Out of the office: Market impacts of professional inattention

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Abstract

Research has long recognized that professional investors possess significant information processing advantages, which become particularly acute during firm information events. We examine how a shock to professional attention, identified using annual Chartered Financial Analyst (CFA) conferences that draw buy-side analyst attendance, impacts information processing. We first validate the setting by showing reductions in the quality of sophisticated trades during earnings announcements that coincide with CFA conferences. Consistent with theory, we find that professional inattention prompts reductions in information asymmetry between investors and improvements in liquidity at these earnings announcements. We observe similar results for non-earnings announcement events that coincide with CFA conferences. Finally, we document slower price formation and more profitable retail trading during these events. In sum, we provide novel evidence that professional inattention during firm information events likely benefits retail traders.

1. Introduction

Professional buy-side analysts play a significant role in how information is incorporated into price. These experts not only provide investment advice to clients but also trade on behalf of their clients or for their brokerage. As investment professionals, buy-side analysts are generally considered to be sophisticated market participants that play important roles in ensuring information is efficiently incorporated into price, particularly at significant information events. However, they also possess significant information processing advantages, which may disadvantage less sophisticated investors. In this study, we explore the market implications of professional investor "inattention." We do so by identifying a plausibly exogenous shock to buy-side analyst attention induced by a popular valuation conference for Chartered Financial Analysts (CFAs).

While this question is interesting in its own right, our study is also motivated by concerns expressed by regulators, investors, and academics about fairness in capital markets. One of the primary objectives of the Securities and Exchange Commission (SEC) is to create and maintain a level playing field across different types of investors, which includes efforts to protect all traders. This has become increasingly difficult with the massive influx of hedge funds over the past few decades, the rise of high-frequency and algorithmic trading, and the emergence of dark pool trading. In fact, many argue that it is fruitless for retail investors to try to compete in an environment where they cannot match the resources, speed, or time allocation of their professional investor counterparts (e.g., Locke 2022). Somewhat paradoxically, these same buy-side investors play a critical role in promoting efficient price formation (e.g., Jiang et al. 2012). While research has examined the ramifications of inattention of *less* sophisticated investors (e.g., Michels 2024), our setting is unique in that it allows us to explore the ramifications of professional inattention.

The annual CFA Equity Research and Valuation Conference (hereafter CFA conference) provides plausibly exogenous shocks to buy-side analyst attention and influence. These conferences are targeted at buy-side analysts with the goal to keep analysts "abreast of the latest advances and developments in equity research techniques, valuation, and portfolio management" (CFA 2019). We argue that the event exogenously decreases the influence of these analysts in markets. To increase the power of our tests, we rely on days when the conference overlaps with an important value-relevant event, quarterly earnings announcements (EAs), where theory and empirical evidence suggest professional investors play an outsized role in information processing (e.g., Kim and Verrecchia 1994; Amiram et al. 2016; Gomez et al. 2024). In sum, this setting provides a relatively novel look into what happens in markets when the influence of professional analysts is exogenously reduced.

Our empirical tests are motivated by Kim and Verrecchia (1994), which shows that when a group of informed investors participate in the processing of significant information events, like earnings announcements, information asymmetry increases due to market makers' attempts to shield themselves from adverse selection risk. This in turn attenuates trading and reduces liquidity. Intuitively, this theory suggests that inattention by professional investors should lessen these effects. In other words, if the information processing capabilities of professional investors are reduced during CFA conferences, this could manifest in lower information asymmetry between informed and uniformed investors. Importantly, this argument does not require less informed investors to be aware of professional inattention, but merely requires the relative advantage of informed traders to be diminished.

However, it is important to acknowledge that prior research provides evidence of capital market benefits from active participation by professional investors, including short sellers (Boehmer et al. 2013), hedge funds (Chen et al. 2020), and other institutional investors (Akbas et al. 2015; Chordia et al. 2014; Green et al. 2011). These benefits include improved price efficiency and reduced mispricing (also see Kokkonen and Suominen 2015, Sias et al. 2016, and Chen et al. 2019). Further, prior research suggests that less sophisticated, retail investors are often not well informed (Cohen et al. 2002; Barber and Odean 2002; Choi and Sias 2012), increase volatility due to noise trading (Foucault et al. 2011), and tend to be net buyers at EAs no matter the news (Lee 1992; Michels 2024). Thus, professional inattention may have adverse effects on overall efficiency despite creating a more level playing field.

To examine the effects of professional inattention, we identify CFA conference dates occurring between 2012 and 2019. The conferences we examine occur in the last calendar quarter of the year, ranging from November 6 to December 7. To validate that CFA conferences induce professional investor inattention, we first examine changes in the quality of institutional trades during EAs that coincide with CFA conferences.[1] Using two proxies for professional trading, we observe declines in trade quality, evidenced by how the proxies for trading map into future returns. This evidence validates that CFA conferences induce the expected shock to professional attention.

We investigate our research question using a treatment sample of 5,127 EAs occurring around CFA conferences and a control sample comprising EAs in the adjacent two-week window surrounding each conference event. Our staggered research design offers extensive coverage of treatment and control firms across multiple market outcomes, with the majority of treated firms experiencing the intervention only once—a characteristic arising from the largely independent timing of CFA conferences and earnings announcements.

Our primary analyses focus on the EA market outcomes that are most likely affected by professional inattention. Specifically, Kim and Verrecchia (1994) suggests that when relatively fewer informed investors trade around EAs, the information disadvantage of uninformed investors should be muted. If this is the case, we should observe lower information asymmetry, higher market liquidity,

[1] We also consider changes in trading volume, including volume likely initiated by professional investors. We find some evidence of market-wide declines in volume, though evidence for trading likely initiated by institutional investors is weak. However, our conversations with buyside analysts suggest that backups are usually identified in the event a primary analyst is absent. Therefore, it is plausible we observe limited evidence in decisions to trade (i.e., volume), but stronger evidence of lower quality trades.

and lower trading volume. Consistent with theory, we find strong evidence of smaller abnormal spreads and higher abnormal depth for treated EAs compared to control EAs. Additionally, we observe weaker evidence of reduced abnormal volume for treated EAs. Collectively, this evidence suggests that the information gap between more informed, sophisticated investors and presumably less informed, unsophisticated investors is significantly smaller for EAs that occur during the CFA conference compared to those that do not.

CFA conferences are not randomly scheduled, and descriptive evidence suggests they may be strategically timed to coincide with relatively quiet EA periods. To address concerns that our evidence is driven by systematic differences between treated firms and those included in the control sample, we conduct several sensitivity analyses and robustness tests. First, we follow Noh et al. (2021) and identify firms that exhibit a pattern of pre-scheduled EA timing and find similar inferences for spreads and depth using this sample. Second, we conduct two sets of placebo tests related to treated firms and dates. Specifically, we replicate our analyses for other quarterly earnings announcements of the same treated and control firms and only observe the CFA treatment effect in the EA coinciding to the conference. Additionally, we repeat our tests using the same treatment and control days in years surrounding the conference. For instance, if the CFA conference occurred on the first Thursday and Friday of November in year *t*, we estimate our tests using pseudo-treatment and control firms announcing earnings around that same period in other years. With the exception of one volume estimate, which was our weakest result, we again find minimal evidence that the effects we document replicate in this environment. In sum, across 24 placebo estimations only one estimate demonstrates a statistically significant association in a manner similar to our main findings.

Next, we consider whether our results vary predictably with certain cross-sectional characteristics. We consider (1) ownership characteristics likely indicating greater influence of professional investors on information processing, (2) the conference location, where attendance by analysts may be higher, and (3) EAs most likely affected by conference activities. More specifically, we examine whether the effects of professional inattention are stronger when the firm has a greater number of institutional owners, when there is greater transient ownership, when conferences are located in New York, and when EAs occur during conference hours. In general, we find that effect sizes are larger in the predicted cross-section, and differences across partitions are often statistically significant.

Our evidence thus far indicates significant market effects of professional inattention during EAs. We focus on EAs for our primary analysis because prior research consistently demonstrates that EAs generate substantial information flows, exacerbating the information processing gap between more and less sophisticated investors. Consequently, we expect EAs to provide the most robust setting for testing our research question. However, it is plausible that our results extend to other non-scheduled events if they occur during the CFA conference, when professionals may be distracted or caught off guard. Using Ravenpack, we identify significant disclosure events beyond EAs, such as newsworthy events like executive turnover or new product announcements. Consistent with our primary findings, we observe that the market effects of professional inattention extend to these unscheduled events during CFA conferences.

We conclude with additional tests that evaluate other potential market consequences of CFA conferences. First, given institutional investors play a key role in the pricing of earnings information, their reduced attention during CFA conferences could make prices less efficient. To examine this, we analyze three aspects of price formation, including the ratio of immediate to longer-term returns (jump ratio), the speed of price formation (intraperiod timeliness, or IPE), and earnings response coefficients (ERCs). We find evidence of reduced jump ratios and lower ERCs for EAs that coincide with the CFA conference but fail to find significant evidence for IPE. Overall, these results suggest that buy-side analyst distraction leads to slower and less efficient price formation following EAs.

Second, we consider retail trading around EAs coinciding with CFA conferences. Research suggests that retail investors often make poor trading decisions at EAs. However, our primary analyses indicate that there is a reduced information processing advantage for informed traders, which could benefit retail traders. To identify trades initiated by retail investors, we employ the methods outlined in Boehmer et al. (2021) and Barber et al. (2024) as well as an alternative measure using retail trading data available from NASDAQ. Our evidence suggests that retail trades made during CFA conference EAs are significantly more informed (i.e., they are more profitable) compared to control EAs. In fact, we fail to find a significant association between retail trade direction and future returns for control firms. Overall, our evidence suggests that retail investors benefit when sophisticated market participants are less engaged at EAs.

Finally, we examine the potential effects of sell-side analyst distraction during the CFA conference. Although the CFA conference is targeted at buy-side analysts, sell-side analysts may also attend, which could influence the information they produce for institutional investors. We explore this by examining the association between the CFA conference and forecast volume, timeliness, accuracy, and bias. We find no evidence that sell-side analysts' volume or timeliness of their forecasts are impacted by CFA conferences. We do, however, find some evidence that sell-side analysts issue forecasts during the CFA conference that are less accurate and more optimistically biased.

We contribute to the literature on the influence of professional investors in markets. Our research complements recent and contemporaneous work examining the impact of *retail* (rather than professional) inattention on EA outcomes (Liu 2022; Friedman and Zeng 2024; Michels 2024), by being the first, to our knowledge, to focus on professional investor attention during EAs. Our findings suggest professional investors' processing advantage is attenuated during CFA conferences, potentially to the benefit of less sophisticated investors. However, we caution against interpreting our results as a recommendation for regulators to implement policies that inhibit analysts or their professional investor clientele in order to level the playing field. Instead, our findings offer new evidence from exogenous variation that certain investors face significant challenges compared to their professional investor counterparts when trading around important corporate events.

