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Two Essays on Investor Attention, Investor Sentiment, and Earnings Pricing

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TWO ESSAYS ON INVESTOR ATTENTION, INVESTOR SENTIMENT, AND EARNINGS PRICING

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ABSTRACT

TWO ESSAYS ON INVESTOR ATTENTION, INVESTOR SENTIMENT, AND EARNINGS PRICING

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This dissertation proposes novel direct measures for both firm-level and market-level investor attention and investor sentiment and provides new empirical evidence on the effects of investor attention and investor sentiment on earnings pricing.

The first essay proposes novel direct measures for both market-level and firm-level attention using user activity data from StockTwits.com. To the best of my knowledge, this is the first direct measure of market-level attention. By measuring market-level and firm-level attention separately, I am be able to not only distinguish between attention allocated on market level and firm level but also detach attention from equilibrium outcomes. I document that both market-level and firm-level attention is lower on non-trading days and days without macro- or micro news announcements. On earnings announcement days, investors are distracted by higher volume of concurrent competing earnings announcements or macro-news announcements. Investors pay less attention to earnings announced on Friday. Firm-level attention is negatively associated with market-level attention, suggesting that investors allocate their limited attention strategically between market-level and firm-level. I find that investors pay more attention to earnings news announced on days with important macro-news announcements, suggesting that firm-level attention is strengthened rather than weakened with concurrent market-level information shocks. I find that investors have more muted initial reactions to earnings announcements if they pay more attention to board market. On the other hand, higher firm-level investor attention and concurrent

important macro-news enhances the immediate price reaction to a firm's earnings surprise and alleviates the post-announcement drift (PEAD). I also find that drift occurs much later than documented in the prior literature.

The second essay develops direct measures for both market-level and firm-level sentiment using sentiment scores data from StockTwits.com. I examine both the impact of sentiment and the joint effect of sentiment and attention on earnings pricing. To the best of my knowledge, this is the first research about the joint effect of sentiment and attention on earnings pricing. I find that good news is actually punished when sentiment is bullish but bad news is punished significantly more when sentiment is bearish. Good news is rewarded the most when sentiment is bearish. The findings suggest that investors do not overreact to good news when sentiment is bullish but overreact to bad news when sentiment is bearish. I document that both firm-level and market-level sentiment are negatively associated with the immediate price reaction to earnings news. For the immediate response, I find that the immediate price reaction to earnings news is weaker when sentiment is bullish. For the drift, I find that the post-announcement drift is stronger following bullish sentiment. Taking into account investor attention, I find that good news is rewarded more with high attention when sentiment is either bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. Bad news is considerably punished with high attention when sentiment is bearish. The immediate price reaction is strengthened with high attention when sentiment is either bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. For the drift, I find that the post-announcement drift is weaker with high attention following bullish sentiment. It is worth noting that good news with bearish sentiment and high attention has both stronger immediate response and post-announcement drift.

I dedicate this dissertation to my beloved family.

To my parents, my parents-in-law, my older sister, thank you for your unconditional love.

To my wife, Jingwen, thank you for standing by my side along my journey.

To my lovely boys, Nathan and Marvin, thank you for making me laugh, bringing me happiness and hope.

I love you.

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INTRODUCTION

A large body of literature suggests that investors underreact to earnings announcements and such inattention causes the earnings momentum (Ball and Brown (1968); Bernard and Thomas (1989); DellaVigna and Pollet (2009); Hirshleifer, Lim and Teoh (2009)). Prior literature also suggests that the attention that investors allocate to stocks not only varies in cross-section, but also over time. Hirshleifer, Lim and Teoh (2009) assume that investors are distracted by concurrent earnings announcements of other firms. Peng and Xiong (2006) develop a conceptual framework of category-learning behavior and contend that investors have priority of processing market- and sector-wide information over firm-specific information because market shocks affect more stocks than firm-specific shocks. Recent studies (Chen, Jiang and Zhu (2018); Sheng (2019)) find that earnings announcements with concurrent macroeconomic news announcements actually have significantly stronger immediate market response and weaker PEAD, which differs from the prediction of category-learning theory, however, they do not find evidence that firm-level attention is higher on days with important market information shocks. DellaVigna and Pollet (2009) assume investor attention is low on Fridays as investors are distracted by other life activities just before the weekend. Hong and Yu (2009) posit that investors are less attentive during the summer vacation and they find that both stock return and stock turnover is lower during the summer.

