Investor Attention Spill-Over Effect: Evidence from DJIA Record Days

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ABSTRACT

Using the Dow Jones Industrial Average Index record breaking days as a proxy for market wide attention, we show that as the aggregate stock market intensifies investor attention, stock market response to individual firms' earnings announcements significantly increases. We hypothesize that there are many channels for the attention spill-over effect and document strong supportive evidence of one important mechanism: the trading volume channel. Heightened investor attention to the aggregate stock market induces investors to trade more before individual earnings announcements and accelerates the stock market reaction. Overall, our empirical results document an important investor attention spill-over effect within the context of earnings announcements.

JEL Classification: G11, G14, G15

Keywords: Investor Attention, DJIA Record Days, Earnings Announcements, Trading Volume, PEAD

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1. Introduction

The behavioral finance literature has argued that investors do not pay attention to all available information in the financial market, nor do they utilize all available information in their decision-making process. In other words, investors have limited attention. This is in sharp contrast to the traditional finance paradigm in that the latter assumes investors have unlimited attention to all relevant information and process such information in a timely manner to make rational decisions. The field of psychology, however, provides the theoretical foundation for the notion of limited attention by arguing that human attention is a scarce cognitive resource and that human brains are subject to the central cognitive-processing capacity constraint (Kahneman 1973). On the empirical side, recent years have witnessed an increase in the number of studies that have documented evidence consistent with investors' limited attention.[1]

Applying the notion of limited attention to corporate earnings announcements (EAs) has greatly enhanced our understanding of how the stock market response to EAs is affected by the level of investor attention. For instance, it has been shown that when investors have limited attention as proxied by *lower trading volume*, or when investors are distracted by *multiple earnings announcements on the same day*, or when the earnings announcements are made on *Fridays* or during *non-trading hours* as compared to other weekdays or trading hours, the stock market response at announcement times becomes weaker and the post-earnings announcement drift (PEAD) is stronger (Francis et al. 1992; Hou et al. 2009; Della Vigna and Pollet 2009; Hirshleifer and Teoh 2003; Hirshleifer et al. 2009 etc.). That is to say, the stock market under-reacts in the presence of limited attention. This under-reaction is usually associated with post-earnings stock price drift pattern.

These studies have shed significant insights on the stock price dynamics surrounding these information events. However, the majority of the existing studies has been vague about whether the attention is at the aggregate market level or firm level. Such a distinction is important and meaningful given that investors have limited attention in general and that attention to the market is different from but related to attention to individual firms. Market level attention can affect firm level attention and vice versa. Uncovering the dynamics between market level and firm level investor attention is interesting and helps market participants better understand the driving force behind the stock market reaction to EAs. Identifying the different forms of investor attention can also have profound investment implications as recent studies have documented profitable investment strategies based on investor attention (Storms et al. 2015, Wang 2016).

This paper attempts to take a first step by making a clear distinction between market level and firm level investor attention and demonstrating that there is a spillover effect between investor attention at these two levels. More specifically, we show that as the aggregate stock market catches investor's attention, investors seem to be more attentive to individual firms as well. Consequently, the stock market response to individual EAs is accelerated.

We propose the use of the record-breaking days of Dow Jones Industrial Average (DJIA) index to capture investor's attention to the aggregate stock market. DJIA record-breaking days are ideal market events to

[1] An incomplete list of empirical studies on investors' limited attention includes: Bernard and Thomas (1989), Francis et al. (1992), Hirst and Hopkins (1998), Lo and Wang (2000), Teoh and Wong (2002), Hirshleifer and Teoh (2003), Peng and Xiong (2006), Cohen and Frazzini (2008), Della Vigna and Pollet (2009), Hirshleifer et al. (2009), Hou et al. (2009), Da et al. (2011).

capture market-wide investor attention and mitigate the challenges of separating market level from firm level attention for at least three reasons. First, with a history dating back to May 26, 1896, DJIA remains the most cited and most widely recognized stock market index despite criticisms on its representativeness. Various financial information outlets such as the Wall Street Journal, Google Finance etc. publish DJIA level on a regular basis. Record-breaking days of DJIA are sensational market events, are extensively covered by the financial media, and generate significant attention among investors. Second, disentangling market level and firm level attention is very demanding given that the aggregate stock market is simply composed of various firms in the market. If stock market index consists of too many stocks, the separation of market-wide from firm level attention is subject to substantial endogeneity and contamination error. The fact that DJIA index is only computed from 30 stocks out of thousands of stocks in the marketplace greatly eases the difficulty of the challenging task. Third, in our empirical design, we impose another constraint on DJIA record-breaking days to better capture market-wide investor attention. More specifically, we require that on record-breaking days, the closing DJIA index level must exceed the previous day's closing level by at least 100 points.[2] This empirical design, while somewhat arbitrary, is supported by anecdotal evidence that there exists substantial coverage when DJIA index exceeds the previous level by a certain threshold, usually 100 points.[3]

Using a broad sample of earnings announcements, we show that as the aggregate stock market intensifies investor attention as proxied by DJIA record-breaking days, stock market response to individual firms' EAs also *increases*. Availing ourselves of the widely used earnings response coefficient (ERC) framework, we are able to quantify the magnitude of the change in the stock market response to EAs. More specifically, we show that the ERC increases reliably as we move from EAs without DJIA record-breaking days in the 30-day period leading up to the earnings announcement dates (EADs) to EAs with such record days. Thus, the stock market reaction is much stronger for EAs that have eye-catching market wide attention prior to the EADs.

A plausible interpretation for such results is that as market wide investor attention increases, so does firm level investor attention. In other words, there exists a spill-over effect from market wide attention to firm level attention. When the DJIA index breaks the record and exceeds the previous closing level by at least 100 points simultaneously, there exists extensive media coverage in the financial marketplace. The effects of such salient events are multifold. First, while the record DJIA level can be driven by any or all of the 30 stocks included in the DJIA index, heightened investor attention to any or all of the 30 stocks can generate substantial attention to other related stocks such as stocks that are operating in the same or related industries and stocks that have supplier-customer relationship with the DJIA component stocks. Second, from a psychological standpoint, investors can have divided or selective attention, and thus, they can be frequently distracted from stock investments and stock trading. In other words, investors can be quite inattentive or even overlook stock trading from time to time. Salient market events can bring back investor's attention to both DJIA constituent stocks as well as any stocks in general. Third, from a market participant perspective, attention-grabbing record days can not only attract marginal investor who may not have traded before to the market but also drive existing investors to pay more attention to stocks they have traded already. Overall, sensational market events generate tremendous attention among investors to the aggregate stock market, which further constitutes an economic externality to other stocks by increasing investors' attention to individual stocks.

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[2] In our empirical exercises, we also check the robustness by using a cutoff level of 80 points and 120 points. Our main results survive this robustness check.

[3] For instance, on April 26, 2012, WSJ reports "Dow Gains Over 100 Points" in its *Today's Market*. See http://www.wsj.com/articles/SB10001424052702304723304577367451780264514 for details.

Intuitively, this interpretation seems appealing. However, it in turn begs the interesting question of what are the exact mechanisms such that the market level attention carries over to firm level attention. Moreover, does the attention spill-over effect have any psychological foundations? We attempt to provide at least partial answers to these questions while resorting to the psychology literature at the same time.