We also contribute to the literature on retail trading behavior. Very few papers attempt to identify causes of retail investors' low-quality trades (e.g., deHaan, Li, and Watts 2023; deHaan and Glover 2024). Research often speculates that excessive and under-informed retail trading stems from a combination of behavioral biases and inferior information processing (Blankespoor et al. 2020). Our study leverages variation in retailers' relative information processing capabilities, while likely holding constant retailers' behavioral biases. By focusing on this specific factor, our evidence suggests retailers' generally low-quality trades are driven, at least in part, by their inferior information processing capabilities relative to their more sophisticated counterparts.

Finally, we contribute to the literature on the role of equity analysts in capital markets. While extensive research examines the influence of sell-side analysts, much less is known about the impacts of *buy-side* analysts, primarily due to data limitations (Jung et al. 2018). By leveraging a plausibly exogenous shock to buy-side analyst attention, we add to the relatively limited body of work that investigates how buy-side analysts affect capital market outcomes.

2. Prior Research and Motivation

Nearly all disciplines identify a set of "experts" that have significant influence on outcomes within their areas of expertise. In medicine, different diagnoses require different expertise. For example, patients suffering from heart attacks generally receive care from a cardiologist in the emergency room admitting the patient. Jena et al. (2015) investigate whether the quality of care provided by these doctors varies when certain types of doctors, such as those likely to attend annual cardiologist meetings sponsored by the American Heart Association, are away. Specifically, the authors identify patients admitted to emergency rooms at prestigious teaching hospitals with three acute cardiac conditions (heart failure, cardiac arrest, and acute myocardial infarction) on meeting and matched non-meeting days. Despite patient characteristics being virtually identical between treatment and control samples, patients with heart failure or cardiac arrest admitted on conference days have much *lower* mortality rates than patients admitted on non-conference days; the magnitude of the effect is striking. The 30-day mortality rate for patients with heart attacks during conferences is 59% compared to 69% on matched non-conference days. This motivates the interesting question of what happens in other settings when the experts in a given field are away.[2]

In capital markets, buy-side analysts are one such influential group.[3] While not as "high stakes" as the role of a cardiologist during a cardiac event, buy-side analysts play an important role in influencing the process through which information is incorporated into security prices. For example, Cheng et al. (2006) find that institutional investors rate buy-side research nearly three times more important to their investment decision-making than that of sell-side analysts. Frey and Herbst (2014) examine one large asset manager and provide evidence that changes in the buy-side analyst stock recommendations at the fund are positively associated with trading in those stocks. Similarly, Jung et al. (2018) find that institutional investors more actively trade in quarters when their buy-side analysts participate on the EA conference call. They further find that buy-side analyst participation is significantly related to future returns, trading volume, institutional ownership, and short interest. These findings suggest that institutional investors rely on the information and recommendations

[2] Jena et al. (2015) find no differences in acute myocardial infarction mortality rates, though they do find significantly fewer percutaneous coronary interventions (PCIs) during conferences. This suggests at least some of the PCIs conducted by doctors likely attending cardiologist meetings do not improve patient outcomes. Jena et al. (2018) uses a similar setting to provide additional insight into the effects of PCIs for certain acute myocardial infarction diagnoses.

[3] Sell-side analysts may also be characterized as capital market experts. We focus primarily on buy-side analysts in this study for two reasons. First, the CFA conferences we study are primarily geared towards the buy-side. Second, buy-side analysts have a direct effect on the trading decisions of financial institutions (Brown et al. 2016), which underlies the crux of the market outcomes we examine. Any influence of sell-side analysts is indirect because they do not trade on their analysis.

provided by the experts at their funds. The question that arises is what effect, if any, will a decline in buy-side analysts' influence have on the market, particularly during significant disclosure events.

A long line of research suggests that capital markets benefit from the active participation of professional investors, who are presumably supported by buy-side analyst research. Green et al. (2011) and Chordia et al. (2014) provide evidence that hedge fund trading has led to an increase in market efficiency as reflected in reduced returns to market anomalies. Similarly, Akbas et al. (2015) find that trades from hedge funds reduce general mispricing in the market. Kokkonen and Suominen (2015), Sias et al. (2016), and Chen et al. (2019) provide additional empirical support for the idea that the activities of sophisticated market participants contribute to more efficient market pricing. To our knowledge, only two prior studies have directly attempted to measure sophisticated investor inattention. Kempf et al. (2017) identify distracted institutions using extreme returns in unrelated parts of their portfolio holdings, finding that firms with distracted shareholders are more likely to engage in value-destroying acquisitions, cut dividends, and grant opportunistically timed stock options. Xiang et al. (2020) present evidence suggesting that stock crash risk is higher for stocks where institutional investors are more distracted by extreme returns in other stocks within their portfolios.[4] In sum, research suggests that the activities of buy-side analysts and their institutional clients help to improve firm governance and align security prices with fundamental value. Most would interpret this as beneficial for markets since all investors can trade on prices that are, on average, more "fair." In this case, any reduction in professional investor trading could be detrimental to markets, particularly given the increased weight that such a reduction in sophisticated trading would give to other, likely less informed investors in the price setting process. For instance, although some research suggests that retail trading can reveal value-relevant information (e.g., Gao and Huang 2020; Boehmer et al.

[4] Several studies examine investor inattention broadly, without trying to isolate sophisticated investor inattention (see, e.g., Aboody et al. 2010; Li and Yu 2012; Drake et al. 2016). These studies, in general find that investor inattention is associated with negative market outcomes.

2021; Farrell et al. 2022) retail traders are often considered to be less sophisticated and not well informed, increasing trading volatility and trading regardless of news content (see, for example, Lee 1992; Foucault et al. 2011; Michels 2024). Further, retailers' relative disadvantage is likely most acute during earnings announcements (Gomez et al. 2024). Taken together, these arguments suggest that the CFA conferences that reduce professional investor participation in the price setting process may be associated with negative capital market effects.

However, it is possible that the trades of professional investors indeed improve market efficiency as a whole, but that it does so *at the expense* of other investors. Theory predicts that informed investors learn more from public information and can trade on the information faster and more efficiently than less-informed traders (Kim and Verrecchia 1994; Fischer and Verrecchia 1999). This creates an information gap between informed (presumably often professional) investors and less-informed (presumably often retail) investors, which theory predicts leads to higher EA information asymmetry, lower liquidity, and higher trading volume. Specifically, Kim and Verrecchia (1994) model market liquidity and volume around EAs as a function of the trading behavior between (1) information processors and/or nondiscretionary liquidity traders (commonly viewed as informed or sophisticated traders) and (2) discretionary traders (commonly viewed as uninformed or unsophisticated traders). Lemma 2 predicts that when informed traders are removed from the market, this leads to relatively lower EA volume, lower bid-ask spreads, and more market liquidity, which could benefit relatively less-informed investors. Empirical evidence supports this theory. Professional investors have both an information advantage and the ability to trade more quickly and with larger dollar amounts than other investors (Chan and Lakonishok 1993; Rogers et al. 2017), which leads to spikes in information asymmetry at the EAs (Lee et al. 1993; Amiram et al. 2016; Gomez et al. 2024). If the CFA conference produces professional inattention and attenuates these information advantages, then we may observe smaller spreads, greater liquidity, and reduced volume at EAs.

3. Setting and Empirical Design

3.1 CFA Conference Setting

Buy-side analyst attention is determined by many factors that likely relate to capital market outcomes, making it difficult to isolate casual effects. To address this challenge, we exploit plausibly exogenous variation in buy-side analyst market involvement using attendance at CFA conferences. The CFA's annual Equity Valuation & Research conference invites buy-side analysts to stay "abreast of the latest advances and developments in equity research techniques, valuation, and portfolio management" (CFA 2019). According to Jen Woods, Director of Event Solutions, the conference draws up to 400 attendees. We believe this scale provides a sufficient shock to examine potential market effects of analyst distraction, particularly because conference participants are dedicated equity research professionals likely to maintain active market engagement.[5]

CFA conferences feature speakers from academia, as well as presidents, CEOs, directors, and vice presidents of various equity research and asset management firms. The sessions cover a range of topics, including the implications of using non-GAAP reporting and the impact of overconfidence in earnings forecasting. The conferences are all-day events. The 2019 conference, for example, ran from 8:30 am to 5:30 pm, limiting buy-side analysts' time for work-related matters during trading hours.[6]

The CFA conferences will only distract buy-side analysts if (1) analysts attend, and (2) their work is disrupted during attendance. To understand the reasonableness of these necessary conditions, we contacted buy-side analysts in our own professional networks and 13 agreed to engage with us. We inquired about their conference attendance and how they manage workloads when absent. Each analyst reported attending at least one conference annually, with half having attended a CFA

[5] While the size of the conference seems sufficiently large to induce professional attention, we acknowledge that the strength of this shock is unclear. To the extent that this shock is relatively weak, it biases against finding a significant treatment effect, and we conduct numerous tests to rule out alternative explanations.
[6] See the conference website here: https://www.cfainstitute.org/en/events/conferences/past/equity-2019.

conference at some point in their career. Regarding workload management, one analyst reported that all work is put on hold during their absence. The others indicate that their duties are either partially or completely handled by colleagues. Thus, the distraction caused by the CFA conference appears to stem from analysts suspending their work and relying on backup analysts that assume some of their responsibilities, in addition to their normal workloads. We suspect that designated backup analysts are likely less familiar with firms outside their portfolio, suggesting that differences in familiarity, expertise, and time can potentially impact the quality of the decision-making.

For our empirical analysis, we identify eight annual CFA conferences held from 2012 to 2019, with dates falling between November 6 and December 7. Appendix B provides the conference dates and locations. Each conference is held over a two-day period on either a Tuesday and Wednesday or a Thursday and Friday. To examine capital market outcomes during the conference, we focus our main tests on earnings announcements (EAs) overlapping with conference dates, but also consider additional events in supplementary analyses. More specifically, we consider EAs one day prior to or during a CFA conference as our treatment observations (we include one day prior to the conference to account for buy-side analysts traveling to the conference location). We use EAs that occur in adjacent weeks (i.e., either one week prior to or one week following) as our control sample.[7]

3.2 Buy-side Analyst Attention, Information Asymmetry, Liquidity, and Volume

Our primary analyses examine whether buy-side analyst distraction impacts the information advantage that professional investors have over retail investors at EAs. Kim and Verrecchia (1994) model information flows at disclosure events and propose that EAs lead to spikes in information asymmetry. This spike occurs because EAs "stimulate informed judgments among traders who process public disclosure into private information" (p. 44). Importantly, their model demonstrates that

[7] We also considered an alternative control sample comprised of treatment firm EAs one year prior to and one year following the CFA conference. Results are qualitatively similar (untabulated).

when there are relatively fewer informed traders engaged at the EA, uninformed traders' information disadvantage should be muted, as evidenced by lower information asymmetry (i.e., bid-ask spreads), higher market liquidity, and lower trading volume. Accordingly, we examine EA spreads, market liquidity, and trading volume for firms that have EAs that occur during the CFA conference.