There is limited prior research on the influence of investor sentiment on earnings pricing and mixed evidence is usually presented. Mian and Sankaraguruswamy (2012) find that the stock price sensitivity to good (bad) earnings news is higher during high (low) sentiment periods than during periods of low (high) sentiment. The result indicates that investors overreact (underreact) to good earnings news and underreact (overreact) to bad news during bullish (bearish) times. However, Livnat and Petrovits (2009) document that the price reaction is greater to extremely good (bad) earnings news during low (high) sentiment periods. For the drift, Mian and Sankaraguruswamy (2012) find that the upward drift for good news is stronger following high sentiment and Livnat and Petrovits (2009) find the drift for good news is greater following low sentiment.

In the first essay, I propose direct measures for market-level and firm-level attention separately. I first examine the temporal allocation of both market-level and firm-level investor attention. I find that both market-level and firm-level attention is lower on non-trading days and days without macro- or micro news announcements. Consistent with DellaVigna and Pollet (2009), I document that market-level and firm-level attention is lower on Friday. Differs from Hong and Yu (2009) and Liu and Peng (2015), I do not find evidence that investor attention is lower in summer.

Then I explore what determines the allocation of attention on earnings announcement days. Consistent with Hirshleifer, Lim and Teoh (2009), I find that investors are distracted by high volume of concurrent competing news, both market-level and firm-specific. Firm-level attention is negatively associated with market-level attention, suggesting that investors allocate their limited attention strategically between market-level and firm-level. I also find that investors pay more attention to earnings announced on days with important macro news, suggesting that firm-level attention is strengthened rather than weakened with concurrent market-level information shocks, which differs from existing theories (Peng and Xiong (2006)).

I further examine the impact of investor attention on earnings pricing. I find that market-level and firm-level attention have different effects on earnings pricing. Investors allocate their limited attention accordingly between market-level and firm-level therefore investors have more muted initial reactions to earnings announcements if they pay more attention to board market. On the other hand, higher firm-level investor attention and concurrent important macro-news enhances the immediate price reaction to a firm's earnings surprise and alleviates the post-announcement drift (PEAD). I also find that drift occurs much later than documented in the prior literature.

Furthermore, I test the impact of attention on trading activities and find a strong concurrent correlation between firm-level attention and trading volume response. But I also find that market-level attention is positively associated with trading volume, thus, using trading volume as a proxy of attention may conflate the different effects of market-level and firm-level attention on earnings pricing.

In the second essay, I propose direct measures for market-level sentiment and firm-level sentiment. I first explore the determinants on firm-level sentiment on earnings announcement days. I find that firm-level sentiment is positively related to market-level sentiment and negatively associated with firm-level attention, i.e., bullish sentiment is moderated by attention.

Then, I explore the impact of firm-level sentiment on earnings pricing. I find that good news is actually punished when sentiment is bullish but bad news is punished significantly more when sentiment is bearish. Good news is rewarded the most when sentiment is bearish. The findings suggest that investors do not overreact to good news when sentiment is bullish but overreact to bad news when sentiment is bearish. I document that both firm-level and market-level sentiment are negatively associated with the immediate price reaction to earnings news, i.e., the more bullish sentiment is, the weaker is the immediate price reaction to earnings news. For the drift, I find that drift is stronger following bullish sentiment.