While there can be many channels through which market wide attention works its way into individual firms, we propose one important channel: the trading volume channel. Trading volume has been advocated as one of the most popular and widely used proxies for investor attention (Lo and Wang 2000; Chordia and Swaminathan 2002; Barber and Odean 2008; Hou et al. 2009 etc.). The intuition is very straightforward. When investors pay little attention to a stock, they are unlikely to trade it; and when they pay more attention to a stock, they are more likely to trade it. In other words, trading volume should be highly correlated with attention. In addition, investor attention may interact with other psychological biases and result in a divergence of opinions among investors about the stock, which presumably generates more trading (Odean 1998; Scheinkman and Xiong 2003).

We hypothesize that as heightened investor attention to the aggregate stock market generates more attention to individual firms, investors will likely trade more before individual earnings announcements. Higher trading volume in turn leads to stronger stock market response at announcement times. This is precisely what we find in the data. EAs that have DJIA record days in the pre-announcement period (30-day window before the EADs) experience significantly higher trading volume as compared to EAs that don't have DJIA record days. In the multivariate analysis, market wide attention has significant explanatory power for the trading volume of the sample EAs. When casted in the ERC framework, the trading volume variable carries a statistically significant and positive coefficient in explaining the stock market response. Overall, the data strongly supports the trading volume channel for the attention spill-over effect.

Our paper contributes to the existing literature along several dimensions. First, this paper adds new perspectives and novel findings to the investor attention literature. It is the first of its kind to advocate the DJIA record-breaking days as a proxy for market-wide investor attention. The emphasis on the importance of the difference and the spill-over effect between market-wide and firm-level investor attention provides a new angle to the economic implications of investor attention for the financial market. In this regard, our paper is closely related to Drake et al. (2016) in that both their paper and ours study investor attention from distinct sources. Specifically, Drake et al. (2016) investigate how investor attention to a firm is explained by attention paid to the firm's industry and the market in general. They propose the notion of attention comovement and show that such comovement is nontrivial for the average firm. Our paper complements their work in that we also examine the relationship between investor attention to the market vs. individual firms. However, our paper deviates from theirs in that we focus on how attention to the market spills over to individual firms whereas they focus on how attention to firms spills over to its peers. They present strong evidence that a firm's earnings announcement helps transfer investor attention from one firm to other firms.

This paper also adds new insights to the EAs literature. EAs are routine channels through which firms disclose material information to the financial market. Recent years have seen increased attention to EAs from both academia and practitioners due to their information-intensive nature. Whether the stock market responds efficiently to EAs is of great importance to the long-lasting theme of market efficiency. The existing literature has well documented two stylized facts about earnings announcements: stock market under-reaction at the time of announcements and post-earnings announcement drift [4], which refers to the

[4] The post-earnings announcement drift anomaly has proved to be one of the strongest anomalies in the literature and many researchers have worked on this issue, including Ball and Brown (1986), Bernard and Thomas (1989, 1990), Bhushan (1994),

phenomenon that the stock price tends to continue drifting in the direction of the earnings surprise. We reinforce the connection between the EAs literature and the investor attention literature in this paper. We show that as the DJIA index breaks record, increased attention to the aggregate stock market spills over to individual firms. As a result, stock market under-reaction is reduced at announcement times.

The rest of the paper is organized as follows. We survey the literature in Section 2. In Section 3, we derive the main empirical hypotheses about the stock market response to EAs and outline the empirical framework used to test these hypotheses. Data and methodologies are discussed in Section 4. We present our main empirical findings in Section 5. In Section 6 we draw our conclusions as well as propose future research along the lines of this paper.

2. Literature Review

In this section, we survey two streams of literature that are closely related to our research purpose. The first strand of literature is about psychological foundation of attention spill-over effect and the second strand is about the measurement and application of investor attention in the financial market.

2.1. Psychological foundation of attention spill-over

Attention is the behavioral and cognitive process of selectively concentrating on some aspect of information while ignoring other perceivable information (Anderson 2004). In this sense, attention has usually been referred to as the allocation of limited processing resources. One conventional way to describe attention is to think of it as the sustained focus of cognitive resources on information while filtering or ignoring extraneous information. It is generally accepted that attention is a very basic function that often precedes other neurological and cognitive functions.

Our investigation of attention spill-over is closely related to the notion of *attentional shift* or *shift of attention* from the field of psychology. Attentional shift occurs usually when there is a stimulus. In the presence of a stimulus, human brains direct attention to a point to increase the efficiency of processing that point by reducing cognitive resources to other unwanted or irrelevant inputs. Shifting of attention is needed to allocate attentional resources to process information from a stimulus more efficiently. Psychological studies have shown that when an object or area is attended, processing operates in a more efficient manner (Posner 1980, Gazzaniga et al. 2002).

Two competing theories have been developed to explain why and how attention is shifted: *the moving-spotlight theory* and the *gradient theory*. According to the moving-spotlight theory, attention is like a moving spotlight that is directed towards intended targets, focusing on each target in a serial manner. When information is illuminated by the spotlight, hence attended, processing proceeds in a more efficient manner, directing attention to a particular point and inhibiting input from any stimuli outside of the spotlight. However, when a shift of attention occurs, the spotlight is, in effect, turned off while attention shifts to the next attended location. The gradient theory, however, attempts to explain attentional shift in a different way. According to this theory, attentional resources are given to a region in space rather than a spotlight so that attentional resources are most concentrated at the center of attentional focus and then decrease the further a stimulus is from the center.

We argue that the notion of attentional shift largely provides the psychological foundation of the attention spill-over effect within our context. With the DJIA index breaking the record, there exists pervasive media coverage about the aggregate stock market, the DJIA component stocks as well as stocks that are closely related to the component stock. Market wide coverage of such events constitutes a strong stimulus

Dontoh et al. (2003), Mendenhall (2004), Sadka (2006), Livnat and Mendenhall (2006), Ng et al. (2008), Sadka and Sadka (2009), Chordia et al. (2009), Konchitchki et al. (2012), among others.

to investors in general. The upcoming EAs further helps the individual stocks (re)gain the spotlight or enable them to stay closer to the center of investors' attentional focus. Consequently, investors' attention is shifted and redirected towards individual stocks.

2.2. Motivation, measurement and application of investor attention in the financial market

We now turn to survey the literature about the motivation, measurement and application of investor attention in the financial market. Traditional finance paradigm assumes that investors utilize all available information to make rational decisions. The psychology and behavioral finance literature, however, argue quite the opposite. Kanehman (1973) points out human beings are subject to cognitive constraints and psychological biases. Moreover, there is a limit to the central cognitive-processing power of the human brain. In contrast, the enormous amount of value-relevant information that is available for a firm requires significant amount of time and cognitive resources to process such information. As a consequence, investors often fail to incorporate all relevant information due to limited attention. In this sense, the finding that the stock market under-reacts to EAs is not surprising.

The notion of limited attention has gained much support from the empirical studies. Abarbanell and Bushee (1998) show that that financial analysts do not efficiently use information that is readily available in a set of financial ratios. Hirst and Hopkins (1998) document experimental evidence that professional analysts often fail to respond properly to information contained in complex financial disclosures. Teoh and Wong (2002) find that analysts do not adequately discount discretionary accruals of new issue firms. Collectively, this evidence seems to suggest that the limited attention applies to not only individual investors but also much more sophisticated investors such as mutual fund managers and security analysts.

Measuring investor attention is challenging since the determinants of investor attention are not entirely clear. To address this challenge, a spectrum of empirical proxies have been proposed. These empirical proxies include firm size, trading hours vs. non-trading hours, Fridays vs. other weekdays, information overload or the number of EAs made on the same day, Google Search Volume (GSV) index, and trading volume, among others.

