting news. These findings provide insight into 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 been a longstanding priority of the SEC, which was reinforced by the Dodd-Frank Act's creation of the SEC Office of Investor Advocate in 2010. As stated by SEC Chairperson Mary Jo White in 2014: "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."[8] A significant component of the SEC's strategy to protect and aid individuals has been enacting regulations to reduce awareness and acquisition costs to put individual investors on more equal footing with their professional counterparts.

Over the past two decades, Regulation FD is likely the SEC's most significant attempt to protect individual investors by reducing information awareness and acquisition costs. FD prohibits firms from disclosing material information "to securities analysts or selected institutional investors or both, before making full disclosure of the same information to the general public" (SEC 2000, p. 2). The primary intended beneficiary is "individual investors" because selective disclosure "puts them at a severe disadvantage in the market" (p. 3). FD was intended not only to increase individual investors' awareness that information exists, but also to reduce their acquisition costs by giving them direct access to public filings and conference calls. Of course, FD likely also benefited many non-individual investors, both directly as well as indirectly, by reducing adverse selection concerns and improving liquidity.

As another example, a major motivation for implementing XBRL was to reduce awareness and acquisition costs.[9] XBRL requires firms to electronically tag information in filings so that it can be extracted using computer code instead of manual searches. For awareness costs, the SEC intended XBRL to create "greater investor awareness" not only of a filing's existence, but also of specific information embedded within "footnotes and supplemental tables, as well as the base financials reported in the standard tables" (SEC 2009, p. 127). XBRL was expected to reduce acquisition costs by eliminating the need to hand collect data or purchase it

[8] 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" throughout this paper.
[9] Again, we do not argue that XBRL was enacted *only* to reduce awareness and acquisition costs. XBRL also has the potential to reduce information integration costs (Blankespoor 2016; Bhattacharya et al., 2017).

from intermediaries. Again, while XBRL likely has direct and indirect benefits for all investors, a particular motivation was to aid individual investors by giving them "fewer informational barriers that separate them from larger investors with greater financial resources" (p. 129).

Very recently, two SEC regulations have been designed to reduce awareness and acquisition costs. The first is the SEC's requirement to hyperlink exhibits within filings. This final rule notes that "hyperlinks will help investors […] access a particular exhibit more efficiently as they will not need to search within the filing or through different filings made over time to locate the exhibit" (SEC 2017b, p. 24). Expected benefits of the new regulation include "more effective monitoring" and "more informed investment and voting decisions" (p. 25). Second, a proposed rule to eliminate and/or simplify redundant disclosures aims to reduce awareness and acquisition costs without significantly altering the information provided (SEC 2016). Finally, the SEC's emphasis on plain language disclosures is also an attempt to reduce investors' costs of accessing information from filings, especially for less sophisticated investors who are "neither lawyers, accountants, nor investment bankers" (SEC 1998, p. 3; SEC 2007).

In sum, while aiding individual investors by reducing information awareness and acquisition costs is not the only intended benefit of SEC regulations, it is frequently discussed as a primary motivation for regulations.

3. Empirical Setting and Predictions

Our empirical setting borrows heavily from BDZ, and we refer readers to that paper for additional details. Section 3.1 summarizes the most important aspects of AP's automated articles for our research question. Section 3.2 develops our empirical predictions.

3.1. Empirical Setting

In October 2014, the Associated Press (AP) began using automated "robo-journalism" technology to write articles about firms' earnings releases. Zacks provides the data used to write the robo-journalism articles, including information from the firm's earnings announcements, analyst reports, and the stock market. 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 the articles in print and online. AP began rolling out automated articles in October 2014, covering over 4,000 U.S. public companies per quarter by the end of 2015.

Appendix A provides an example of an automated article for a typical company in our sample with a market capitalization of approximately $200M. The article includes the firm's reported earnings (both GAAP and adjusted), the pre-announcement analyst consensus, and the firm's raw stock returns over the last twelve months and year-to-date. AP distributed the article 2.5 hours after the earnings announcement and, as with all of AP's earnings articles, it was immediately republished on Yahoo Finance. Although we do not have complete data on outlets that republished AP's articles, RavenPack shows that the articles for this company are at least republished on *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, in a setting where the existence of the articles is largely exogenous to the firm's earnings news. Using generalized DID models, BDZ find significant increases in trading volume following the implementation of automated 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. In particular, sophisticated investors can obtain the information more quickly from the original sources, data providers such Zacks, and subscription outlets such as 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.[10] Second, BDZ find increased volume in a sample nearly certain to be individuals' trades. Third, the increased volume is accompanied by an increase in depth, which indicates that depth-setting market participants are not concerned that the increase in trading is driven by sophisticated investors with private information.