We explore this question using the following model:

$$\begin{aligned} &Market\ Outcome_{[0,1]} \\ &\quad = \alpha_0 + \alpha_1 Conference + \sum \alpha Controls + Year\ FE + Weekday\ FE + \epsilon \end{aligned} \tag{1}$$

Market Outcome is one of three variables. Our first market outcome, bid-ask spread, is a commonly used proxy for information asymmetry. We define $AbSpread_{[0,1]}$ as the natural logarithm of average daily percent effective spread over trading days [0,1] divided by the average daily percent effective spread over trading days [-41,-11] (Blankespoor et al. 2020).[8] Our second market outcome, depth, is a commonly used proxy for market liquidity. We define $AbDepth_{[0,1]}$ as the natural logarithm of average daily depth over trading days [0,1] divided by the average daily depth over trading days [-41,-11]. Daily depth is calculated as the sum of time-weighted best bid dollar depth and best offer dollar depth. Our third market outcome, $AbVolume_{[0,1]}$, is abnormal volume defined as the natural logarithm of average daily turnover during trading days [0,1] divided by the average daily turnover during trading days [-41,-11].

Our independent variable of interest, $Conference$, is an indicator variable equal to one for EAs that occur one day prior to or on the day of a CFA conference, and zero otherwise. The coefficient of interest α_1 can be interpreted as the incremental abnormal spread, depth, or volume for firms announcing earnings during a CFA conference. A significantly positive (negative) α_1 indicates that the EA spreads, depth, or volume is higher (lower) when buy-side analysts are distracted.

[8] All variables are defined in Appendix A.

We include in Equation (1) control variables that could influence both our dependent variables and buy-side analyst attention. These controls include the natural logarithm of market-value of equity (*Size*), the market-to-book ratio at the beginning of the period (*MB*), the decile ranked magnitude of the earnings surprise (*Abs[Surprise]*), the natural logarithm of one plus the number of EAs on the respective EA date (*Busy EA*), the natural logarithm of one plus analyst following (*Following*), and accounting reporting complexity (*ARC*). In addition, we include year and day-of-the-week fixed effects to control for cross-sectional correlation across these dimensions. The day-of-week fixed effects ensure that α_1 captures any effect of the CFA conference incremental to the day of the week the EA occurs. Finally, we cluster standard errors by EA date.

Data and Sample

4.1 Sample

Our sample comprises earnings announcements from the IBES consensus file during eight CFA Equity Research and Valuation conferences (2012-2019), spanning the conference period (conference days and day before) and a control period (week before and after). This results in 1,123 treatment EAs and 4,131 control EAs for a total of 5,254 observations. We require bid-ask spread, depth, and retail trading data from TAQ. We also require stock return and volume data from CRSP, financial data from Compustat, analyst forecast data from IBES, and accounting reporting complexity data made available by Hoitash and Hoitash (2018; 2022). After screening on these data requirements, the sample is reduced by 127 observations (2.4% sample loss) to a final sample of 5,127 EAs, comprising 1,102 treatment observations and 4,025 control observations.[9]

We note that our sample includes EAs from 2,444 unique firms. Within the treatment sample of 1,102 EAs, there are 916 unique firms, indicating that few firms in our sample have EAs that

[9] We exclude observations with Cook's Distance greater than 4/N in our regressions to address influential observations (Leone et al. 2019). Thus, the number of observations differ from 5,127 in each regression.

coincide with multiple CFA conferences. This evidence supports our assumption that firms' EA calendars are largely independent of when these conferences are scheduled.

4.2 Descriptive Statistics

In Table 1, Panel A we report descriptive statistics for our final sample of 5,127 EAs from 2012 to 2019. We winsorize all continuous variables, except returns, at the 1st and 99th percentiles. On average, we find that EAs have positive abnormal bid-ask spread (0.171), positive abnormal depth (0.010), and positive abnormal trading volume (0.586). These statistics are consistent with the inferences of prior research and support the use of EAs as a powerful setting to examine information asymmetry between investors. The mean value of 0.215 for *Conference* suggests that treatment observations represent 21.5% of all observations.

4.3 Industry and Covariate Balance

We assume that CFA conference timing creates a plausibly exogenous shock to buy-side analyst attention, which implies that we should find reasonable covariate balance between treatment and control firms. To test this assumption, we examine industry and covariate balance between our treatment and control samples. In Table 1, Panel B, we present the number of observations in our sample separately for treatment and control firms, partitioned by Fama-French 12 industry. Overall, we find that industry distributions appear highly consistent across the treatment and control panels, suggesting CFA conference treatment does not tend to cluster around a specific industry's EA season.[10]

In Panel C of Table 1, we assess covariate balance between treatment and control samples to identify potential confounding factors. Overall, we find that differences in means are statistically insignificant for most variables. Specifically, mean treatment and control observations appear to

[10] Despite the balance across Fama-French 12 industry classifications, we acknowledge that our inferences could be limited to firms that announce earnings during these periods (i.e., November and early December).

capture similar firm types (industry, size, profitability, and market-to-book ratios), firms with similar information environments (analyst following and accounting reporting complexity), and firms with similar investor bases (institutional concentration and transient institutional ownership). This industry and covariate balance is consistent with CFA conference timing producing as-if random treatment.

Although most variables exhibit covariate balance, there are a few minor exceptions. We observe statistically significant but economically minor differences (within one-quarter of a decile) in *Surprise* and *Abs(Surprise)* between conference and non-conference EAs. Additionally, the average number of concurrent EAs (*Busy EA*) during the CFA conference is noticeably lower, which may suggest some intentionality with conference scheduling. However, as noted previously, the majority of firms are treated only once, suggesting the intentionality relates to general business and not specific firms' earnings. We control for all of these variables in our regressions (Shipman et al. 2017).

4.4 Validation Tests

Cheng et al. (2006) find that institutional investors rely heavily on buy-side analysts when making trading decisions, and Jung et al. (2018) find that institutional investors more actively trade when their buy-side analysts are more engaged at the EA. Accordingly, we use this intuition to motivate a set of validation tests meant to confirm that the CFA conferences appear to alter trading behavior by institutions. Specifically, we evaluate whether the quality of trades made by institutions at EAs declines during CFA conferences. We first identify institutional trades as those exceeding $50,000, following the approach in Bhattacharya et al. (2007). While this method is intuitively appealing, it is noisy because institutions often break up orders for large trades (e.g., Hirshleifer et al. 2008; Campbell et al. 2009; Cready et al. 2014; Lawrence 2013; Bhattacharya et al. 2018). This results in significant Type II error (i.e., we fail to identify many institutional trades).[11] Thus, we also examine a second measure that captures the intensity of "informed trading" as measured in Bogousslavsky et al. (2024), which we assume primarily stems from professional investors relying on buy-side advice. We evaluate how each of these measures correlates with post-EA returns starting two trading days after the earnings announcements and ending 5, 10, and 20 trading days later ($BHAR_{[2,5]}$, $BHAR_{[2,10]}$, and $BHAR_{[2,20]}$), conditioned on whether the EA occurs during a CFA conference. Specifically, *Conference* equals one for days prior to or contemporaneous with the CFA conference, and equal to zero during the control window period. We present these results in Table 2.

In columns 1 through 3 of Table 2, we present results using the direction of large trades as our first proxy for institutional trading (*Inst OIB*). We identify large trades as noted above and compute order imbalance based on trade direction inferred as in Lee and Ready (1991). If institutions make trades that are, on average, positively correlated with future returns, we should observe a positive coefficient on *Inst OIB.* If the quality of these trades declines during CFA conference, then we expect the coefficient on the *Inst OIB×Conference* interaction to be negative. We fail to observe a positive coefficient on *Inst OIB* or a significant negative coefficient on the interaction of interest, although the interaction in column 2 falls just below conventional significance levels in column 2 (*t*-statistic = -1.55).

In columns 4 through 6 of Table 2, we present results using our second proxy for sophisticated trading activity, informed trading intensity (*ITI*). While unsigned, Bogousslavsky et al. (2024) find that informed trading positively predicts future returns, which they use as evidence that informed

[11] In addition to trade quality, one might find it intuitive to examine whether CFA conferences reduce institutional trading quantity (i.e., volume). We do not examine institutional trading volume because our method to identify institutional trading has a high type II error rate, indicating that we cannot cleanly identify *total* institutional volume. Instead, we focus on measuring the profitability of institutional trades that we can identify. The focus on trading profitability instead of trading volume is consistent with insights from our discussions with buy-side analysts who suggest that during conferences, while trading volume may remain stable, trade quality potentially declines as backup analysts carry the load.

trading is driven by institutions with superior private information. Consistent with Bogousslavsky et al. (2024), we find the coefficient on *ITI* is positive and significant in columns 4 and 5. Importantly the coefficient on the *ITI×Conference* interaction is significantly negative in columns 5 and 6 (*t*-statistics = -3.21 and -4.22, respectively). This suggests that trades made by institutional investors are of significantly lower quality when buy-side analysts are distracted. Overall, the results in Table 2 provide evidence validating the idea that the quality of sophisticated trading declines during CFA conferences, particularly when measuring these trades with the informed trading proxy.

5. Empirical Results

5.1 Primary Analyses

We now present our primary analyses that examine the firm-specific effects of announcing earnings during a CFA Conference. In Table 3, column 1 we report the estimation results for Equation (1) using $AbSpread_{[0,1]}$ as the dependent variable. We find a negative and statistically significant coefficient on *Conference* in column 1 (coefficient = -0.044; t-statistic = -3.10). This suggests that the spike in information asymmetry at EAs is significantly attenuated for EAs that occur during a CFA conference. This result is economically meaningful, indicating that abnormal spreads are approximately 4.4% lower on conference days, which is approximately 12% of a standard deviation in *AbSpread*.

In column 2 of Table 3, we present results using $AbDepth_{[0,1]}$ as the dependent variable. We find a positive and statistically significant coefficient on *Conference* in column 2 (coefficient = 0.045; t-statistic = 2.40), which is consistent with CFA conferences leading to higher liquidity. Economically, this coefficient translates to an increase of about 10% of a standard deviation in *AbDepth*.