Firm size seems to be a natural empirical proxy to start with. Understandably, larger firms receive more attention from investors due to a variety of reasons. For instance, large firms usually have more analyst coverage and following, which presumably helps attract investor attention. News media also has more coverage for large firms as compared to smaller ones. However, using firm size as a proxy for investor attention suffers from a major drawback: firm size can also proxy for a lot of other variables such as information asymmetry, and hence, it is a very noisy measure and subject to substantial contamination. Moreover, although firm size and analyst coverage may proxy for the amount of available information, it is at best an indirect measure since to what extent investors process this information remains unknown.

In view of these limitations, Francis, Pagach, and Stephan (1992), and Bagnoli, Clement, and Watts (2005) propose the use of trading hours. They document a greater under-reaction to earnings releases made during non-trading hours. Della Vigna and Pollet (2009) advocate the use of Fridays vs. other weekdays. They argue that since investors are more distracted on Fridays due to the upcoming weekend, investors are less attentive to EAs that are made on Fridays as compared to other weekdays. Consistent with this notion, they show more muted immediate stock market reactions to Friday EAs followed by stronger stock price drift, compared to non-Friday EAs. Hirshleifer, Lim and Teoh (2009) recommend the use of the number of earnings announcements on the same day. They argue that too many EAs made on the same day overloads investors with too much information and constitute much stronger distraction. Consistent with this information overload argument, they show that the announcement day response is weaker and the post-earnings announcement drift is stronger when the earnings announcement is made on days with many competing announcements, and that same day earnings announcements from unrelated industries are more distracting than industry-related announcements.

In an influential paper, Da et al. (2011) propose the use of Google Search Volume Index (Google SVI) as an innovative proxy for investor attention. The construction procedure of Google Search Volume Index (Google SVI) allows for a more direct measure of investor's attention. They argue that a large search volume for a stock in Google suggests that many investors are paying attention to and looking for information about that stock. They document a strong positive relation between search volume changes and investor trading.

Among all these empirical proxies, trading volume stands out as one of the most popular and widely used measures. The argument is simple. When investors pay little attention to a stock, they are unlikely to trade it; and when they pay more attention to a stock, they are more likely to trade it. In other words, trading volume should be highly correlated with attention. Trading volume proxy has the additional advantage of easy implementation.

Empirical evidence has strongly supported the link between investor attention and trading volume. Chordia and Swaminathan (2000) show that even after controlling for size, high volume stocks tend to respond more quickly to information in market returns than do low volume stocks. Thus, trading volume seems to contain information about investor attention beyond firm size. Lo and Wang (2000) demonstrate that trading volume is generally higher among large stocks which tend to attract more investor attention. Gervais, Kaniel and Mingelgrin (2001) show that the increase in trading volume raises a stock's visibility and attracts more investor attention. Barber and Odean (2008) show that trading volume is more directly related to actual attention, since it is a direct outcome of investor attention, and use a stock's abnormal daily trading volume to capture the change in investor attention to the stock. Also using trading volume as a proxy for investor attention, Hou et al. (2009) find that earnings momentum profits are higher among low volume stocks. They attribute this finding to reduced investor attention and stock market under-reaction to earnings announcements.

Overall, existing empirical studies using various proxies for investor attention have generated a vast amount of interesting and insightful findings on the stock price dynamics surrounding significant corporate information events including earnings announcements, analyst recommendations, and salient and attention-grabbing events etc. Given the pervasive evidence confirming the validity of trading volume as a proxy for investor attention, we also investigate the application of trading volume proxy within the context of EAs.

3. Hypothesis Development

3.1. Market wide attention and individual EAs

Our analysis starts with an initial investigation of the economic role of market wide investor attention within the context of EAs. Our first hypothesis pertains to the implication of market wide investor attention in shaping the stock market response to EAs.

As we argue in the introduction section, heightened investor attention to the aggregate market can help generate or renew investor attention to individual firms. Marginal investors who have not traded before can be stimulated to enter the market for the first time because of the pervasive coverage and discussion of the DJIA index breaking the historical record. Existing investors who have traded already will likely trade more aggressively because of the salient market movements. In other words, investor's trading behavior can change due to increased attention, which certainly opens the door for the economic relevance of market wide attention.

The information-intensive nature of EAs can further reinforce the link between increased attention and investor's trading behavior. Through earnings releases, firms typically announce their performance in the most recent quarters and also their outlook for future quarters. Substantial uncertainty about the nature of the earnings news builds up before the EADs. Such uncertainty is not resolved until the announcements are actually made. Increased attention allows investors to collect and process value-relevant information more efficiently. More attentive investors can also form or revise their expectation about the upcoming announcements and trade accordingly in a timelier fashion.

Given that it is now generally accepted that stock market under-reacts to EAs, we argue that as investors become more attentive to stock investments and stock trading, increased investor attention should mitigate the stock market under-reaction and make it close to a complete response (i.e., in the absence of under-reaction). Since we have not touched upon the exact mechanisms through which the market level attention affects firm level attention, this is essentially a first pass test. This test is necessary as it is reassuring to confirm or refute that market level attention bears on the stock market response to EAs of individual firms.

We follow the standard practice in the literature and use the ERC framework to examine the stock market response. This framework typically uses the announcement return (*AnnRet*) to proxy for the stock market reaction and the standardized unexpected earnings (*SUE*) to proxy for the amount of new information.[5] Regressing *AnnRet* on *SUE* while controlling for other covariates helps quantify the magnitude of stock market response. A positive and statistically significant estimated slope for *SUE* is interpreted as a strong stock market response to EAs. The baseline ERC framework is generally specified as follows:

$$AnnRet = \alpha_0 + \alpha_1 \cdot SUE + \sum_{k=2}^{K} \alpha_k \cdot Control\,Variables + \varepsilon$$

The ERC framework appeals intuitively and provides enough flexibility to incorporate the addition of interaction terms between *SUE* and other variables of particularly interest to researchers. These additional variables are usually dummy variables taking the value of 1 for certain economic attributes and 0 otherwise. For example, when examining the implication of options listing on the informational efficiency of the underlying stock price, an interaction term between *SUE* and a dummy variable for options listing status is included (Skinner 1990; Mendenhall and Fehrs 1999; Turong and Corrado 2014; Lei et al. 2016). The use of interaction terms greatly facilitates the comparison of differential stock market response to earnings news, thus allowing researchers to gauge the stock market response across firms with different characteristics. The caveat is that *SUE* is a noisy measure for new information and the ERC regression test may not have the desired statistical power.

We construct a dummy variable *Attid* to capture market wide investor attention. The following procedure is used when constructing *Attid*. We first extract all the days on which the DJIA index breaks historical record. We further require that on such record days, the closing level of the DJIA index exceeds the previous day's closing level by 100 points. We then turn to the 30-day window leading up to the EAD for each EA in our sample. *Attid* takes the value of 1 if there are DJIA record days with the 30-day window and 0 otherwise. [6]

[5] There are at least three alternative measures of *SUEs*. In this paper we follow Livnat and Mendenhall (2006) and define *SUE* as the actual EPS minus the analyst consensus estimate, scaled by the closing price at the end of the quarter. We conduct robustness check using the other two measures of *SUE* and the main results are largely unaffected.

[6] We choose a time window of 30 days so that investors have enough time to react after the DJIA index breaks historical record. In our robustness check, we experiment with 20-day and 40-day windows and our main results survive this robustness check.