Last, I examine the joint effect of sentiment and attention on earnings pricing. I find that good news is rewarded more with high attention when sentiment is either bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. Bad news is considerably punished with high attention when sentiment is bearish. The immediate price reaction is strengthened with high attention when sentiment is either bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. For the drift, I find that the post-announcement drift is weaker with high attention following bullish sentiment. It is worth noting that good news with bearish sentiment and high attention has both stronger immediate response and post-announcement drift.

This dissertation proposes promising big-data-based direct measures for both market-level and firm-level attention and sentiment. This dissertation not only confirms the key assumptions made by prior research but also offers new evidence on the impact of attention and sentiment on earnings pricing. First, this research provides direct evidence that firm-level attention is strengthened rather than weakened with concurrent market-level information shocks. Second, this study also offers new evidence about the determinants of attention allocation and the different effects of market-level and firm-level attention on investor reactions to earnings announcements. Third, this paper provides direct evidence that both firm-level and market-level sentiment are negatively associated with the immediate price reaction to earnings news. In particular, this study extends the evolving literature which studies the influence of investor behavior and belief on assets (mis)pricing by connecting the sentiment-related (mis)pricing of earnings to the attention-related (mis)pricing of earnings. It shows that investor attention and sentiment do jointly affect the source of excess returns documented in the prior earnings-based market anomaly literature.

MARKET-LEVEL ATTENTION, FIRM-LEVEL ATTENTION, MACRO NEWS, AND EARNINGS PRICING

INTRODUCTION

A number of studies investigate the impact of investor attention on the stock market but the empirical challenge is the lack of direct measures of investor attention. Widely used indirect measures include equilibrium outcomes such as abnormal return and abnormal trading volume (Barber and Odean (2008); Hou, Xiong and Peng (2009); Huang, Huang and Lin (2018); Loh (2010)), and proxies for exposure rate such as advertising expense (Chemmanur and Yan (2009); Lou (2014)), price limits (Seasholes and Wu (2007)), and media coverage (Barber and Odean (2008); deHaan, Shevlin and Thornock (2015); Peress and Schmidt (2018)). However, as suggested by Da, Engelberg and Gao (2011), using equilibrium outcomes as proxies of attention may conflate attention and information because they are functions of economic factors in addition to investor attention. On the other hand, appearing in the banner headline or ranking the first place in a best-performing stock list does not guarantee increased investor attention. Huberman and Regev (2001) and Cohen and Frazzini (2008) show that investors often cannot effectively process the huge amount of information delivered by the media.

It was only recently that the availability of big data from online systems provided the possibility for employing a large-scale investigation of investor attention in financial markets. The high frequency of generation and the low cost of acquisition make big data an important source of real time estimation in the decision-making process of economic agents. It represents an interesting intersection of finance and technology. The most widely used direct measure of investor attention is Google Search Volume Index (SVI) which capturing investors’ information demanding activity

(Da, Engelberg and Gao (2011); deHaan, Shevlin and Thornock (2015); Drake, Roulstone and Thornock (2012); Yung and Nafar (2017)).[1]

In this paper, I propose novel direct measures for both market-level and firm-level investor attention based upon the source of proprietary data from StockTwits. StockTwits, founded in 2008, is a social media communications platform where market participants come to share real time insights and ideas. As of July 2016, StockTwits attracts more than 1.5 million monthly active users, most of them are young professionals, 60% of its users under 44.[2] The ever-growing users on StockTwits are active and involved. StockTwits users post about 220 messages a minute during the trading day and spend an average of 51 minutes a day on StockTwits' website.[3]

StcokTwits has granted me access to their firehose for research purposes.[4] I pick StockTwits as my real-world laboratory because it provides an ideal setting of measuring investor attention for several reasons. First, it is a Twitter-like micro-blogging platform but is more user-friendly for investors. It is much easier for investors to find the right tweets on StockTwits. On Twitter, only a small fraction of tweets matters to stock-related issue. As re-tweeting is not an accurate proxy for news value therefore important news in finance can happen without anyone retweeting or liking it. This makes investors difficult to identify the relevant news on Twitter. Second, StockTwits is an investor community specifically dedicated to discussing investment related topics. Therefore, my results are based on observations of actual active market participants who engage in investing activities on an ongoing basis, better reflecting "investor attention" than