Finally, column 3 of Table 3 reports the estimation result for when abnormal volume ($AbVolume_{[0,1]}$) is the dependent variable. Consistent with Kim and Verrecchia (1994), we observe a negative coefficient in column 3, though statistical significance is marginal (coefficient = -0.055; t-statistic = -1.70). This translates to a decrease in volume on conference days that is almost 7% of its standard deviation. This result provides some evidence of a change in total EA abnormal volume when buy-side analysts are away at the annual CFA conference.

Taken together, the results in Table 3 are largely consistent with theory in Kim and Verrecchia (1994) suggesting a reduced information processing advantage of informed traders in the market during CFA conferences.[12] Specifically, we document evidence of lower EA bid-ask spreads, higher liquidity, and reduced trading volume when the firm's EA coincides with the CFA conference. In sum, the results in Table 3 are consistent with a more level playing field during EAs associated with reduced buy-side analyst attention.[13]

5.2 Robustness and Falsification Tests

5.2.1 Firms' Choice of Earnings Announcement Timing

While conference and earnings announcement timing appear exogenous, strategic scheduling could potentially bias our analysis.[14] We consider it unlikely that firms opportunistically schedule EAs based on conference dates because EA dates are often set in advance before incentives to time disclosure may be known. Nonetheless, to more directly mitigate this concern, we identify firms with

[12] Kim and Verrecchia (1997) show that *pre-earnings announcement* trading is influenced by private information, which is incorporated into prices through the actions of informed investors before the public disclosure and influences how the market responds to the eventual public announcement. If CFA conferences affect analysts' pre-announcement information gathering, it could potentially explain the effects we observe. To test this possibility, we estimate a future earnings response coefficient (FERC) model by regressing pre-EA returns (days -5 to -1) on the earnings surprise, our conference treatment indicator, the interaction of the two, and the controls included in equation (1). Inconsistent with this alternative explanation, we observe no differences in FERCs between treatment and control firms.

[13] One potential concern with these results relates to intra-industry information transfers. Specifically, recall that we scale our dependent variables by a pre-EA window to obtain a measure of abnormal activity. If earlier announcing peers influence the liquidity or volume of focal firms, then the denominator of our dependent variables will capture different information for treatment versus control firms. To address this concern, we re-estimate our primary results when we scale dependent variables by the first three weeks of the fourth quarter (a time period before any control EA in our sample). Our inferences are consistent with our primary tests.

[14] Prior research provides some evidence of the strategic timing of earnings announcements (see, e.g., Doyle and Magilke 2009).

pre-scheduled EAs, following Noh et al. (2021), and limit our sample to these firms. This approach further reduces the likelihood of strategic EA timing affecting our inferences.

In Table 4, we present the results of our primary tests using the sample of pre-scheduled announcement firms. We note that our sample size is significantly reduced after imposing this restriction. For example, for our abnormal spread test, we retain only 15% of the sample (i.e., only 711 observations of the 4,858 in Table 3), which is consistent with the percentage of pattern firms identified in Noh et al. (2021). Our inferences in Table 4 are largely similar to those of our earlier tables that employ the full sample. The only minor exception is that we find an insignificant coefficient on *Conference* in column 3 when abnormal volume ($AbVolume_{[0,1]}$) is the dependent variable (this coefficient was marginally significant in Table 3).

To further address the concern that firms may strategically time their EAs around the CFA conference, we re-estimate our results separately for firms that announce good and bad earnings news (results untabulated). This test is motivated by the idea that firms might schedule bad news announcements during CFA conferences when professional attention is lower. Inconsistent with a strategic disclosure timing explanation, however, we find no statistical differences between any of our primary results when considering good versus bad news EAs.

5.2.2 Placebo Tests

To provide corroborating evidence that our results stem from the CFA conference, we conduct two sets of placebo tests. First, we consider EAs for the same set of treatment and control firms (i) two quarters before the CFA conference, (ii) one quarter before the CFA conference, and (iii) one quarter after the CFA conference. We use these alternative time periods because the annual CFA conferences in our study predominately coincide with third quarter earnings announcements (covering about 80% of our sample). Thus, the alternative placebo dates generally capture EAs for the first, second, and fourth quarters for firms in our sample. If the results in our study are attributable to the CFA conference, rather than to firm characteristics held constant each quarter, then we should fail to observe significant results in these placebo tests.

Second, we define a set of placebo treatment dates based on when each conference occurs in fixed calendar time. For example, the 2019 conference was held on Thursday and Friday of the 7th week of the fourth quarter (November 14-15). We generate placebo observations by examining EAs for these same calendar positions in years 2012-2018, excluding 2019. While our sample spans eight conference years, these placebo tests result in five unique sets of treatment and control firms due to recurring week/day-of-week combinations.[15] In total, we conduct eight sets of tests, consisting of three from the first placebo test and five from the second placebo test. Given three independent variables (spread, depth, and volume), this equates to 24 placebo regressions.

Figure 1 presents the results of these 24 regressions, providing the coefficient on *Conference* with 90% confidence intervals. The red dashed line in the figure represents the coefficient estimate from Table 3, our actual estimated treatment effect. As described in the figure notes, the three relative EA dates (quarters *q-2, q-1,* and *q+1*) correspond to *a, b,* and *c* on the *x*-axis. Estimations *d* through *h* correspond to the fixed-calendar time approach. Beginning with abnormal spreads, two estimations (*e* and *f*) appear somewhat similar to the treatment effect, but neither is statistically significant. One estimate, column *h,* is significantly *positive*. With regards to depth, we observe no positive, statistically significant estimates. Estimate *d* does exhibit some overlap with the treatment effect, but it is still much smaller in magnitude. Finally, for abnormal volume, one of eight coefficients is significantly negative and larger in magnitude than our treatment effect. Others are generally

[15] Specifically, the 2013, 2014, and 2016 conferences all occur in the seventh week of the quarter on Thursday and Friday, and the 2015 and 2017 conference both occur in the seventh week of the quarter on Tuesday and Wednesday. Accordingly, we have five unique week/day-of-week combinations: (1) 2012, (2) 2013, 2014, 2016, (3) 2015, 2017, (4) 2018, and (5) 2019.

insignificant, and recall that our estimated treatment effect for volume in Table 3 is only marginally significant.

Overall, we interpret the 24 regressions illustrated in Figure 1 as further evidence that the effects we observe in our primary analyses are likely attributable to the CFA conferences, and not to other factors, such as the characteristics of treatment firms.[16]

5.2.3 Measurement of Professional Inattention

Recall that in our research design, we consider the day *before* the conference as treatment day to account for buy-side analysts traveling to the conference location. However, one could argue that the day before the conference is not a treatment day if many analysts live in the city in which the conference takes place or are only travelling in the evening the day prior to the conference. To address this issue, we re-run our tests using two alternative specifications: (1) dropping the day before the conference from our sample, unless the EA occurs after hours, and (2) dropping the day before the conference from our sample, regardless of EA timing (untabulated). In both cases, our results on spread and depth hold, but the marginally significant result on volume in Table 3 becomes insignificant (t-statistics of -1.34 and -1.05 for each test, respectively).[17]

5.3 Cross-Sectional Analysis

In this section, we consider cross-sectional variation in our primary results. For our first two tests, we examine how the CFA conference effects differ based on professional attention to EAs, measured using the concentration of institutional ownership and transient institutional ownership

[16] Another potential concern is that our results are affected by the Thanksgiving holiday, where attention, particularly from retail traders, is likely attenuated. Although none of the CFA conferences occur during the week of Thanksgiving, it is possible that some of our control period weeks occur during Thanksgiving because the CFA conference generally occurs in November or the beginning of December. If trading behavior is systematically different during this holiday period, then using this week as a control period may be inappropriate. To address this concern, we re-estimate our primary results after removing control firm-days that overlap with Thanksgiving week. Our results are unaffected (untabulated). We also note that only 197 controls observations (4.8% of our control firm-days) overlap with the week of Thanksgiving, further suggesting that the Thanksgiving holiday does not influence our results.

[17] We also find similar results using this specification when we examine retail order imbalance (Table 8).

(Bushee 1998).[18] For concentration, we expect firms with less concentrated institutional ownership to be more influenced by the absence of buyside analysts because there is likely greater competition for information at EAs for firms with more disperse ownership structures, implying greater reliance on buyside analysts' advice. Similarly, since transient investors are the group most likely to trade on EA information and rely on buy-side analyst research when making their investment decisions, we expect our main results to be more concentrated in this group.

We report all cross-sectional tests in Table 5. Panel A of Table 5 presents results using institutional ownership concentration and Panel B presents the results for transient ownership. For each measure, we partition the sample at annual medians. As shown in Panel A of Table 5, we observe noticeably larger coefficients in the low concentration partition for both *AbSpread* and *AbVol* (columns 1 vs. 2, and 5 vs. 6). Both differences in coefficients are also statistically different (p = 0.087 and 0.052, respectively). Coefficients for estimates with *AbDepth* as the dependent variable are statistically and economically similar. Panel B of Table 5 reports evidence for partitioning on transient institutional ownership, and, consistent with expectations, we find evidence that the CFA conference effect on bid-ask spreads (columns 1 vs. 2) and abnormal volume (columns 5 vs. 6) is economically and statistically stronger for firms with high transient institutional ownership (p = 0.044 and 0.026, respectively). Effects on *AbDepth* are economically similar, as in Panel A. Overall, the evidence in Panels A and B suggest our results are stronger in the expected ownership-based partitions.

Next, we consider cross-sectional variation in conference location. Specifically, we examine whether the distraction effect of CFA conferences is strongest for conferences located in New York. Our rationale for this test is that conferences in New York likely attract larger number of attendees due to the large number of New York-based analysts and the ease of traveling to New York. Panel C

[18] Note that the Bushee transient institutional ownership data ends in 2018, so for this analysis we drop all observations corresponding to 2019.

of Table 5 reports these results. Consistent with expectations, results for all three EA outcomes appear economically strongest when conferences are located in New York (tests of differences are significant at *p*-values between 0.070 and 0.097).

Finally, we examine cross-sectional variation based on EA timing. The test is motivated by the idea that the distraction effect will be heightened for EAs that occur during conference hours compared to EAs that occur before the conference begins or after the conference has concluded for the day. In Panel D of Table 5, we split the sample between EAs that occur during conference hours (8:30 am to 5:30 pm) versus outside of conference hours. For all three outcomes, coefficient magnitudes are noticeably larger for EAs—often two to three times greater in magnitude—during conference hours. However, statistical tests of differences fall below conventional significance levels (*p*-values between 0.102 and 0.159).

Overall, the results in Table 5 provide some evidence that the impact of CFA conferences is stronger for firms in which professional investors are more likely to rely on buy-side analyst research, when the conference garners greater attendance, and when the EA occurs during conference hours.