To quantify the stock market response to EAs in the presence of market wide investor attention, we augment the baseline ERC framework with the interaction term between *SUE* and *Attid*. The regression equation is revised to the following:

$$AnnRet = \alpha_0 + \alpha_1 \cdot SUE + \alpha_2 \cdot SUE \cdot Attid + \sum_{k=3}^{K} \alpha_k \cdot Control\,Variables + \varepsilon$$

Our focal variable is the interaction term between *SUE* and *Attid*. A positive and statistically significant coefficient estimate before the interaction term α_2 lends support to the economic role of market wide attention on the stock market response to individual EAs. Our first hypothesis is formally stated as follows:

Hypothesis 1: If pre-announcement market wide attention helps mitigate stock market under-reaction, then we expect stronger stock market response to EAs that have pre-announcement DJIA record days as compared to those without such record days.

3.2. Market wide attention and trading volume

Our next hypothesis attempts to examine the mechanisms through which market wide attention affects firm level response to EAs. While the psychology literature provides the theoretical foundation for the attention spill-over effect, we want to understand exactly how market level attention translates to firm level attention. Uncovering such mechanisms is not only a test of spill-over effect in general but also allows us to gain new insights on the stock market response through its manifestation in the financial market.

As we argue in the introduction section, sensational market events can generate tremendous investor attention to the aggregate stock market, which in turn spills over to individual firms in a variety of ways. The spill-over effect could take place through stocks that are related to DJIA component stocks, or through redirecting attention of investors who are initially distracted from stock investments and stock trading, or through attracting new investors to the market for the first time.

As investors become more attentive to certain stocks or become interested in certain stocks for the first time, they are more likely to trade those stocks. The strong correlation between investor attention and trading volume suggests that trading volume can be a valid proxy for investor attention. Empirical evidence has lent strong support to the validity the trading volume proxy (Lo and Wang 2000; Chordia and Swaminathan 2000; Gervais et al. 2001; Barber and Odean 2008; Hou et al. 2009).

Given that trading volume has been widely established as a proxy for investor attention, we hypothesize that if market level attention increases firm level attention, then the increased firm level attention should manifest itself by higher trading volume of individual firms. In other words, individual firms' trading volume should be higher for EAs that have witnessed DJIA record days. This intuition is formally summarized in Hypothesis 2.

Hypothesis 2: If market wide attention leads to higher firm level attention and trading volume is a valid proxy for firm level attention, then higher trading volume is expected for those EAs that have DJIA record days.

To test this hypothesis using rigorous regression analysis, we adopt the following regression specification:

$$Trd\,Volume = \beta_0 + \beta_1 \cdot Attid + \sum_{k=2}^{K} \beta_k \cdot Control\,Variables + \varepsilon$$

A positive and significant slope coefficient estimate β_1 would lend a preliminary support to the trading volume channel.

3.3. Trading volume and ERC

The next two hypotheses focus on the implication of trading volume. If investors are more attentive to individual firms because of the spill-over effect from increased market level attention, then we would expect higher trading volume for those EAs that have DJIA record days. Higher trading volume should accelerate the stock market response and mitigate the stock market under-reaction. Consequently, we should also expect weaker PEAD given that more information has been incorporated into the stock price via higher trading volume during announcement times. Hypothesis 3 and 4 are formally stated as follows:

Hypothesis 3: The stock market response should be stronger for those EAs that have higher trading volume.

Hypothesis 4: The PEAD should be weaker for those EAs that have higher trading volume.

To test Hypothesis 3, we adapt the baseline ERC framework with a trading volume variable:

$$AnnRet = \gamma_0 + \gamma_1 \cdot SUE + \gamma_2 \cdot SUE \cdot Trd\,Vol + \sum_{k=3}^{K} \gamma_k \cdot Control\,Variables + \varepsilon$$

A positive and significant γ_2 estimate would lend strong support to the under-reaction reduction argument.

To test Hypothesis 4, we propose the following regression specification to test this intuition.

$$PEAD = \delta_0 + \delta_1 \cdot SUE + \delta_2 \cdot SUE \cdot Trd\,Vol + \sum_{k=3}^{K} \delta_k \cdot Control\,Variables + \varepsilon$$

Our prediction is that the slope coefficient estimate δ_2 should be negative.

4. Data and Methodologies

This paper utilizes data from a variety of sources. In what follows we provide more detailed information about the data and methodologies used in our empirical analysis.

4.1 DJIA record-breaking days and *Attid*

Historical data on the DJIA Index are retrieved from the Wall Street Journal website. We extract all the days on which the DJIA index breaks the historical record. Table 1 presents the frequency distribution of these record days. We present the frequency distribution of the record days by year, month and weekday in Panel A, Panel B, and Panel C respectively. Our sample period starts from 1986 and ends in 2015. Note that as a stock market index, the DJIA index has an upward trend over time. Over the course of the sample period, the DJIA index breaks the record 542 times with all-time record level of 18312.39 on May 19, 2015. The top five years by the number of days on which the DJIA index breaks the record are 1995, 1987, 2013, 1996, and 1997. Notice that during the dot.com bubble and the most recent financial crisis, the DJIA index has not logged a single record day from 2001 to 2005 and from 2008 to 2012. It is interesting to notice that the top four months by the number of days on which the DJIA index breaks the record are May, January, March and November. In addition, while the conventional wisdom argues that Fridays are usually bad for the stock market as compared to other weekdays, the DJIA index breaks the historical record 19.56 percent out of all the five weekdays, only trailing behind Wednesdays and Thursdays.

4.2 Announcement Returns (*AnnRet*) and post-earnings announcement drift (*PEAD*)

Daily returns and trading volume on individual stocks and the stock market index are retrieved from the Center for Research in Securities Prices (CRSP). We follow a procedure that is similar to Livnat and Mendenhall (2006) when constructing our core variable *AnnRet*. More specifically, we calculate the daily abnormal returns as the raw daily return from CRSP minus the daily return on the portfolio of firms with approximately the same size.[7] The returns on the portfolio of firms of different sizes are available from Wharton Research Data Service (WRDS) at the University of Pennsylvania. The daily abnormal returns are then cumulated over [t-1, t+1] to obtain *AnnRet*, where t is the EAD. To estimate the post-earnings announcement drift, we cumulate the daily abnormal returns over the period from two days after the earnings announcement through one day after the subsequent quarterly earnings announcements. This is also consistent with Livnat and Mendenhall (2006).

4.3 Earnings announcements data and *SUE*

We rely on the Institutional Brokers' Estimate System (I/B/E/S) database for earnings announcements data. The actuals file from the I/B/E/S database provides earnings announcements data, including firm names, firm identifiers and earnings announcement dates. Following Livnat and Mendenhall (2006), we apply a number of filters to the universe of the earnings announcements obtained from the I/B/E/S database. These filters are: the earnings announcement date reported in Compustat and I/B/E/S should not differ by more than one calendar day; the price per share is available from Compustat at each fiscal quarter end; the price is greater than $1; and the market and book values of equity at fiscal quarter end are available and are larger than $5 million. From IB/E/S database, we also extract information on the number of analysts who have provided earnings per share (EPS) estimates (earnings per share) estimates for each firm quarter. Our core variable the standardized unexpected earnings *SUE* is defined as the actual reported earnings per share minus the median analyst forecast within 90 days prior to the earnings announcement date, scaled by the closing price at the end of the quarter. The *SUE* variable is the main explanatory variable in the ERC framework.