AP's automated articles have three helpful features for investigating our research question. First, the articles induce an identifiable increase in individual investor trading. Second, investors trading on the AP articles are presented with both the current earnings news and trailing stock returns, which allows us to compare investors' use of value-relevant accounting information to their use of technical trends. Third, a subset of articles includes the analyst consensus to calculate the earnings surprise while others provide only current earnings, creating variation that allows us to examine acquisition costs separately from awareness costs.

3.2. Empirical predictions

Our predictions examine the extent to which individuals use earnings and other information in trading decisions. Many prior 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).[11] Analytical models provide several reasons why larger earnings surprises are more informative and drive more trading (e.g., Karpoff 1986; Holthausen & Verrecchia 1990; Kim & Verrecchia 1991; Bamber et al. 2011). Thus, following

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

[11] As noted by Holthausen and Verrecchia (1990): "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).

prior studies, we use the correlation between 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 in trading decisions. Our predictions are depicted in Figure 2.

Our first prediction examines awareness costs. We assume that investors who observe an AP article are aware that an earnings announcement has taken place. If awareness costs are typically a binding constraint, then investors who choose to trade in response to the AP article will incorporate earnings news into their trading decisions; i.e., they will invest the resources necessary to acquire and integrate the earnings information. If lowering awareness costs is insufficient to motivate the use of earnings information, those investors will either refrain from trading or they 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), potentially because the representativeness heuristic motivates investors to believe that return trends will continue or reverse in a predictable fashion (Griffin & Tversky 1992; Barberis et al. 1998). In addition, investors likely understand what a return represents, so trailing returns are likely to elicit a response from processing-constrained investors searching for trends. Thus, if investors disregard earnings news, we predict they instead focus on the trailing returns presented in the AP articles.

> <u>*Prediction 1*</u>*: If awareness costs are primarily responsible for individual investors' neglect of earnings information, then incremental trading generated by automated articles* ***will be*** *correlated 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 be*** *correlated with earnings surprise, and instead will correlate with the magnitude of the trailing returns stated in the articles.*

Our second prediction investigates acquisition costs. All articles provide the current EPS.

AP's algorithm only includes the pre-announcement analyst consensus when Zacks has at least three analyst forecasts.[12] 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.

> <u>Prediction 2</u>: *If acquisition costs are a primary barrier to individual investors using earnings information, then incremental trading generated by automated articles **will be** correlated with the size of the earnings surprise when the analyst consensus is presented 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 be** correlated with earnings surprise even when the analyst consensus is presented in the article, and instead will correlate with the magnitude of the trailing returns stated in the articles.*

4. Sample Construction

Our sample construction follows BDZ. The primary dataset is an index of earnings news articles by AP between 1/1/2012 and 11/12/2015. 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 both before and after AP began distributing automated articles.

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[12] Within our data, 94% of articles comply with this rule. We were unable to 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 non-complying articles provides 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. Also, we note that pre-announcement analyst coverage is not exogenous. Section S8 of the Supplementary Materials discusses potential concerns due to non-random analyst coverage, and why we do not view these concerns as significant threats to our conclusions or contribution.

Consistent with BDZ, we retain only firms that received zero earnings-related articles from AP before the beginning of automation in October 2014. These firms likely 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 errors occasionally delay article creation long enough that AP chooses not to distribute it. To maintain our sharp DID design, we follow BDZ in dropping 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 and 29,776 earnings announcements.

Panel A of Table 1 shows how many firms 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 "non-treatment 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 $1.3B ($253M), 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, we use the correlations between trading volume and each of unexpected earnings and trailing returns to gauge the extent to which investors use each signal in trading decisions.

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 individual investors to discover and respond to the AP articles and because BDZ (2018) find evidence of heightened trading through two days after the announcement.[13]

In firm-quarters where analyst forecast data is 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 twelve months as well as year-to-date. It is not obvious which return is most relevant to investors, so we measure stock performance as the average of the two returns. 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. Analyses in the Supplementary Materials examine alternate specifications of both variables.

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 generalized 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.

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[13] Analyses in the Supplementary Materials find qualitatively unchanged results using shorter and longer windows.