5.4 Non-EA Events

Our main analyses focus on EAs as important value-relevant events that draw the attention of buy-side analysts. In our next set of analyses, we examine whether our results hold using other information events, which may not be scheduled in advanced like EAs. We identify non-EA events using RavenPack's PR dataset. Specifically, we identify firm events and filter out firms with EAs during a CFA conference (i.e., those included in our primary sample). Events include things like new product, M&A, or executive turnover announcements. To ensure each event produces some directional news that likely prompts trading, we require a non-zero value for RavenPack event sentiment. Consistent with prior research (e.g., Drake, Guest, and Twedt 2014), we require relevance scores of 100 to ensure the event wholly relates to the target firm. We then collapse firm-dates with multiple RavenPack events into single firm-date observations. After requiring other data to estimate Equation (1), we are left with 1,490 events which we match to 4,142 control events.

Table 6 reports results from estimating Equation (1) for this alternative set of non-EA events. The control variables we include are the same as in Equation (1), except that we replace *EarnSurp* with an indicator equaling one if RavenPack codes the event as having positive sentiment. Consistent with professional inattention attenuating sophisticated traders' informational advantage during these non-EA events, we observe a negative and marginally significant coefficient on *Conference* in column 1, where *AbSpread* is the dependent variable. Similarly, column 2 (3) reports a statistically significant positive (negative) coefficient on *Conference* with *AbDepth* (*AbVolume*) as the dependent variable. Overall, Table 6 provides evidence that the effect of CFA conferences on professional inattention extends to non-EA events.

6. Additional Analysis

Our final set of analyses considers outcomes beyond those related to theoretical predictions in Kim and Verrecchia (1994). Specifically, we consider the potential effects of CFA conferences on market efficiency at EAs, retail trading, and sell-side analyst outputs.

6.1 Price Formation

In this section, we consider the implications of distracted buy-side analysts on price formation around EAs. As discussed previously, institutional investors play a key role in the pricing of earnings information. A reduction in professional attention may make prices less efficient, even if the overall playing field appears "more level." To examine this possibility, we consider three aspects of price formation, including the ratio of immediate to longer-term returns ("jump ratio"), the speed of price formation (intraperiod timeliness), and earnings response coefficients (ERCs).

We present the results in Table 7 using these three measures of price formation. In column 1 we present the results for *Jump Ratio*, which measures the portion of the day 0 to day 5 return that occurs in days 0 and 1 relative to the EA. A larger (smaller) jump ratio implies faster (slower) price formation following the EA. Consistent with buy-side distraction impeding overall price formation, we report a significantly negative coefficient on *Conference* in column 1. In column 2, we consider intraperiod price efficiency (*IPE*; Blankespoor et al. 2020). *IPE* evaluates the area under the curve of a cumulative price response from the EA to 5 days after the EA. *IPE* is similar in spirit to *Jump Ratio*, though it includes an adjustment for potential overreactions (i.e., price reversals) within the measurement window.[19] We find results directionally consistent with our results using *Jump Ratio*, but statistically insignificant. In column 3, we examine earnings response coefficients. For this test, we define *Surprise* as a continuous measure of earnings surprise, consistent with prior research. Our variable of interest is the interaction of *Surprise* and *Conference.* If buy-side analyst distraction leads to lower price response to earnings surprise news, we should find a negative coefficient on this interaction term. Consistent with expectations, column 3 displays a statistically negative coefficient on this interaction term. Overall, the results in Table 7 suggest that buy-side analyst distraction leads to slower and less efficient price formation following EAs.

6.2 Retail Trading

We next examine whether professional inattention leads to better outcomes for less sophisticated, retail investors. Analogous to results in Table 2, we compare the quality of retail trading at EAs that coincide with CFA conferences to those that do not. If CFA conferences reduce retail investors' relative information disadvantage, we expect to observe retailers trading with more profitable outcomes.

We consider two measures of retail trading for these analyses. First, we identify retail trades using the method developed in Boehmer et al. (2021), and subsequently improved in Barber et al.

[19] Following Campbell et al. (2023), we require an absolute 5-day cumulative abnormal return of at least 2% for the tests of *Jump Ratio* and *IPE*.

(2024). We infer trade direction based on Lee and Ready (1991). Research generally assumes the Boehmer approach has a low type II error rate at the expense of a relatively high type I error rate (i.e., it misses a large number of retail trades).[20] As an alternative measure, we obtain retail trading data from NASDAQ.[21] This data includes a volume measure based on the rank of the relative intensity of retail trading (i.e., retail trading in firm *i* scaled by total retail trading) as well as a "sentiment" measure derived from order flows. The advantage of this data is that it more cleanly identifies retail trading; however, one limitation is that it only provides the rank of retail trading and not the actual level. Further, inclusion of the variable reduces our sample by approximately 29% because it is only available during the latter portion of our sample. For both of these measures, we assess whether CFA conferences influence their ability to predict future returns, similar to tests in Table 2.

Similar to Table 2, we consider three different trading day return windows (5-day, 10-day, and 20-day) to shed light on the duration effect. We present the results in Table 8. Columns 1 to 3 report results using *Retail OIB*, the measure derived using the Boehmer et al. (2021) method, and columns 4 to 6 reports the results using *NDAQ OIB*, the measure derived from NASDAQ data. In columns 2 (10-day window) and 3 (20-day window), we observe significantly positive coefficients on the interaction between *Conference* and *Retail OIB*, implying that the direction of retail trades at EAs during CFA conferences is significantly more predictive of future returns than trades for control EAs. In fact, *Retail OIB* is not significant for control observations, suggesting retail trades are typically neither systematically profitable nor unprofitable. Columns 4 through 6 provide the results using *NDAQ OIB*. Here we also find that retail trade direction maps into future returns (i.e., trades are more profitable) when trades are made at EAs coinciding with CFA conferences in columns 4 and

[20] Contemporaneous work by Battalio et al. (2024) suggests that institutional trades often trade on sub-penny increments, challenging the efficacy of the Boehmer et al. (2021) approach. Accordingly, we also use retail trading data available from NASDAQ that should not be subject to the same concerns.
[21] These data are available here: https://data.nasdaq.com/databases/RTAT/data

5, but not for control EAs. Overall, the results in Table 8 are consistent with reduced attention from buy-side analysts during the CFA conferences allowing for more profitable trading by retail investors, and we find no evidence that these returns reverse as we extend the return accumulation window.

6.3 Sell-side Analysts

Next, we consider the potential impact of *sell-side* analyst inattention during CFA conferences. Although the CFA conference we study is geared towards buy-side analysts, it is possible that sell-side analysts also attend and that their research activities are similarly impacted by periods of inattention during the conference. This consideration is important, as the production of information for institutions is a significant part of sell-side analysts' cost recovery strategies. To evaluate the degree to which sell-side attendance influences our results, we examine the treatment effect on four characteristics of sell-side analyst forecasts issued in the 2-day EA window: (i) the number of forecasts issued (*Fcst_N*), (ii) the average number of hours between the EA and forecasts issued (*Fcst_Lag*), (iii) the average forecast error (*Fcst_Error*), and (iv) the average forecast bias (*Fcst_Bias*).

In columns 1 and 2 of Table 9, we report estimates of the effect of CFA conferences on the number of sell-side forecasts issued and their average time lag. Overall, we find no evidence of an effect on sell-side analyst forecast frequency or timing. Columns 3 and 4 report results for forecast quality (absolute error and bias). We find that *Conference* is positively associated with sell-side forecast errors in column 3 (coefficient = 0.004; t-statistics = 2.48). Similarly, this increase in error appears to come from more optimistically biased forecasts (coefficient = 0.002; t-statistics = 1.68). Overall, we document some evidence that sell-side analysts may also be distracted during CFA conferences.

6.4 Annual CFA Conference

Our tests focus on the Equity Research & Valuation conference because it targets buy-side equity research analysts, which is the group of CFAs most likely to influence trading around EAs. However, we recognize that there are other conferences that attract a greater number of analysts. The Annual CFA conference, for example, attracts very large attendance (often in the thousands), is relatively longer (typically one week), and is often held outside of the U.S. While a conference like this could provide a larger shock, the breath of analysts that attend, the length, and the location introduce potential confounds. Further, the annual conference appears to be more strategically scheduled in the summer to avoid the busy earnings announcement season.

We conducted supplementary analyses using the annual conference as an alternative shock. Some of our results hold and even strengthen in some tests. Specifically, we continue to find evidence of more profitable retail trades, less efficient price formation, larger analyst forecast errors, and (weakly) less profitable institutional trades during the annual conference. However, we de-emphasize these findings for three main reasons. First, the covariate balance between treated and control firms is very poor. Although we observe insignificant differences in most independent variables in Panel C of Table 1, nine of ten variables exhibit significant differences in the annual conference setting. Second, placebo analyses similar to those reported in Figure 1 often produce similar inferences to treatment period tests. Due to these factors, we believe that fundamental differences between treated and control firms likely confound the results when considering the annual conference.

7. Conclusion

Research has long recognized professional investors' trading advantages during earnings announcements, characterized by higher information asymmetry, reduced liquidity, and increased trading volume. By examining professional inattention through CFA conferences, we find evidence of a significant attenuation of professional investors' information advantage, suggesting a more level market playing field. We find these effects are strongest with lower institutional investor ownership concentration, greater transient institutional ownership, when the conference is held in New York, and when earnings are announced during conference hours. We also find these effects extend to non-EA events. Finally, additional tests provide some evidence of lower price efficiency, more profitable retail trading, and poorer sell-side analyst outputs during CFA conferences. In sum, we provide novel evidence on the impact of professional inattention on important market outcomes.

Our study is subject to several caveats and limitations. First, CFA conference dates are non-random and are likely scheduled to avoid overlapping with a large number of EAs. Although we observe reasonable covariate balance between treatment and control firms, any systematic differences in firms that announce earnings during a CFA conference could limit the generalizability of our study. Second, due to the absence of data on participants and other institutional details, we are unable to empirically examine the longer-term effects of analyst inattention. Our study primarily addresses the short-term effects. That said, we acknowledge that the long-run effect may lead to a less equitable playing field. Exploring the long-term effects of buy-side analyst inattention presents a compelling direction for future research.