Many drift studies classify firms into decile portfolios based on the *SUE* (Bernard and Thomas 1990; Bhushan 1994; Bartov et al. 2000, Livnat and Mendenhall 2006). We follow the standard practice and transform the *SUE* variable into its decile ranks. More specifically, all announcements are sorted into ten deciles based on the *SUE* every quarter. The decile rank *DSUE* is then assigned to each announcement within a decile. Adjusted *DSUE* is then calculated as *DSUE* divided by 9 minus 0.5. The advantage of this transformation is that it mitigates the impact of any possible *SUE* outliers and the potential non-linearity in the earnings surprise-return relation. In addition, the slope coefficient in the regression of the abnormal returns on the *SUE* decile rank (*DSUE*) may be interpreted as the return to a hedge portfolio that is long on the most positive *SUE* decile and short on the most negative *SUE* decile.

Della Vigna and Pollet (2009) argue that Friday announcements receive weaker stock market reaction since investors are distracted more on Fridays than other weekdays. To control for this Friday effect, we construct a dummy variable *IsFri* that takes the value of one if the announcement is made on a Friday and zero otherwise. Hirshleifer et al. (2009) document that information overload, as proxied by the number of announcements made on the same day, affect the stock market response to EAs. To control for this effect, we construct a variable *NumAnns* that calculates the number of announcements that are made on each EAD.

4.4 Supporting databases and control variables

[7] Alternatively, we calculate the abnormal returns from a market model that is estimated using data from [t-210, t-31]. Our main results survive this robustness check.

In addition to the two key variables *AnnRet* and *SUE*, we calculate a number of control variables to capture firm- and event-specific characteristics using data from CRSP, Compustat, Thomson Reuters Institutional holdings (13F), and I/B/E/S. We compute the market capitalization for each firm (*Size*) as the natural log of shares outstanding multiplied by the closing price on date t-31. The pre-announcement stock price run-up (*Runup*) is defined as abnormal stock returns cumulated over $[t-30, t-2]$. It serves as a proxy for information leakage in the days immediately before the EADs. Past stock returns (*PastRet*) are defined as the buy-and-hold stock return cumulated over $[t-210, t-31]$. Book-to-market ratio (*BM*) is the book value of equity divided by the market value of equity. Institutional Ownership (*IOR*) is defined as the institutional ownership as specified in the Thomson Reuters 13F filings database divided by the number of shares outstanding at the end of each quarter. Table 2 provides the definition and summary statistics of these core and control variables.

5. Empirical Results

5.1. Market wide attention and stock market response to EAs

To test hypothesis 1, we estimate the following regression equation:

$$AnnRet = \alpha_0 + \alpha_1 \cdot DSue + \alpha_2 \cdot DSue \cdot Attid + \sum_{i=3}^{K} \alpha_i \cdot Control\ Variables + \varepsilon$$

The dependent variable *AnnRet* is the announcement abnormal return measuring the stock market response. The main explanatory variable is *DSUE*, the adjusted decile ranks of *SUE* and its interaction term with the dummy variable we construct to capture the market wide attention for each EA, *Attid*. Consistent with the standard ERC literature, we expect a positive and significant slope coefficient estimate before *DSUE*. Our focal variable is the interaction term between *DSUE* and *Attid*. Hypothesis 1 states that if attention-grabbing market events help intensify investor attention and mitigate the stock market under-reaction, we should expect a positive sign before the interaction term between *DSUE* and *Attid*. Thus, a positive and significant α_2 will lend support to Hypothesis 1.

We include a collection of control variables to address the potential confounding factors: the book-to-market ratio *BM*, the institutional ownership ratio *IOR*, the number of analysts providing EPS estimates *NumEst*, the market capitalization of the firm *Size*, the past stock return *PastRet*, and the pre-announcement stock price run-up *Runup*. The inclusion of such control variables is intended to capture the return effect that has been documented to be related to these variables. For instance, *Size* is included because firms of different sizes have potentially different information structures. There normally exist better analyst coverages among larger firms and investors of large firms could be more attentive to earnings announcements. To account for return reversal or continuation, we include *PastRet*. As a proxy for information leakage, *Runup* is expected to have a negative relationship with *AnnRet*.

The estimation result is presented in Table 3. Since many firms make multiple announcements in our sample, the standard errors of the parameter estimates are calculated using firm clustering. We estimate a total of three alternative models, depending on whether we include the Friday effect and the information overload effect. Column 2 of Table 3 presents the baseline model estimation whereas Column 3 and 4 augment the baseline model with the Friday effect and the information overload effect.

As we can see clearly, the slope coefficient estimates before *BM* and *IOR* are statistically significant. Higher book-to-market ratio firms tend to have lower announcement returns whereas firms with larger institutional ownership are associated with higher announcement returns. The parameter estimates before

PastRet and *Runup* are negative and only statistically significant at 1 percent level for *Runup*. This is consistent with the notion that more information leakage prior to the EAD and higher pre-announcement stock price run-up helps incorporate information into the EAs. As a result, as the announcement is actually made, the stock market is less surprised, leading to lower announcement returns. *Size* carries a negative and statistically significant slope coefficient estimate. Thus, there is strong evidence that larger firms have smaller stock market response.

Not surprisingly, our focal variable *DSUE* carries a positive and significant slope coefficient estimate. More importantly, the interaction term between *DSUE* and *Attid* carries a positive and highly significant slope coefficient estimate. This is clear evidence that firms that have experienced the DJIA record days in the 30 days prior to the EADs experience greater stock market response, thus lending support to Hypothesis 1.

Turning to the Friday effect, we see that the parameter estimates before *IsFri* and *DSUE*IsFri* are negative and highly significant. Thus, our sample strongly supports the Friday effect. Evidence for the information overload effect is somewhat mixed. On one hand, *NumAnns* carries a negative and significant parameter estimate. Thus, more announcements made on the same day is associated with lower announcement returns. On the other hand, the interaction term *DSUE*NumAnns* carries a positive and highly significant estimate. More importantly, we notice that including the Friday effect and the information overload effect has very little impact on the magnitude of the parameter estimate before *DSUE*Attid* and no impact on its statistical significance. Overall, the result in Table 3 lends strong support to the first hypothesis.

5.2. Market wide attention and trading volume of individual firms

While the result in the previous section is comforting, it does not shed lights on the exact mechanisms through which the stock market under-reaction is mitigated. We now turn to the investigation of such mechanisms. As we hypothesize in Section 3, market wide attention can work its way to individual firms via many channels. To the extent that there is a strong correlation between investor attention and trading volume, these different mechanisms should eventually boil down to the trading volume. As investors become more attentive to individual firms' EAs, they start to trade more shares of individual firms.

Trading volume is defined as the natural log of shares traded scaled by the number of shares outstanding. Applying the log transformation to the share turnover makes the variable closer to a normal distribution (Chae 2005). We then calculate the cumulative abnormal trading volume *Abvol* for each announcement in our sample by employing the widely used fixed mean model. More specifically, normal trading volume is calculated by averaging the log turnover over the benchmark window [t-60, t-31], where t is the EAD. [8] Abnormal trading volume is then obtained by subtracting the normal trading volume from the daily trading volume and further cumulated over the event window [t-30, t+1] to arrive at *Abvol*.

To examine whether there is any difference between the trading volume between EAs that have DJIA record days and EAs that don't have DJIA record days, we split the sample into two subsamples on the basis of *Attid*. We then test for the difference in the average trading volume between the two subsamples. Table 4 provides the test results.