We next examine which articles drive this 0.20 treatment 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), we should observe that the treatment effect is 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 are both similar to 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 the effect 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 (although these point estimates shrink to 10%-14% and 34%, respectively, in our regression tests). This concentration of treatment effect is consistent with readers using trailing returns to inform their trades. We formally test these findings below.

5.2 Initial model setup - isolating trading volume driven by automated articles

We first use models from BDZ to isolate the incremental trading volume generated by the AP articles around earnings announcements:

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

Group are fixed effects for each group of staggered treatment and non-treatment firms (e.g., 2014'Q4 firms, 2015'Q1 firms) and eliminate average differences in *Abn_Vol* across the groups.[14] *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 yet begun receiving articles. Assuming parallel trends in *Abn_Vol* between *Groups* in the absence of AP articles, β_1 is a point estimate of the incremental trading volume generated by these articles.[15] Column (i) of Table 2 presents results of estimating model (1). Like BDZ, the *Post* coefficient is positive and significant, consistent with automated AP articles driving an increase in trading volume.

5.3 Analyses of Prediction 1

We next incorporate *UE_Abs* and *Ret_Abs* to examine whether the incremental trading generated by automated articles is correlated with earnings news versus trailing returns.

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

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*

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[14] The generalized DID model requires group and time fixed effects. Like Gipper, Leuz, and Maffett (2016), 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).

[15] BDZ find no differences in trends in *Abn_Vol* between treatment and non-treatment groups prior to the beginning of automated AP articles, which provides support for the parallel trends assumption. Analyses of pre-treatment trends for our model extensions below can be found in the Supplementary Materials.

and earnings surprises to vary by quarter. Interactions between *Ret_Abs* and each of $Group_n$ and $YearQtr_q$ perform similar functions.[16] *UE_Abs* and *Ret_Abs* are de-meaned so that main effects of interacted variables can be interpreted at the sample averages.

β_1 now estimates the average increase in trading volume generated by automated AP articles, *conditional* on average values of *UE_Abs* and *Ret_Abs*. The interaction between *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 to inform their trades, we expect $\beta_2 > 0$. We expect $\beta_2 = 0$ if incremental traders disregard earnings.[17] Similarly, the interaction *Ret_Abs *Post* estimates the extent to which the incremental trading generated by the AP 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 is insignificantly different from zero, which is inconsistent with investors responding to the AP article 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 decisions. Rather, investors responding to the AP articles appear to rely on returns-based technical strategies.

Model (2) imposes a linear relation between *Abn_Vol* and *UE_Abs*, but prior research finds that extreme earnings surprises generate a disproportionate amount of trading.[18] Thus, we

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[16] Note that the main effects of *UE_Abs* and *Ret_Abs* are absorbed by the fixed effect interactions.
[17] 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 investors from making trades they otherwise would have.
[18] Individual investors likely respond more to larger earnings surprises because large surprises cause more belief revision or because they 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.

modify (2) to examine whether extreme earnings surprises motivate investors to use earnings news. Following Hirshleifer et al. (2008), the variable *Extreme UE_Abs* is equal to *UE_Abs* for quarters with signed *UE* in the top or bottom decile. *Non-Extreme UE_Abs* is equal to *UE_Abs* for other firm-quarters. We similarly define *Extreme Ret_Abs* and *Non-Extreme Ret_Abs* based on signed *Ret*.

$$
\begin{aligned}
Abn\_Vol = {} & \beta_1 Post \\
& + \beta_2(Non\text{-}Extreme\ UE\_Abs * Post) + \beta_3(Extreme\ UE\_Abs * Post) \\
& + \beta_4(Non\text{-}Extreme\ Ret\_Abs * Post) + \beta_5(Extreme\ Ret\_Abs * Post) \\
& + \Sigma\beta_n Group_n \\
& + \Sigma\beta_n(Non\text{-}Extreme\ UE\_Abs * Group_n) + \Sigma\beta_n(Extreme\ UE\_Abs * Group_n) \\
& + \Sigma\beta_n(Non\text{-}Extreme\ Ret\_Abs * Group_n) + \Sigma\beta_n(Extreme\ Ret\_Abs * Group_n) \\
& + \Sigma\beta_q YearQtr_q \\
& + \Sigma\beta_q(Non\text{-}Extreme\ UE\_Abs * YearQtr_q) + \Sigma\beta_q(Extreme\ UE\_Abs * YearQtr_q) \\
& + \Sigma\beta_q(Non\text{-}Extreme\ Ret\_Abs * YearQtr_q) + \Sigma\beta_q(Extreme\ Ret\_Abs * YearQtr_q) \\
& + \varepsilon
\end{aligned}
\tag{3}
$$