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[1] Google queries are considered in this paper as big data since it offers insight about the interest of investors in the searched topic.
[2] https://techcrunch.com/2016/07/06/stocktwits-raises-funding-gets-new-ceo/
[3] https://xconomy.com/san-diego/2017/01/24/new-stocktwits-ceo-looks-to-expand-share-of-investor-community/
[4] I would like to thank StockTwits for their generous support and provision of proprietary data for use in this research.

aggregated Google searches with unknown demography. Third, StockTwits is the inventor of "cash tag". The cashtagging makes it easier for investors to identify the tweets on individual stocks in real time with no misclassification.[5] Therefore StockTwits reflects a more ticker-like live conversation. Fourth, StockTwits public timeline accurately captures the up to date development of market conversation. The time stamp of each tweet makes it easier to connect investor reactions to market events, containing more temporal information with higher resolutions than weekly aggregated Google search volumes.

By measuring market-level and firm-level attention separately, I am be able to not only distinguish between attention allocated on market level and firm level but also detach attention from equilibrium outcomes. I first examine the temporal allocation of both market-level and firm-level investor attention. I find that both market-level and firm-level attention is lower on non-trading days and days without macro- or micro news announcements. Consistent with DellaVigna and Pollet (2009), I document that market-level and firm-level attention is lower on Friday. Differs from Hong and Yu (2009) and Liu and Peng (2015), I do not find evidence that investor attention is lower in summer.

Then I explore what determines the allocation of attention on earnings announcement days. Consistent with Hirshleifer, Lim and Teoh (2009), I find that investors are distracted by high volume of concurrent competing news, both market-level and firm-specific. Firm-level attention is negatively associated with market-level attention, suggesting that investors allocate their limited attention strategically between market-level and firm-level. I also find that investors pay more attention to earnings announced on days with important macro news, suggesting that firm-level

[5] Cashtags help alleviate the misclassification problem associated to Google searches. Ambiguity happens when users use non-standard format (e.g. common word ticker) in Google searches.

attention is strengthened rather than weakened with concurrent market-level information shocks, which differs from existing theories (Peng and Xiong (2006)).

I further examine the impact of investor attention on earnings pricing. I find that market-level and firm-level attention have different effects on earnings pricing. Investors allocate their limited attention accordingly between market-level and firm-level therefore investors have more muted initial reactions to earnings announcements if they pay more attention to board market. On the other hand, higher firm-level investor attention and concurrent important macro-news enhances the immediate price reaction to a firm's earnings surprise and alleviates the post-announcement drift (PEAD). I also find that drift occurs much later than documented in the prior literature.

Furthermore, I test the impact of attention on trading activities and find a strong concurrent correlation between firm-level attention and trading volume response. But I also find that market-level attention is positively associated with trading volume, thus, using trading volume as a proxy of attention may conflate the different effects of market-level and firm-level attention on earnings pricing.

This paper contributes to the literature on investor attention on several aspects. First, this paper proposes promising big-data-based direct measures for both market-level and firm-level attention and provides direct evidence that firm-level attention is strengthened rather than weakened with concurrent market-level information shocks. Second, this paper not only confirms the key assumptions made by prior research but also offers new evidence about the determinants of attention allocation. Third, this study extends the line of research by providing direct evidence of the different effects of market-level and firm-level attention on investor reactions to earnings announcements.