As we can see clearly, the group of EAs that have DJIA record days experience much higher trading volume before and during the announcement period. The cumulative abnormal trading volume averages at 0.5275 for the without-record-day EAs whereas it averages at 0.9696 for the with-record-day EAs. The difference in mean is statistically significant at 1 percent level. Thus, there is strong evidence that EAs

[8] We carefully choose [t-60, t-31] as the normal trading window since it is in the middle of two consecutive earnings announcements.

that have DJIA record days indeed have much higher trading volume, thus lending support to Hypothesis 2.

While the univariate result in Table 3 is supportive of Hypothesis 2, it is only descriptive and does not accommodate for other factors that may affect trading volume. We now employ a more rigorous statistical analysis to test Hypothesis 2. The following regression specification is used to examine whether market wide attention drives much higher trading volume for individual EAs:

$$Abvol = \beta_0 + \beta_1 \cdot Attid + \beta_2 \cdot IsFri + \beta_3 \cdot NumAnns + \beta_4 \cdot BM + \beta_5 \cdot IOR + \beta_6 \cdot Numest + \beta_7 \cdot Size + \beta_8 \cdot PastRet + \beta_9 \cdot Runup + \varepsilon$$

Abvol is the cumulative abnormal trading volume. The explanatory variables are as defined in the previous sections. To control for other factors that may affect the trading volume, we include a host of control variables: *IsFri*, *NumAnns*, *BM*, *IOR*, *Numest*, *Size*, *PastRet*, and *Runup*. Our expectations are that Friday announcements and announcements that are made on days with more competing announcements should receive lower trading volume. In addition, larger firms, or firms with better prior returns, or firms with higher pre-announcement stock price run-up will likely experience higher trading volume. Our focal variable is *Attid*. Hypothesis 2 predicts a positive sign for β_1.

The estimation result is presented in Table 5. For the same reason, we calculate the regression standard errors by firm clustering. We immediately notice that almost all the control variables carry the expected sign and are statistically significant at 1 percent level. For instance, the trading volume is significantly lower for Friday announcements and announcements overloaded with other competing announcements. Larger firms, higher stock price run-up firms, and better prior returns indeed experience higher trading volume. More importantly, our focal variable *Attid* carries a positive and highly significant parameter estimate of 0.200. Note the magnitude of the estimate is close to the univariate result in the previous section. Combined together, the results in Table 4 and Table 5 are strongly supportive of Hypothesis 2.

5.3. Trading volume and ERC vs. PEAD

Results in the previous section show that the difference in trading volume between the two subsamples stratified by *Attid* is economically and statistically significant. We now attempt to explore the economic implications of trading volume. Hypothesis 3 states that if trading volume captures firm level investor attention, then intensified investor attention should lead to stronger stock market response to EAs. To test Hypothesis 3, we employ the following regression specifications:

$$AnnRet = \gamma_0 + \gamma_1 \cdot DSUE + \gamma_2 \cdot DSUE \cdot Abvol + \sum_{i=3}^{K} \gamma_i \cdot Control\ Variables + \varepsilon$$

We include the same set of control variables. Our focal variable is the interaction term between *DSUE* and *Abvol*. Hypothesis 3 argues that to the extent that increased investor attention to individual EAs is captured by higher trading volume, EAs that have experienced higher trading volume should witness stronger stock market reaction. In other words, γ_2 should be positive.

While we emphasize the importance of trading volume, the trading volume channel does not have to be the only channel through which market wide attention affects investor attention to individual EAs. Consequently, it is important to know whether the inclusion of *Attid* in the above regression drives out the explanatory power of *Abvol*, if any. To assess this possibility, we rerun the above regression by including the interaction term between *DSUE* and *Attid*.

Table 6 presents the estimation result for three regression specifications. The baseline regression of *AnnRet* on *DSUE* and its interaction term with *Attid* while controlling for other variables is estimated in Column 2 of Table 6 (Model 1). Column 3 and Column 4 present the estimation results for two alternative regression specification: Model 2 includes only *DSUE* and its interaction term with *Abvol*, whereas Model 3 includes not only *DSUE* and its interaction term with *Attid* but also its interaction term with *Abvol*. Again the regression standard errors are firm clustered.

We immediately notice that across the three specifications, the parameter estimates the control variables are mostly consistent with what we observe from Table 3. For instance, *Size* carries a negative slope coefficient and is highly significant. In all specifications, *DSUE* carries a positive and highly significant slope coefficient. These results are certainly in line with that in Table 3. More importantly, we notice that the interaction term between *DSUE* and *Abvol* shows a positive and highly significant parameter estimate with and without including the interaction term between *DSUE* and *Attid*. Interestingly enough, the interaction term between *DSUE* and *Attid* in Model 3 carries a positive estimate and is highly significant at 1 percent level. Thus, it seems to suggest that while the trading volume channel is supported by the data, there remains other important channels beyond trading volume that are only captured by *Attid*.

We finally turn to examine the PEAD anomaly. Stock market under-reaction and PEAD are two well established stylized facts. Any theories or hypotheses that are proposed to explain the stock market under-reaction should be subject to the PEAD test. Stronger stock market reaction and weaker PEAD are essentially the two sides of the same coin. Given that we have found stronger stock market response for those EAs that have experienced much higher trading volume, we should expect weaker PEAD for those EAs.

To test Hypothesis 4, we adopt the following regression specification:

$$PEAD = \gamma_0 + \gamma_1 \cdot DSUE + \gamma_2 \cdot DSUE \cdot Abvol + \sum_{i=3}^{K} \gamma_i \cdot Control\ Variables + \varepsilon$$

PEAD the post-earnings announcement drift, defined as the daily abnormal returns cumulated over the period from two days after the EAD to one day after the next EAD. [9] We include the same set of explanatory variables to control for other variables that can affect the *PEAD*. Our focal variable is the interaction term between *DSUE* and *Abvol*. A negative slope coefficient estimate before the interaction term between *DSUE* and *Abvol* would lend support to Hypothesis 4.

Table 7 presents the estimation result. The standard errors for the parameter estimates are again calculated by firm clustering. We immediately notice that DSUE carries a positive and significant slope coefficient estimate, thus lending support to the notion of the post-earnings announcement drift. However, the interaction term between *DSUE* and *Abvol* shows up a positive estimate and is statistically insignificant at any conventional level. Thus, our sample is not able to confirm the weaker post-earnings announcement drift effect. While this is disappointing, we think that one possible explanation is that the PEAD test generally lacks the statistical power, as pointed out by Mendenhall and Fehrs (1999).

6. Conclusions

In this paper, we examine one type of sensational market events: the DJIA index breaks the historical record and exceeds the previous day's closing level by at least 100 points. We argue that these DJIA record days constitute an ideal proxy for market wide attention for a number of reasons. Availing

[9] In our robustness check, we experiment with alternative time windows of 60 days and 80 days after the EAD. The results are qualitatively the same. These untabulated results are available upon request.

ourselves of a broad sample of EAs, we further investigate the economic implications of market wide attention on the stock market response to the EAs of individual firms. We start off by showing that the stock market responds a lot more to those EAs that have DJIA record days in the 30-day period leading up to the EADs. We interpret this finding as strong evidence that market wide attention plays an important role in the stock market response to individual EAs.

We further explore the link between market wide attention and individual EAs. We hypothesize that as market wide attention is intensified by the pervasive media coverage of the DJIA record days, investor attention to individual firms also increases. In other words, there exists an attention spill-over effect.

We hypothesize that there are many channels through which market wide attention spills over to individual firms. Building on the existing literature about the link between investor attention and trading volume, we formally derive testable hypotheses about the trading volume channel and conduct a set of rigorous regression tests. These test results strongly support the trading volume channel in that trading volume is significantly higher for those EAs that have witnessed much higher level of investor attention. Consequently, the stock market response at announcement times is much stronger and the PEAD is much weaker for those EAs that experience higher trading volume.