Each information variable (e.g., *Extreme* and *Non-Extreme UE_Abs*) 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 (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 trade in response to extreme trailing returns.[19]

<u>*5.3.1. Additional analyses: positive news, negative news, buys and sells*</u>

Results in Table 3 further investigate trading along two dimensions. Our analyses are based on extensions of model (3) because it is likely better specified than (2). First, we

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[19] Section S4 of the Supplementary Materials investigates extensions of models (3) and (4) with control variables.

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 measures 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. An important 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. 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 are 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 method in Boehmer, Jones, & Zhang (2017). This set of trades does not include nonmarketable limit orders or any orders fulfilled on an exchange, so it has a low type I error rate but a high type II error rate (i.e., trades identified as individuals are likely correct, but 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; we find significant coefficients for extreme trailing returns but not for earnings.

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 articles without a benchmark are designated as high acquisition cost (*HighAcqCost*). We partition the benchmark 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 significant barrier to investors' use of earnings information. In contrast, continuing to find 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). Columns (ii) repeats (i) but uses *Abn_IndivVol* as the dependent variable. Across the two models, there is little evidence that investors respond to earnings, regardless of whether the components of earnings news are readily available in the articles or not. The coefficient on *HighAcqCost Non-Extreme UE_Abs*Post* is significantly positive at 10% in column (i) but is insignificant in model (ii). These results indicate that reducing information acquisition costs is not enough to motivate these investors to use earnings news.[20] Turning to returns, our models find that the association between trading volume and extreme trailing returns is concentrated in the *HighAcqCost* firms.[21]

6. Profits to Trading on UE and Past Returns

This section investigates potential 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 from the articles. 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 around the earnings announcement would be better off trading on earnings information.[22]

If momentum returns are compensation for risk, then returns to a momentum-based strategy are not "abnormal." Thus, we must assume that momentum is not a risk factor in calculating abnormal returns. 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, which is similar to Daniel et al. (1997) but without momentum.

Panel A of Table 6 presents the unconditional average post-earnings 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. A long-short strategy based on extreme positive versus negative trailing returns generates

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[20] Given that the analyses in Section 5.2.2 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.
[21] 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.
[22] 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. See further discussion in the Supplementary Materials.

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 the transaction costs likely incurred, these results are consistent with prior findings that individual investors trade “too much” (Odean 1999).

Panel C of Table 6 presents 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 they 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 twelve-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 take a step toward investigating the extent to which awareness costs and acquisition costs are primarily responsible for individual investors' under-use of earnings information while trading around earnings announcements.

Our tests are based on an archival setting where individual investors are presented with both earnings announcement news and trailing returns. Despite having value-relevant earnings surprises readily at hand, the investors in our sample disregard earnings and instead trade in response to extreme trailing returns. Disregarding earnings even in the absence of awareness and acquisition costs indicates that the under-use of accounting information is due to high integration costs and/or behavioral biases. While our sample likely includes less sophisticated individuals and may not generalize to more sophisticated individuals, our sample is large and thus is relevant for consideration by academics and regulators. Our findings indicate that regulations designed to reduce awareness and acquisition costs are unlikely to benefit the types of investors appearing in our sample. Alternative regulatory strategies might be to limit the scope of regulations to exclude individual investors who lack a minimum threshold of financial sophistication, increase efforts to mitigate investors' integration costs or behavioral biases, and/or increase efforts to educate investors about the benefits of low-cost investments in diversified index funds.

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Appendix A: Example Article

Below is the automated AP article following Inventure Foods' earnings announcement at approximately 8 AM on 10/30/14.

Inventure Foods misses Street 3Q forecasts

Inventure Foods posts 3Q profit, results miss Street Expectations

October 30, 2014 10:40 am

PHOENIX (AP) _ Inventure Foods Inc. (SNAK) on Thursday reported net income of $3.1 million in its third quarter.

The Phoenix-based company said it had profit of 15 cents per share. Earnings, adjusted for non-recurring gains, were 11 cents per share.

The results did not meet Wall Street expectations. The average estimate of analysts surveyed by Zacks Investment Research was for earnings of 13 cents per share.