LITERATURE REVIEW

Investor (in)attention and earnings pricing

Earnings announcements, perhaps the most important regular disclosure a firm makes, are natural attention-grabbing events. Traditional asset pricing models typically assume that all investors are attentive and receive the price relevant information immediately and undertake trading actions instantly. However, investors have limited attention and such limited attention leads to underreaction to earnings announcements (price is too low after positive earnings surprise and too high after negative surprise) (Hirshleifer and Teoh (2003)). Such inattention-driven underreaction is not the same as the conservatism bias-driven underreaction in Barberis, Shleifer and Vishny (1998) because limited attention is not a behavioral bias (Hou, Xiong and Peng (2009)). Ball and Brown (1968) first document the post-earnings price drifts, known as PEAD (post-earnings announcement drift) or earnings momentum. They find that prices continue to drift in the direction of the earnings news over a period after the announcement. A large body of literature suggests that investor (in)attention affects the pricing of earnings and causes the drift. Bernard and Thomas (1989) show that investors underreact to earnings announcements and an implementable trading strategy based on earnings momentum (i.e., longing stocks in the top decile of earnings surprise and shorting stocks in the bottom decile) generates an 18% annualized return, during the quarter following the announcement. Hirshleifer, Lim and Teoh (2009) and DellaVigna and Pollet (2009) both document that investor inattention is associated with lower immediate price reactions and higher post announcement price drifts to firms' earnings announcements. Aboody, Lehavy and Trueman (2009) find that stocks with stronger investor attention experience a significant positive return just before their earnings announcements and an immediately following significant negative return. Hou, Xiong and Peng (2009) argue that investor attention is associated with weaker earnings momentum but stronger price momentum. Curtis (2014) support that investor attention observed in social media activity affects the (mis)pricing of earnings announcements. Huang, Huang and Lin (2018) find that stock returns are less sensitive to earnings surprises on investor inattentive days. Ben-Rephael, Da and Israelsen (2017) find that the post announcement price drifts are driven by announcements with institutional investor inattention. Chapman (2018) find that attention, returns and trading volume are higher on earnings notification days but are lower on the following earnings announcement days, consisting with notifications attenuating investor attention around the earnings announcements.

Attention allocation and concurrent competing information shocks

Hirshleifer, Lim and Teoh (2009) assume that investors are distracted by concurrent earnings announcements of other firms. As a result, earnings news made on a high-news day (a large number of firms announce earnings on the same day) receive lower immediate price reaction and are associated with higher PEAD. They discover that the number of announcements is lowest on Fridays thus the earnings announced on Fridays will receive higher attention according to the distracting hypothesis. In contrast, DellaVigna and Pollet (2009) argue that investors likely pay less attention to earnings announcements on Fridays as they are distracted by out-of-market activities just before the weekend. Hirshleifer, Lim and Teoh (2009) imply that investors allocate equal amount of attention to the stock market on every trading day. However, according to Kahneman (1973), attention allocation is related to the amount of stimulus. Attention can be deliberately allocated when there is an onset of stimulus and salient events (Yantis (1998)). Consequently, how investors allocate the total attention between the concurrent competing information shocks becomes the key question of interest. It is worth emphasizing that concurrent competing information shocks include not only concurrent firm-specific announcements but also market-wide events.