Perhaps the most important finding of this paper is the attention spill-over effect. While our findings provide strong support to the trading volume channel of the attention spill-over effect, we realize that our discussion and investigation of the trading volume channel is still preliminary. We certainly agree with the argument that market wide attention can work its way to individual EAs through other unidentified channels as well. The estimation result for Model 3 in Table 6 seems to suggest that this is indeed the case. When the two interaction terms *DSUE*Attid* and *DSUE*Abvol* are both included in the same time, the statistical significance and the magnitude of the slope coefficient estimate before the interaction term *DSUE*Attid* remain largely the same. We leave these unidentified channels to future research.

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Table 1: Frequency Distribution of DJIA Record Days from 1986 – 2015

This table presents the frequency distribution of the days on which the DJIA index breaks the historical record. Data on the DJIA index level are retrieved from the Wall Street Journal website. Panel A, Panel B, and Panel C present the frequency distribution of these record days by year, month and weekdays respectively.

Panel A: Frequency Distribution by Year				
Year	Frequency	%	Cumulative Freq.	Cumulative %
1986	30	5.54	30	5.54
1987	55	10.15	85	15.68
1989	8	1.48	93	17.16
1990	15	2.77	108	19.93
1991	11	2.03	119	21.96
1992	22	4.06	141	26.01
1993	34	6.27	175	32.29
1994	12	2.21	187	34.50
1995	69	12.73	256	47.23
1996	44	8.12	300	55.35
1997	39	7.20	339	62.55
1998	30	5.54	369	68.08
1999	35	6.46	404	74.54
2000	4	0.74	408	75.28
2006	22	4.06	430	79.34
2007	16	2.95	446	82.29
2013	52	9.59	498	91.88
2014	38	7.01	536	98.89
2015	6	1.11	542	100
Panel B: Frequency Distribution by Month				
Month	Frequency	%	Cumulative Freq.	Cumulative %
January	61	11.25	61	11.25
February	53	9.78	114	21.03
March	60	11.07	174	32.10
April	43	7.93	217	40.04
May	64	11.81	281	51.85
June	35	6.46	316	58.30
July	54	9.96	370	68.27
August	25	4.61	395	72.88
September	12	2.21	407	75.09
October	34	6.27	441	81.37
November	60	11.07	501	92.44
December	41	7.56	542	100
Panel C: Frequency Distribution by Weekday				
Week	Frequency	%	Cumulative Freq.	Cumulative %
Monday	102	18.82	102	18.82
Tuesday	106	19.56	208	38.38
Wednesday	114	21.03	322	59.41
Thursday	114	21.03	436	80.44
Friday	106	19.56	542	100

Table 2: Summary Statistics of Main Variables

This table presents the summary statistics of the main variables used in the empirical analysis. *AnnRet* is the announcement return defined as the daily abnormal returns cumulated over [t-1, t+1], where t is the EAD. Daily abnormal return is calculated by the daily return from CRSP minus the return on the portfolio of firms with similar sizes. *DSUE* is the adjusted decile ranks for the standardized unexpected earnings (SUE), defined as the actual reported earnings per share (EPS) minus the median analyst forecast within 90 days prior to the earnings announcement date, scaled by the closing price at the end of the quarter. All announcements are sorted into ten deciles based on the *SUE* every quarter. The decile rank *DSUE* is then assigned to each announcement within a decile. Adjusted *DSUE* is then calculated as *DSUE* divided by 9 minus 0.5. *Attid* is a dummy variable that takes the value of 1 if there are DJIA record days with the 30-day window leading up to the EAD and 0 otherwise. *Abvol* is the abnormal trading volume cumulated over [t-30, t+1], where t is the EAD. Trading volume is defined as the raw number of shares traded, scaled by the number of shares outstanding. Abnormal trading volume is calculated by the raw trading volume over [t-30, t+1] minus the average trading volume over [t-60, t-31]. *IsFri* is a dummy variable that takes the value of one if the EAD is a Friday and zero otherwise. *NumAnns* is the number of announcements made on the EAD. *BM* is the book-to-market ratio. *IOR* is the institutional ownership ratio defined as the aggregate institutional holdings divided by the number of shares outstanding at the end of each quarter. *Numest* is the number of analysts that provide quarterly EPS estimates. *Size* is the natural log of the market capitalization at t-31. *PastRet* is the past stock return defined as the buy-and-hold stock return cumulated over [t − 210, t − 31]. *Runup* is the pre-announcement stock price run-up, defined as abnormal stock returns cumulated over [t − 30, t − 2].

Variable	**N**	**Mean**	**Std Dev**	**Min.**	**25th Pctl.**	**75th Pctl.**	**Max.**
Annret	264,402	0.003	0.086	-0.968	-0.034	0.04	4.839
DSUE	264,402	-0.054	0.289	-0.5	-0.3	0.2	0.4
Attid	264,402	0.133	0.339	0	0	0	1
Abvol	264,402	0.586	6.981	-60.564	-3.482	4.45	83.954
IsFri	264,402	0.082	0.275	0	0	0	1
NumAnns	264,402	108.787	80.776	2	39	173	319
BM	264,402	0.608	0.826	-101.736	0.301	0.812	36.37
IOR	264,402	0.547	0.267	0	0.337	0.753	7.125
Numest	264,402	5.39	5.355	1	2	7	50
Size	264,402	13.37	1.782	6.823	12.084	14.51	20.424
PastRet	264,402	0.081	0.417	-0.96	-0.122	0.216	25.23
Runup	264,402	0.003	0.137	-1.564	-0.058	0.062	3.244

Table 3: Market Wide Attention and Earnings Response Coefficient

This table explores the stock market response to EAs in the presence of market wide investor attention. The estimated regression equation is as follows:

$$AnnRet = \alpha_0 + \alpha_1 \cdot Sue + \alpha_2 \cdot Sue \cdot Attid + \alpha_3 \cdot Sue \cdot IsFri + \alpha_4 \cdot Size + \alpha_5 \cdot Pastret + \alpha_6 \cdot Runup + \varepsilon$$

AnnRet is the announcement return defined as the daily abnormal returns cumulated over [t-1, t+1], where t is the EAD. A market model is first estimated using the daily returns data over [t-210, t-30]. Market model parameters are then used to predict the daily returns. Daily abnormal returns are then obtained by subtracting the predicted returns from the daily returns. *SUE* is the standardized unexpected earnings, defined as the actual reported earnings per share (EPS) minus the median analyst forecast within 90 days prior to the earnings announcement date, scaled by the closing price in the previous quarter. *PastRet* are defined as the buy-and-hold stock return cumulated over [t − 210, t − 31]. *Size* is defined as the natural log of shares outstanding multiplied by the closing price on date t-31. *Runup* is defined as abnormal stock returns cumulated over [t − 30, t − 2]. *IsFri* is a dummy variable that takes the value of 1 if the EAD is a Friday and 0 otherwise. *Attid* is a dummy variable that takes the value of 1 if there are DJIA record days within 30 days leading up to the EAD. The standard errors are calculated by firm clustering. P-values are in the parentheses.