The snack maker posted revenue of $72.6 million in the period, also missing Street forecasts. Analysts expected $73.6 million, according to Zacks.

Inventure Foods shares have climbed 2 percent since the beginning of the year. The stock has increased 19 percent in the last 12 months.

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This story was generated by Automated Insights using data from Zacks Investment Research. SNAK stock research report from Zacks.

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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 (2001) convention, which classifies a trade as a liquidity-demander "buy" when the trade price is greater 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 buys for all CRSP firms.	TAQ, CRSP
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 (2001) 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.	Thomson
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 upper portion of this Figure depicts the three sequential steps to using accounting information 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.

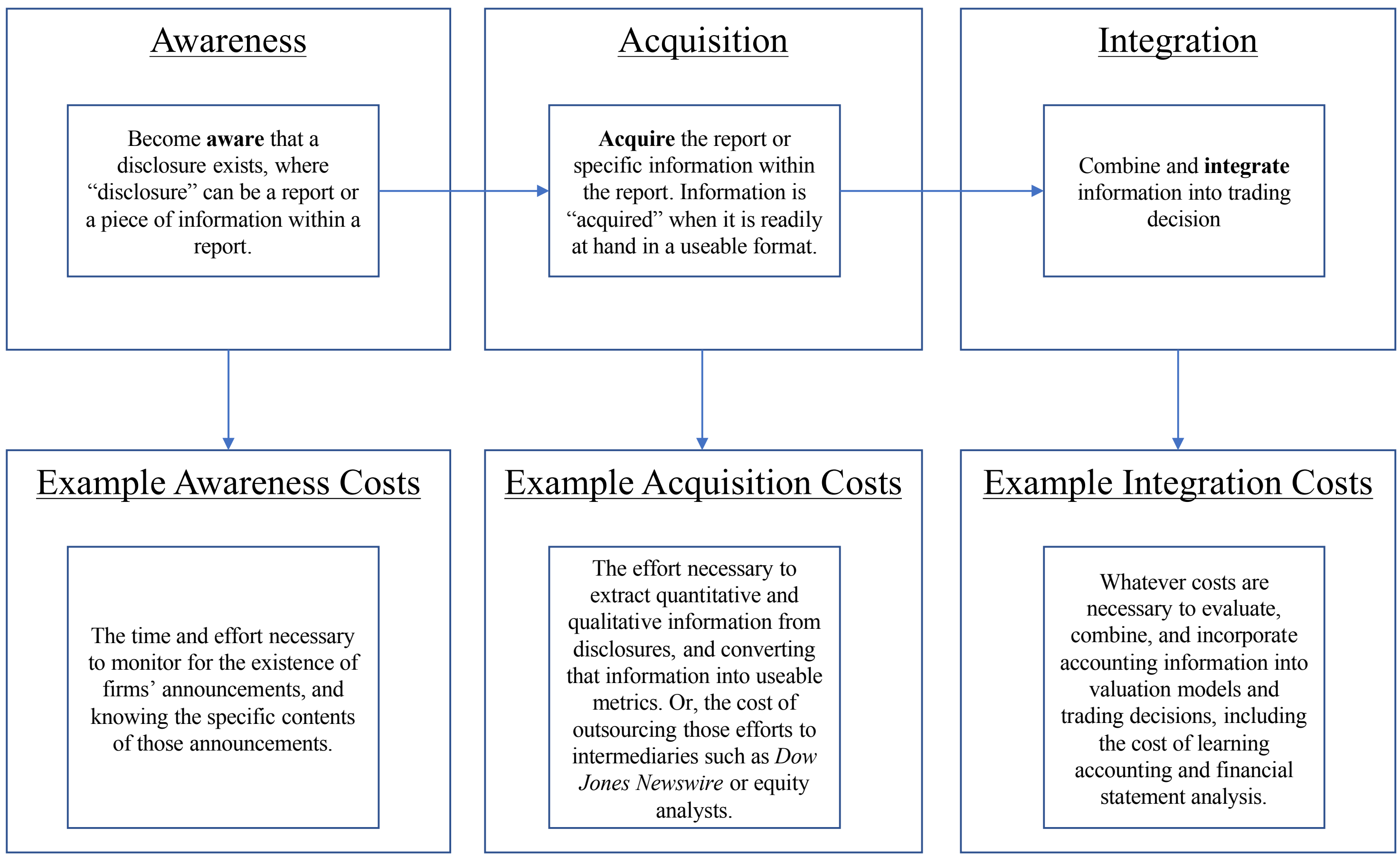


Figure 2: Predictions Based on the Information Costs Framework

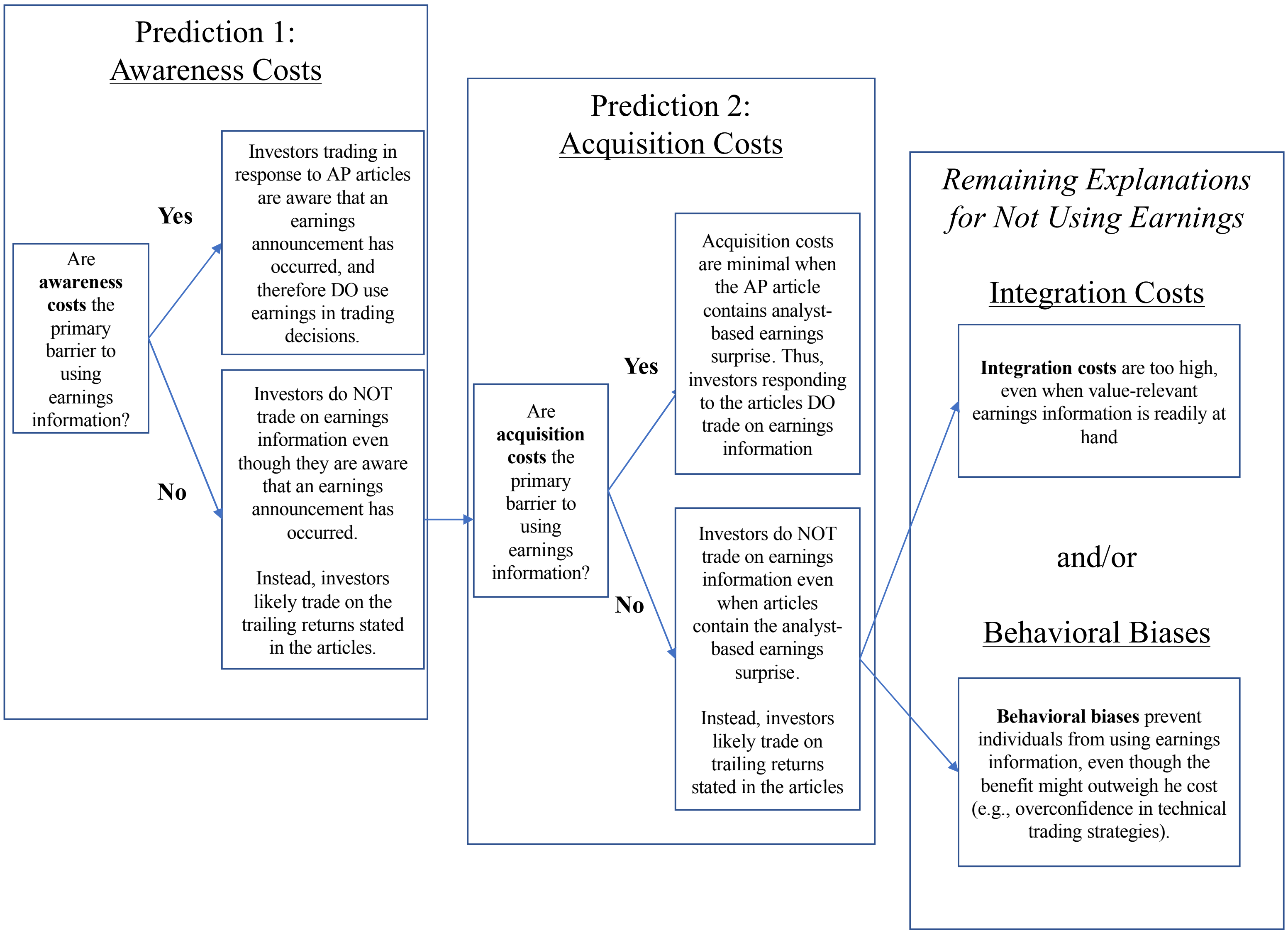
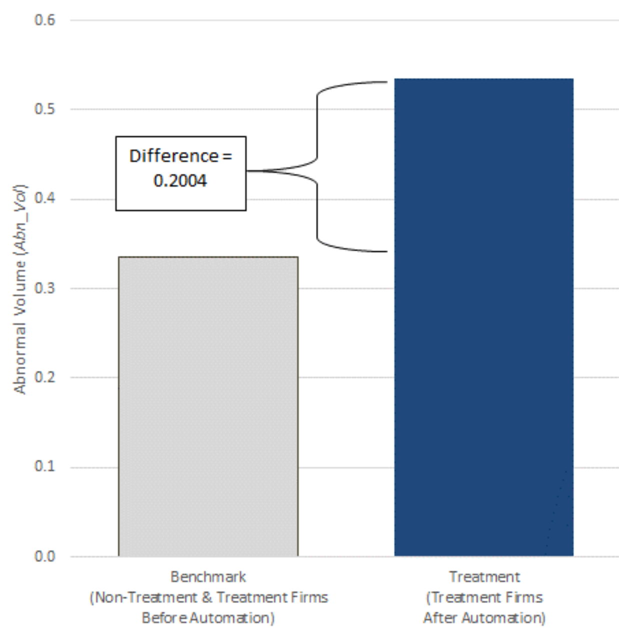