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Appendix A

Variable Definitions

Variable	Definition
AbDepth[0,1]	The natural logarithm of average daily depth over trading days [0,1] divided by the average daily depth over trading days [-41,-11]; all days are indexed relative to the EA date. Daily depth is calculated as the sum of time-weighted best bid dollar depth and best offer dollar depth.
AbSpread[0,1]	The natural logarithm of average daily percent effective spread over trading days [0,1] divided by the average daily percent effective spread over trading days [-41,-11]; all days are indexed relative to the EA date.
AbVolume[0,1]	The natural logarithm of average daily turnover during trading days [0,1] divided by the average daily turnover during trading days [-41,-11]; all days are indexed relative to the EA date. Daily turnover is calculated as the total number of shares traded divided by total shares outstanding.
ARC	Accounting reporting complexity based on the count of monetary items disclosed in annual XBRL filings (developed by Hoitash and Hoitash, 2018).
BHAR[x,y]	Buy and hold abnormal returns (using portfolio returns calculated from Daniel, Grinblatt, Titman, and Wermers 1997, and if missing, the value-weighted return from CRSP) over day x to day y relative to the EA date; days are indexed relative to the EA date.
Busy EA	The natural logarithm of 1 + the total number of EAs on the respective EA date.
Conference	Indicator equal to 1 if the earning announcement occurs 1 day before or during a CFA conference, and zero otherwise.
Conf Hours (Not Conf Hours)	Indicator equal to 1 if the earning announcement occurs (does not occur) between 8:30 am and 5:30 pm, and zero otherwise.
Fcst_Error	The average unsigned forecast error for annual EPS forecasts issued over trading days [0,1] relative to the EA scaled by price per share at the end of the previous fiscal-period. Unsigned forecast error is calculated as the absolute value of forecast EPS less actual EPS.
Fcst_Bias	The average signed forecast error for annual EPS forecasts issued over trading days [0,1] relative to the EA divided by price per share at the end of the previous fiscal-period. Signed forecast error are calculated as forecast EPS less actual EPS such that a positive value indicates analyst optimism.
Fcst_Lag	The natural logarithm of 1 + the average hourly lag between the EA and analyst forecast issuance for annual EPS forecasts issued over trading days [0,1] relative to the EA.
Fcst_N	The natural logarithm of 1 + the number of annual EPS forecasts issued over trading days [0,1] relative to the EA.
Following	The natural logarithm of 1 + analyst following prior to the EA of interest.
IPE	Intraperiod efficiency calculated over the window [0,5] following Blankespoor et al. (2020). Specifically, it is the average of: $[1-(\lvert AR_5 - AR_t\rvert)/\lvert AT_5\rvert]$, where AR_t is the cumulative market-adjusted return from [0,t].
ITI	A machine-learning based measure of informed trading intensity developed by Bogousslavsky, Fos, and Muravyev (2024). *ITI* is standardized to have standard deviation of one and a mean of zero.
Inst OIB	Large trade imbalance calculated as total buy volume greater than $50,000 over trading days [0,1] less total sell volume greater than $50,000 over trading days [0,1], divided by total volume over trading days [0,1]; all days are indexed relative to the EA date. Trade direction is inferred following the method developed by Lee and Ready (1991).
IO Concentration	Institutional concentration captured by the Herfindahl–Hirschman Index.
Jump Ratio	The ratio of the cumulative abnormal return over the window [0,1] over the cumulative abnormal return over the window [0,5].
MB	Market to book ratio at the beginning of the period.

NDAQ OIB	The change in retail sentiment score during the window [0,1], where retail sentiment score equals retail net flows (buy-sell) of the most recent 10 trading days. Retail sentiment score ranges from +100 to -100, whereby the more positive (negative) the score, the greater the proportion of recent retail net buying (selling). Data obtained from NASDAQ. *NDAQ OIB* is standardized to have standard deviation of one and a mean of zero.
NYC (Not NYC)	Indicator equal to 1 if the CFA conference was (not) held in New York City, and zero otherwise.
Retail OIB	Retail order imbalance calculated as total retail buy volume less total retail sell volume over trading days [0,1] divided by total volume over trading days [0,1]; all days are indexed relative to the EA date. Retail trades are identified following the method developed by Boehmer et al. (2021) and modified in Barber et al. (2024), and trade direction is inferred following the method developed by Lee and Ready (1991). Multiplied by 100 for expositional purposes.
Size	The natural log of 1 + the market value of equity.
Surprise	The annual decile ranked earnings surprise calculated as actual EPS less the consensus EPS forecast preceding the EA scaled by price per share at the end of the previous fiscal-period.
TRA	Percentage of total shares held by transient institutions in the most recent 13F filing preceding the EA. Transient institutions are identified using the classification method developed by Bushee (1998).

Appendix B

CFA Conference Dates & Locations

Conference Year	Conference Dates	Days of the week	Conference Location	Sample Observations
2012	December 6-7	Thursday – Friday	Philadelphia	123
2013	November 21-22	Thursday – Friday	New York	204
2014	November 20-21	Thursday – Friday	Boston	256
2015	November 17-18	Tuesday – Wednesday	Philadelphia	517
2016	November 17-18	Thursday – Friday	New York	452
2017	November 14-15	Tuesday – Wednesday	New York	926
2018	November 6-7	Tuesday – Wednesday	New York	1,679
2019	November 14-15	Thursday – Friday	New York	970

Figure 1: Placebo Analyses

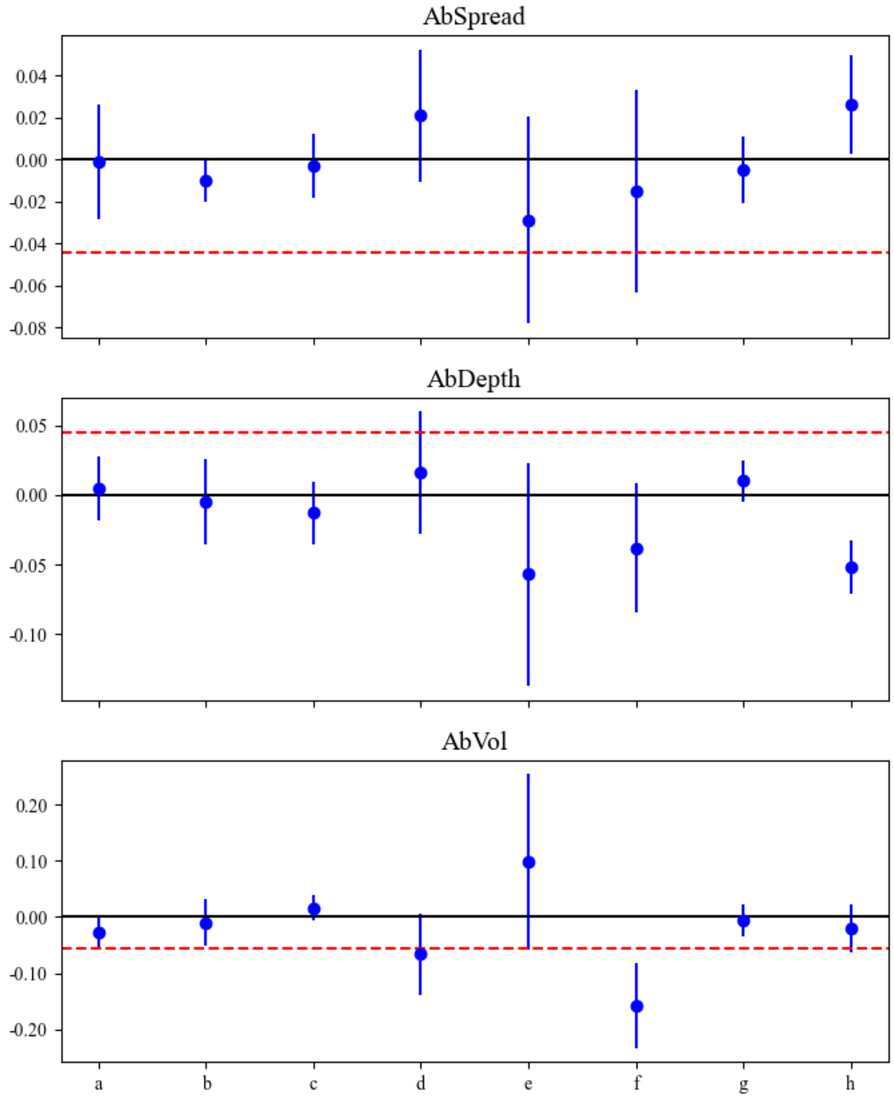

Figure 1 plots coefficient estimates from 8 different placebo tests corresponding to tests in Table 3. The dashed red line represents the estimate from Table 3, and placebo coefficients are in blue with 90% confidence intervals. The eight placebo estimates, marked on the x-axis, are as follows:

a. Same treatment and control firms from two calendar quarters prior to the CFA conference
b. Same treatment and control firms from one calendar quarter prior to the CFA conference
c. Same treatment and control firms from one calendar quarter following the CFA conference
d. Week 9 of Q4, days 4-6, years 2013-2019
e. Week 7 of Q4, days 4-6, years 2012, 2015, 2017-2019
f. Week 7 of Q4, days 2-4, years 2012-2014, 2016, 2018-2019
g. Week 5 of Q4, days 2-4, years 2012-2017, 2019
h. Week 6 of Q4, days 4-6, years 2012-2018

TABLE 1

Primary Sample Descriptive Statistics and Balance

Panel A: Descriptive Statistics

Variable	N	Mean	Lower Quartile	Median	Upper Quartile	Std Dev
<u>*Dependent Variables*</u>						
AbSpread$_{[0,1]}$	5,127	0.171	-0.027	0.188	0.402	0.354
AbDepth$_{[0,1]}$	5,127	0.010	-0.246	0.032	0.268	0.479
AbVolume$_{[0,1]}$	5,127	0.586	0.116	0.630	1.078	0.806
BHAR$_{[2,5]}$	5,127	0.000	-0.032	-0.001	0.028	0.084
BHAR$_{[2,10]}$	5,127	0.000	-0.047	-0.002	0.041	0.125
BHAR$_{[2,20]}$	5,127	-0.004	-0.073	-0.007	0.052	0.170
Jump	5,127	0.721	0.275	0.750	1.145	2.234
IPE	5,127	0.502	1.573	3.771	4.817	11.531
<u>*Independent Variables*</u>						
Conference	5,127	0.215	0.000	0.000	0.000	0.411
*Size**	5,127	3,742	134	609	2,537	9,874
MB	5,127	3.674	1.250	2.371	4.604	8.369
*Surprise**	5,127	-0.002	-0.003	0.000	0.004	0.041
*Abs(Surprise)**	5,127	0.019	0.001	0.003	0.011	0.055
*Busy EA**	5,127	233.3	127.0	256.0	355.0	126.5
*Follow**	5,127	6.953	2.000	5.000	9.000	6.425
ARC	5,127	197.43	134.00	181.00	241.00	84.75
Inst OIB	5,127	-0.100	-1.179	0.000	1.165	4.474
ITI	2,792	0.405	0.276	0.395	0.522	0.168
NDAQ OIB	3,663	0.019	0.000	0.000	0.009	0.065
Retail OIB	5,127	-0.553	-1.207	-0.175	0.553	3.687