Variable	**Model 1**	**Model 2**	**Model 3**
Intercept	0.0276	0.0275	0.0321
	(<0.01)	(<0.01)	(<0.01)
DSUE	0.0817	0.0831	0.0683
	(<0.01)	(<0.01)	(<0.01)
*DSUE*Attid*	0.0068	0.0065	0.0055
	(<0.01)	(<0.01)	(<0.01)
IsFri		-0.0012	-0.0025
		(0.0488)	(<0.01)
*DSUE*IsFri*		-0.0158	-0.0123
		(<0.01)	(<0.01)
NumAnns			-0.0013
			(<0.01)
*DSUE*NumAnns*			0.0035
			(<0.01)
BM	-0.0027	-0.0027	-0.0027
	(<0.01)	(<0.01)	(<0.01)
IOR	0.0087	0.0086	0.0090
	(<0.01)	(<0.01)	(<0.01)
NumEst	0.0000	0.0000	0.0001
	(0.9983)	(0.9835)	(0.7741)
Size	-0.0018	-0.0017	-0.0017
	(<0.01)	(<0.01)	(<0.01)
PastRet	-0.0005	-0.0005	-0.0005
	(0.4369)	(0.4391)	(0.4580)
Runup	-0.0469	-0.0469	-0.0469
	(<0.01)	(<0.01)	(<0.01)

Table 4: Market Wide Attention and Trading Volume: Univariate Analysis

This table tests the difference in the average trading volume for EAs that have DJIA record days vs. EAs that don't have DJIA record days. Trading volume is defined as the natural log of shares traded scaled by the number of shares outstanding. We calculate the cumulative abnormal trading volume *Abvol* for each announcement in our sample by employing the widely used fixed mean model. More specifically, normal trading volume is calculated by averaging the log turnover over the benchmark window [t-60, t-31], where t is the EAD. Abnormal trading volume is then obtained by subtracting the normal trading volume from the daily trading volume and further cumulated over the event window [t-30, t+1] to arrive at *Abvol.*

Panel A: Summary Statistics of *Abvol* by *Attid*						
Attid	N	Mean	Std. Dev	Std. Err	Minimum	Maximum
0	229343	0.5275	6.9759	0.0146	-60.5638	83.9541
1	35059	0.9696	7.0021	0.0374	-58.9196	67.7234
Diff (1-2)		-0.4421	6.9794	0.04		

Panel B: Test of difference in Means				
Method	Variances	DF	t Value	Prob > |t|
Pooled	Equal	264400	-11.05	<.0001
Satterthwaite	Unequal	46341	-11.02	<.0001

Table 5: Market Wide Attention and Trading Volume: Multivariate Analysis

This table explores the relationship between market wide attention and trading volume for individual firms' EAs using a multivariate analysis. The regression equation is specified as follows:

$$Abvol = \beta_0 + \beta_1 \cdot Attid + \beta_2 \cdot IsFri + \beta_3 \cdot NumAnns + \beta_4 \cdot bm + \beta_5 \cdot IOR + \beta_6 \cdot Numest + \beta_7 \cdot Size + \beta_8 \cdot PastRet + \beta_9 \cdot Runup + \varepsilon$$

Abvol is the cumulative abnormal trading volume calculated from the widely used fixed mean model. More specifically, normal trading volume is calculated by averaging the log turnover over the benchmark window [t-60, t-31], where t is the EAD. Abnormal trading volume is then obtained by subtracting the normal trading volume from the daily trading volume and further cumulated over the event window [t-30, t+1] to arrive at *Abvol*. The explanatory variables are as defined in Table 2. Regression errors are calculated using firm level clustering. P-values are in the parentheses.

Variable	Parameter Estimate
Intercept	-1.2736 (<0.01)
Attid	0.4244 (<0.01)
IsFri	-0.2455 (<0.01)
NumAnns	-0.1747 (<0.01)
BM	-0.0078 (0.774)
IOR	0.9936 (<0.01)
Nmest	0.0074 (0.044)
Size	0.1491 (<0.01)
PastRet	-0.0690 (0.104)
Runup	3.0853 (<0.01)

Table 6: Trading Volume and ERC

This table investigates the relationship between trading volume and the ERC. The baseline regression equation is specified as follows:

$$AnnRet = \gamma_0 + \gamma_1 \cdot DSUE + \gamma_2 \cdot DSUE \cdot Attid + \sum_{i=3}^{K} \gamma_i \cdot Control\,Variables + \varepsilon$$

To examine the implication of trading volume on the stock market response, the baseline model is augmented with an interaction term between *DSUE* and *Abvol*. The augmented regression model is specified as follows:

$$AnnRet = \gamma_0 + \gamma_1 \cdot DSUE + \gamma_2 \cdot DSUE \cdot Abvol + \sum_{i=3}^{K} \gamma_i \cdot Control\,Variables + \varepsilon$$

All the variables are as defined in Table 2 and Table 5. The standard errors for the parameter estimates are calculated by firm clustering. P-values are reported in the parentheses.

Variables	**Model 1**	**Model 2**	**Model 3**
Intercept	0.0321 (<.01)	0.0319 (<.01)	0.0319 (<.01)
DSUE	0.0683 (<.01)	0.0671 (<.01)	0.0670 (<.01)
*DSUE*Attid*	0.0055 (<.01)		0.0049 (0.011)
Abvol		0.0003 (<.01)	0.0003 (<.01)
*DSUE*Abvol*		0.0012 (<.01)	0.0001 (<.01)
IsFri	-0.0025 (<.01)	-0.0024 (0.027)	-0.0024 (0.027)
*DSUE*IsFri*	-0.0123 (<.01)	-0.0120 (<.01)	-0.0120 (<.01)
NumAnns	-0.0013 (<.01)	-0.0013 (<.01)	-0.0013 (<.01)
*DSUE*NumAnns*	0.0035 (<.01)	0.0038 (<.01)	0.0037 (<.01)
BM	-0.0027 (<.01)	-0.0027 (<.01)	-0.0027 (<.01)
IOR	0.0088 (<.01)	0.0088 (<.01)	0.0088 (<.01)
Numest	0.0001 (0.776)	0.0001 (0.814)	0.0001 (0.827)
Size	-0.0017 (<.01)	-0.0017 (<.01)	-0.0017 (<.01)
PastRet	-0.0005 (0.456)	-0.0005 (0.429)	-0.0005 (0.431)
Runup	-0.0470 (<.01)	-0.0486 (<.01)	-0.0486 (<.01)

Table 7: PEAD and Trading Volume

This table investigates the relationship between the post-earnings announcement drift and the trading volume. The baseline regression equation is specified as follows:

$$PEAD = \gamma_0 + \gamma_1 \cdot DSUE + \gamma_2 \cdot DSUE \cdot Abvol + \sum_{i=3}^{K} \gamma_i \cdot Control\,Variables + \varepsilon$$

The dependent variable is the post-earnings announcement drift PEAD, defined as the abnormal daily returns cumulated over the period from two days after the EAD to one day after the next EAD. All other variables are as defined in Table 2. The standard errors for the parameter estimates are calculated by firm clustering. P-values are reported in the parentheses.

Variables	**Parameter Estimate**
Intercept	0.0562 (<.01)
DSUE	0.0303 (<.01)
Abvol	0.0007 (<.01)
*DSUE*Abvol*	0.00002 (0.938)
IsFri	-0.0005 (0.772)
*DSUE*IsFri*	0.0093 (0.125)
NumAnns	-0.0013 (<.01)
*DSUE*NumAnns*	0.0018 (0.327)
BM	0.0155 (<.01)
IOR	0.228 (<.01)
Numest	-0.0008 (0.406)
Size	-0.0047 (<.01)
PastRet	0.0035 (0.066)
Runup	-0.0244 (<0.01)