Figure 3: Visual Representation of Univariate Treatment Effect

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

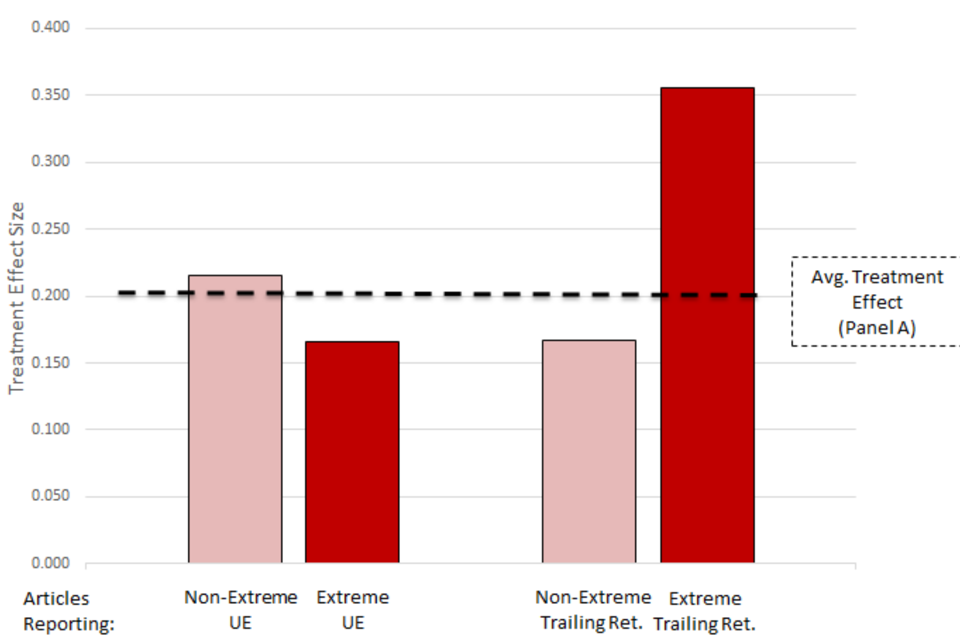


Table 1: Sample Summary Information

The sample includes earnings announcements for 2,264 firms (29,776 earnings announcements) 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) Model 1	(ii) Model 2	(iii) 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 (1.42)	0.047 (1.46)
Post * Non-Extreme Positive UE_Abs	-0.000 (-0.05)	0.001 (0.09)
Post * Non-Extreme Negative UE_Abs	-0.001 (-0.15)	-0.004 (-0.44)
Post * Extreme Positive UE_Abs	-0.008 (-0.49)	-0.010 (-0.71)
Post * Extreme Negative UE_Abs	-0.012 (-1.27)	-0.014 (-1.13)
Post * Non-Extreme Positive Ret_Abs	0.006 (0.73)	0.009 (0.96)
Post * Non-Extreme Negative Ret_Abs	0.007 (1.09)	0.008 (1.10)
Post * Extreme Positive Ret_Abs	0.041** (2.30)	0.039** (2.18)
Post * Extreme Negative Ret_Abs	0.024 (1.22)	0.021 (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) 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 or high. 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) *Abn_Vol* Model 4		(ii) *Abn_IndivVol* 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	
Controls & Interactions included?	No		No	
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)