Panel B: Industry Balance

		Treat		Control	
Industry	FF12	# of obs	% of total	# of obs	% of total
NoDur	1	54	4.9%	168	4.2%
Durbl	2	31	2.8%	98	2.4%
Manuf	3	87	7.9%	317	7.9%
Energy	4	56	5.1%	181	4.5%
Chems	5	34	3.1%	88	2.2%
BusEq	6	199	18.1%	735	18.3%
Telcm	7	21	1.9%	116	2.9%
Utils	8	25	2.3%	101	2.5%
Shops	9	159	14.4%	401	10.0%
Hlth	10	289	26.2%	1,179	29.3%
Money	11	50	4.5%	269	6.7%
Other	12	97	8.8%	372	9.2%
Total		1,102	100.0%	4,025	100.0%

Panel C: Covariate Balance

	N		Mean		
Variables	Treat	Control	Treat	Control	Difference
Size	1,102	4,025	6.466	6.396	-0.070
ROA	1,102	4,025	-0.042	-0.045	-0.003
MB	1,102	4,025	3.940	3.601	-0.340
Surprise	1,102	4,025	5.186	5.423	0.237**
Abs(Surprise)	1,102	4,025	6.118	6.292	0.174*
Busy EA	1,102	4,025	4.957	5.250	0.293***
Follow	1,102	4,025	1.811	1.792	-0.018
ARC	1,102	4,025	195.58	197.94	2.36

Panel A presents descriptive statistics for variables used in our analyses. Variables with an * are presented before log or decile rank transformations. Panel B reports the industry composition of treatment and control samples. Panel C reports mean values of potential covariates for treatment and control samples. All continuous variables except returns are winsorized at the 1st and 99th percentiles. *** (**, *) denotes two-tailed significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level. All variables are defined in Appendix A.

TABLE 2

The Impact of Professional Attention on Institutional Traders

DV =	$BHAR_{[2,5]}$	$BHAR_{[2,10]}$	$BHAR_{[2,20]}$	$BHAR_{[2,5]}$	$BHAR_{[2,10]}$	$BHAR_{[2,20]}$
	[1]	[2]	[3]	[4]	[5]	[6]
Conference	0.028**	0.028*	-0.008	0.017*	0.052***	0.000
	(2.55)	(1.85)	(-0.41)	(1.76)	(3.63)	(0.01)
Inst OIB $_{[0,1]}$ **× *Conference***	**-0.000**	**-0.001**	**-0.000**			
	(-0.43)	**(-1.55)**	**(-0.73)**			
Inst OIB $_{[0,1]}$	-0.000	-0.000	-0.001*			
	(-0.46)	(-0.93)	(-1.96)			
ITI $_{[0,1]}$ **× *Conference***				**-0.002**	**-0.005*** **	**-0.009*** **
				(-1.13)	**(-3.21)**	**(-4.22)**
ITI $_{[0,1]}$				0.002**	0.005***	0.006***
				(2.60)	(4.41)	(4.81)
Size	0.003***	0.006***	0.008***	0.001	0.002	0.004**
	(5.19)	(5.17)	(4.85)	(1.15)	(1.09)	(2.10)
MB	0.000**	0.000	0.000	0.000**	0.000	0.000
	(2.06)	(0.97)	(0.79)	(2.12)	(0.68)	(0.25)
Surprise	0.001**	0.001**	0.001	0.001***	0.001	0.001
	(2.28)	(2.48)	(1.53)	(2.72)	(1.26)	(1.24)
Busy EA	0.001	0.001	-0.001	-0.002	-0.003	-0.005*
	(1.27)	(0.52)	(-0.26)	(-1.41)	(-1.55)	(-1.84)
Following	-0.003	-0.004	-0.005	-0.004**	-0.005*	-0.011***
	(-1.62)	(-1.58)	(-1.44)	(-2.59)	(-1.68)	(-2.78)
ARC	-0.000**	-0.000***	-0.000*	0.000	-0.000	0.000
	(-2.17)	(-3.47)	(-1.93)	(0.34)	(-0.66)	(0.14)
Observations	4,950	4,950	4,916	2,654	2,654	2,669
Adjusted R-squared	0.006	0.014	0.018	0.020	0.020	0.019
Cook's Distance	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year

This table reports estimates of our institutional trading validation test. The dependent variable is abnormal buy-and-hold returns from 2 to 5, 2 to 10, or 2 to 20 trading days following the earnings announcement date ($BHAR_{[2,5]}$, $BHAR_{[2,10]}$, or $BHAR_{[2,20]}$, respectively). *Conference* is an indicator variable equal to one for earnings announcements that occur one day prior to or during a CFA conference. *Inst OIB* is large trade (>$50,000) order imbalance over trading days [0,1]. *ITI* is informed trading intensity from Bogousslavsky, Fos, and Muravyev (2024) over trading days [0,1]. *ITI* is standardized to have a standard deviation of one and a mean of zero. Controls interactions with *Conference* are included but not tabulated. All continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by earnings announcement date. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N=5,127 in columns 1 to 3 and N=2,792 in columns 4 to 6. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 3

The Impact of Professional Inattention on Information Asymmetry, Liquidity, & Volume

DV =	$AbSpread_{[0,1]}$	$AbDepth_{[0,1]}$	$AbVolume_{[0,1]}$
	[1]	[2]	[3]
Conference	**-0.044*** **	**0.045** **	**-0.055* **
	(-3.10)	**(2.40)**	**(-1.70)**
Size	0.047***	0.045***	0.059***
	(10.41)	(10.54)	(5.58)
MB	-0.000	-0.000	-0.001
	(-0.38)	(-0.63)	(-1.66)
Abs(Surprise)	-0.007***	0.001	0.007*
	(-3.83)	(0.63)	(1.81)
Busy EA	0.006	-0.002	-0.166***
	(0.66)	(-0.22)	(-8.93)
Following	-0.027***	-0.007	0.147***
	(-2.93)	(-0.62)	(6.39)
ARC	0.000*	-0.000***	0.000**
	(1.79)	(-2.81)	(2.09)
Observations	4,858	4,827	4,822
Adjusted R-squared	0.167	0.117	0.134
Cook's Distance	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year

This table reports estimates of Equation (1). The dependent variable in column 1 is abnormal bid-ask spread at the earnings announcement date ($AbSpread_{[0,1]}$). The dependent variable in column 2 is abnormal depth at the earnings announcement date ($AbDepth_{[0,1]}$). The dependent variable in column 3 is abnormal total volume at the earnings announcement date ($AbVolume_{[0,1]}$). *Conference* is an indicator variable equal to one for earnings announcements that occur one day prior to or during a CFA conference. All continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by earnings announcement date. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N=5,127. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 4

Pattern Earnings Announcement Firms

DV =	*AbSpread*$_{[0,1]}$ [1]	*AbDepth*$_{[0,1]}$ [2]	*AbVolume*$_{[0,1]}$ [3]
Conference	**-0.048****	**0.044***	**-0.000**
	(-2.03)	**(1.92)**	**(-0.01)**
Size	0.045***	0.001	-0.024*
	(5.85)	(0.11)	(-1.67)
MB	-0.001	-0.002*	-0.001
	(-1.27)	(-1.72)	(-0.71)
Abs(Surprise)	-0.018***	-0.003	0.022***
	(-2.92)	(-0.63)	(3.19)
Busy EA	0.018	-0.000	-0.155***
	(1.15)	(-0.00)	(-6.16)
Following	-0.041**	0.017	0.223***
	(-2.02)	(0.77)	(5.93)
ARC	-0.000	-0.000**	0.000
	(-0.34)	(-2.28)	(1.43)
Observations	711	701	706
Adjusted R-squared	0.160	0.121	0.162
Cook's Distance	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year

This table reports estimates of Equation (1) for firms with predictable earnings announcement date patterns. The dependent variable in column 1 is abnormal bid-ask spread at the earnings announcement date (*AbSpread*$_{[0,1]}$). The dependent variable in column 2 is abnormal depth at the earnings announcement date (*AbDepth*$_{[0,1]}$). The dependent variable in column 3 is abnormal total volume at the earnings announcement date (*AbVolume*$_{[0,1]}$). *Conference* is an indicator variable equal to one for earnings announcements that occur one day prior to or during a CFA conference. All continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by earnings announcement date. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N=751. *** (**, *) denotes two-tailed significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level. All variables are defined in Appendix A.

TABLE 5

Cross-sectional Tests

Panel A: IO Concentration	*AbSpread*$_{[0,1]}$		*AbDepth*$_{[0,1]}$		*AbVolume*$_{[0,1]}$	
	Low Concent [1]	*High Concent* [2]	*Low Concent* [3]	*High Concent* [4]	*Low Concent* [5]	*High Concent* [6]
Conference	**-0.065******	**-0.027**	**0.047******	**0.046***	**-0.065******	**-0.034**
	(-4.39)	**(-1.38)**	**(2.91)**	**(1.78)**	**(-3.14)**	**(-0.59)**
Test of difference:						
Low − High	-0.038*		0.001		-0.031*	
(p-value)	(0.087)		(0.922)		(0.052)	
Observations	2,411	2,395	2,405	2,378	2,413	2,394
Adjusted R-squared	0.172	0.106	0.157	0.084	0.116	0.093
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cook's Distance	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year

Panel B: Transitory Ownership	*AbSpread*$_{[0,1]}$		*AbDepth*$_{[0,1]}$		*AbVolume*$_{[0,1]}$	
	High TRA [1]	*Low TRA* [2]	*High TRA* [3]	*Low TRA* [4]	*High TRA* [5]	*Low TRA* [6]
Conference	**-0.076******	**-0.038**	**0.049***	**0.045***	**-0.101******	**-0.021**
	(-5.52)	**(-1.55)**	**(1.82)**	**(1.78)**	**(-4.48)**	**(-0.41)**
Test of difference:						
High − Low	-0.038**		0.004		-0.08**	
(p-value)	(0.044)		(0.408)		(0.026)	
Observations	1,963	1,951	1,958	1,947	1,954	1,944
Adjusted R-squared	0.176	0.165	0.136	0.085	0.101	0.125
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cook's Distance	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year

Panel C: NYC vs Not NYC	*AbSpread[0,1]*		*AbDepth[0,1]*		*AbVolume[0,1]*	
	NYC	*Not NYC*	*NYC*	*Not NYC*	*NYC*	*Not NYC*
	[1]	[2]	[3]	[4]	[5]	[6]
Conference	**-0.051*****	**-0.009**	**0.068*****	**-0.007**	**-0.054**	**0.034**
	(-3.40)	**(-0.33)**	**(3.58)**	**(-0.14)**	**(-1.52)**	**(0.58)**
Test of difference:						
NYC − Not NYC	-0.042*		0.075*		-0.088*	
(p-value)	(0.077)		(0.070)		(0.097)	
Observations	3,980	836	3,980	832	3,980	854
Adjusted R-squared	0.118	0.051	0.100	0.085	0.118	0.159
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cook's Distance	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year

Panel D: During Conference Hours	*AbSpread[0,1]*		*AbDepth[0,1]*		*AbVolume[0,1]*	
	Conf Hours	*Not Conf Hours*	*Conf Hours*	*Not Conf Hours*	*Conf Hours*	*Not Conf Hours*
	[1]	[2]	[3]	[4]	[5]	[6]
Conference	**-0.051*****	**-0.028**	**0.060****	**0.028**	**-0.072***	**-0.024**
	(-3.51)	**(-1.28)**	**(2.51)**	**(1.12)**	**(-1.92)**	**(-0.65)**
Test of difference:						
Conf Hours − Not Conf Hours	-0.023		0.032		-0.048	
(p-value)	(0.148)		(0.159)		(0.102)	
Observations	2,935	1,909	2,914	1,897	2,907	1,913
Adjusted R-squared	0.149	0.189	0.117	0.137	0.124	0.154
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cook's Distance	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year

Panel A reports estimates of Equation (1) for samples partitioned into low and high institutional ownership concentration (*Low Concent* and *High Concent*, respectively). Panel B reports estimates of Equation (1) for samples partitioned into low and high transient institutional ownership (*High TRA* and *Low TRA*, respectively). Panel C reports estimates of Equation (1) for samples partitioned on whether the conference was held in New York City or not (*NYC* and *Not NYC*, respectively). Panel D reports estimates of Equation (1) for samples partitioned on whether the earnings announcement occurred between 8:30 am and 5:30 pm or outside of those hours (*Conf Hours* and *Not Conf Hours*, respectively). *Conference* is an indicator variable equal to one for earnings announcements that occur one day prior to or during a CFA conference. Controls are included in all regressions but not tabulated. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by earnings announcement date. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N=5,073 in Panel A, N=4,150 in Panel B, and N=5,127 in Panels C and D. Coefficient differences are tested across sample partitions using Wald Tests. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 6

Professional Inattention and Non-EA Events

DV =	*AbSpread*$_{[0,1]}$ [1]	*AbDepth*$_{[0,1]}$ [2]	*AbVolume*$_{[0,1]}$ [3]
Conference	**-0.018***	**0.033*****	**-0.064****
	(-1.66)	**(2.82)**	**(-2.48)**
Observations	5,284	5,330	5,295
Adjusted R-squared	0.192	0.128	0.102
Controls	Yes	Yes	Yes
Cook's Distance	Yes	Yes	Yes
Cluster	Date	Date	Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year

This table reports estimates of Equation (1) for firms with non-EA news events. The dependent variable in column 1 is abnormal bid-ask spread at the news date (*AbSpread*$_{[0,1]}$). The dependent variable in column 2 is abnormal depth at the news date (*AbDepth*$_{[0,1]}$). The dependent variable in column 3 is abnormal total volume at the news date (*AbVolume*$_{[0,1]}$). *Conference* is an indicator variable equal to one for news events that occur one day prior to or during a CFA conference. All continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by news events date. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N=5,632. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 7

The Impact of Professional Inattention on Market Efficiency

DV =	*Jump Ratio*	*IPE*	$BHAR_{[-1,1]}$
	[1]	[2]	[3]
Conference	**-0.040****	**-0.082**	-0.019
	(-2.01)	**(-1.15)**	(-0.95)
Surprise × Conference			**-0.172****
			(-2.03)
Surprise			0.455***
			(10.80)
Size	0.039***	0.141***	0.004***
	(4.80)	(7.35)	(2.96)
MB	-0.002	-0.004	-0.000
	(-1.32)	(-1.43)	(-0.29)
Abs(Surprise)	-0.006*	-0.013*	
	(-1.83)	(-1.94)	
Busy EA	-0.020	-0.138***	-0.002
	(-1.66)	(-3.17)	(-0.63)
Following	0.011	0.030	-0.002
	(0.62)	(0.50)	(-0.64)
ARC	0.000	0.001***	0.000
	(1.46)	(3.70)	(0.11)
Observations	3,996	4,066	4,902
Adjusted R-squared	0.032	0.065	0.031
Cook's Distance	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year

The dependent variable in column 1 is the ratio of abnormal returns during the [0,1] trading day window to abnormal returns during the [0,5] trading day window (*Jump Ratio*). The dependent variable in column 2 is intraperiod price efficiency calculated using the 5-day trading window starting at the earnings announcement (*IPE*). Columns 1 and 2 drop all observations where the absolute value of 5-day cumulative abnormal returns is less than 2%. The dependent variable in column 3 is abnormal buy-and-hold returns from -1 to +1 trading days around the earnings announcement date ($BHAR_{[-1,1]}$). *Conference* is an indicator variable equal to one for earnings announcements that occur one day prior to or during a CFA conference. Controls interactions with *Conference* are included in column 3 but not tabulated. All continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by earnings announcement date. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N=4,262 in column 1 and 2, and N=5,127 in column 3. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 8

The Impact of Professional Attention on Retail Trading Profitability

DV =	$BHAR_{[2,5]}$	$BHAR_{[2,10]}$	$BHAR_{[2,20]}$	$BHAR_{[2,5]}$	$BHAR_{[2,10]}$	$BHAR_{[2,20]}$
	[1]	[2]	[3]	[4]	[5]	[6]
Conference	0.029***	0.026*	-0.007	0.032*	0.033	0.047
	(2.92)	(1.91)	(-0.37)	(1.93)	(1.20)	(1.39)
Retail $\boldsymbol{OIB_{[0,1]}}$ **× *Conference***	**0.001**	**0.001****	**0.003****			
	(1.34)	**(2.07)**	**(2.05)**			
Retail $OIB_{[0,1]}$	0.000	-0.000	-0.000			
	(0.41)	(-0.18)	(-0.52)			
NDAQ $\boldsymbol{OIB_{[0,1]}}$ **× *Conference***				**0.005*****	**0.005***	**0.006**
				(3.67)	**(1.95)**	**(0.92)**
NDAQ $OIB_{[0,1]}$				-0.001	0.000	0.001
				(-0.52)	(0.34)	(0.64)
Size	0.003***	0.006***	0.007***	0.002**	0.005***	0.008***
	(5.18)	(4.88)	(4.33)	(2.61)	(3.98)	(4.73)
MB	0.000**	0.000	0.000	0.000	0.000	0.000
	(2.14)	(1.18)	(0.85)	(1.52)	(1.08)	(0.65)
Surprise	0.001**	0.001**	0.001**	0.001	0.000	-0.000
	(2.39)	(2.57)	(2.02)	(1.32)	(0.82)	(-0.00)
Busy EA	0.001	0.001	0.000	0.001	0.003	0.002
	(1.13)	(0.41)	(0.06)	(1.08)	(1.08)	(0.47)
Following	-0.003*	-0.004*	-0.004	-0.002	-0.004	-0.007*
	(-1.69)	(-1.70)	(-1.13)	(-0.98)	(-1.40)	(-1.81)
ARC	-0.000*	-0.000***	-0.000	0.000	-0.000*	-0.000
	(-1.93)	(-3.38)	(-1.62)	(0.33)	(-1.87)	(-1.04)
Observations	4,938	4,942	4,893	3,510	3,539	3,511
Adjusted R-squared	0.008	0.014	0.020	0.004	0.009	0.014
Cook's Distance	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year

The dependent variable is abnormal buy-and-hold returns from 2 to 5, 2 to 10, or 2 to 20 trading days following the earnings announcement date ($BHAR_{[2,5]}$, $BHAR_{[2,10]}$, or $BHAR_{[2,20]}$, respectively). *Conference* is an indicator variable equal to one for earnings announcements that occur one day prior to or during a CFA conference. *Retail OIB* is retail order imbalance over trading days [0,1]. *NDAQ OIB* is the change in retail sentiment during trading days [0,1]. *NDAQ OIB* is standardized to have a standard deviation of one and a mean of zero. Controls interactions with *Conference* are included but not tabulated. All continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by earnings announcement date. In all regressions, outliers are removed using a Cook’s distance threshold of 4/N, where N=5,127 in columns 1 to 3 and N=3,663 in columns 4 to 6. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 9

The Impact of Professional Inattention on Sell-Side Analysts

DV =	*Fcst_N*	*Fcst_Lag*	*Fcst_Error*	*Fcst_Bias*
	[1]	[2]	[3]	[4]
Conference	**-0.002**	**0.008**	**0.004****	**0.002***
	(-0.24)	**(0.30)**	**(2.48)**	**(1.68)**
Size	0.029***	-0.008	-0.011***	-0.001***
	(9.51)	(-1.11)	(-17.78)	(-2.71)
MB	0.002***	-0.008***	-0.000***	-0.000
	(4.04)	(-9.86)	(-4.20)	(-0.64)
Surprise	0.003***	-0.013***	-0.001***	-0.002***
	(3.06)	(-4.23)	(-4.05)	(-10.06)
Busy EA	-0.003	0.047***	-0.001	-0.002**
	(-0.64)	(3.12)	(-1.26)	(-2.29)
Following	0.850***	-0.019	0.004***	-0.002*
	(106.15)	(-1.05)	(3.52)	(-1.81)
ARC	-0.000*	0.001***	0.000***	0.000***
	(-1.94)	(8.02)	(10.52)	(4.58)
Observations	4,251	4,287	4,329	4,235
Adjusted R-squared	0.899	0.098	0.215	0.045
Cook's Distance	Yes	Yes	Yes	Yes
Cluster	EA Date	EA Date	EA Date	EA Date
Fixed Effects	Weekday & Year	Weekday & Year	Weekday & Year	Weekday & Year

The dependent variable in column 1 is the number of sell-side analyst forecasts issued in the 2-day earnings announcement window (*Fcst_N*). The dependent variable in column 2 is the average time lag (in hours) of sell-side analyst forecasts issued in the 2-day earnings announcement window (*Fcst_Lag*). The dependent variable in column 3 is the average forecast error (i.e., unsigned error) of sell-side analyst forecasts issued in the 2-day earnings announcement window (*Fcst_Error*). The dependent variable in column 4 is the average forecast bias (i.e., signed error) of sell-side analyst forecasts issued in the 2-day earnings announcement window (*Fcst_Bias*). *Conference* is an indicator variable equal to one for earnings announcements that occur one day prior to or during a CFA conference. All continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects, weekday fixed effects, and standard errors clustered by earnings announcement date. In all regressions, outliers are removed using a Cook's distance threshold of 4/N, where N=4,460. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.