Peng (2005) predicts that when facing information shocks investors actively increase attention and optimally allocate their attention to minimize their wealth uncertainty. When uncertainty becomes large, investors may shift more attention from firm-specific to common factors. Peng and Xiong (2006) develop a conceptual framework of category-learning behavior and contend that limited attention leads to naturally selective processing between market and firm-specific shocks. Investors have priority of processing market- and sector-wide information over firm-specific information because market shocks affect more stocks than firm-specific shocks. In consistency with Peng and Xiong (2006), Liu and Peng (2015) find that the macro-news announcements attenuate the attention to earnings announcements and investors give priority to processing systematic information, suggesting there is a ceiling on investor attention. Huang, Huang and Lin (2018) assume that when investors pay less attention to stock market, they disproportionately reduce more attention allocated to firm-specific shocks than that allocated to market shocks. The authors use large jackpot as an exogenous shock distracting investor from market and trading activities and they find that the stock returns co-move more with the market on large jackpot days and they also find that the market response to earnings surprises is weaker on large jackpot days. Hence, Peng (2005), Peng and Xiong (2006), Liu and Peng (2015) and Huang, Huang and Lin (2018) implicitly imply a substitute relationship between market-wide shocks and firm-specific shocks. However, other authors propose a complementary relationship between the market news and firm-level news. Chen, Jiang and Zhu (2018) provide evidence that consistent with category-learning behavior, investors allocate more attention to macroeconomic news than to firm-level news. Investors pay less attention to firms' earnings announcements on days with important macroeconomic news than on other days. But they argue that macroeconomic news attracts investor attention to the overall market therefore the total attention allocated to earnings news and macroeconomic news is higher on days with macroeconomic news announcements. They find that earnings announcements with concurrent macroeconomic news announcements actually have significantly stronger immediate market response and weaker PEAD. Similarly, Sheng (2019) find that the immediate price response to earnings announcements with concurrent macro-news is 17% stronger and the PEAD is 71% weaker. Sheng (2019) also show that institutional investor attention is higher but retail investor attention is lower on days with macroeconomic news announcements. In this paper I extend the existing literature and use direct measures for both market-level and firm-level investor attention to explore how investors allocate attention between these concurrent and competing information shocks, i.e., between concurrent competing earnings announcements and between earnings announcements (firm-specific news) and macroeconomic news.

Temporal allocation of investor attention

The attention that investors allocate to stocks not only varies in cross-section, but also over time. Attention is a scarce cognitive resource (Kahneman (1973)) and it could not be truer in the information age. The limited attention is a necessary consequence of scarcity in cognition and abundance in information. With limited capacity, attention must be selective both spatially and temporally (Kahneman (1973)). Therefore, how investors allocate their limited attention temporally becomes a question of interest. Prior studies posit that investor attention varies over time. DellaVigna and Pollet (2009) assume investor attention is low on Fridays as investors are distracted by other life activities just before the weekend. They attribute the lower price reactions on Fridays to lower investor attention. However, Michaely, Rubin and Vedrashko (2016) argue that investor inattention on Fridays is an outcome of selection bias, firms announcing earnings on Fridays have unobserved characteristics and also experience weaker market reaction on any weekday. deHaan, Shevlin and Thornock (2015) also find evidence that investor attention is actually no different on Fridays than other weekdays. They find that attention is lower after market close. Hong and Yu (2009) posit that investors are less attentive during the summer vacation and they find that both stock return and stock turnover is lower during the summer. The literature still lacks direct evidence about the temporal variation in investor attention. I investigate the temporally allocating of investor attention by using the direct measures of investor attention.

DATA AND RESEARCH DESIGN

Measuring investor attention by StockTwits data

My complete data set contains the comprehensive metadata of users' activity kindly provided by StockTwits.com over the period from January 2010 to December 2018. However, I focused my analysis in the more recent period from January 2013 to December 2018 given that StockTwits was not so popular during the earlier years and the tweet activity was significantly less.[6] By retrieving the cashtag "$" (e.g., $AAPL, $DELL, $GRPN), I can aggregate the conversation per ticker. If a message mentions more than one ticker symbols, I treat each ticker symbol as a unique post. The other additional metadata of a typical message referring to a specific stock includes information such as message content, post date and time, trader/investor specific data, and the exchange this stock is traded on. I filtered the symbols by choosing those are traded on NYSE and NASDAQ and the initial sample consists of approximately 66 million tweets. I then match stock symbols to firms' PERMNOs, a unique firm identifier provided by CRSP. Finally, I

[6] The data from 2012 was used to compute the abnormal attention of January 2013.

require the stocks have a share code of 10 or 11 in the Center for Research in Securities Prices (CRSP) database.

Firm-level attention

I measure daily investor attention to a specific stock by using unique dynamic analytics from StockTwits. Specifically, I compute the daily message volume of a specific stock on StockTwits to measure the abnormal attention of this stock on that day. To capture the deviation of investor attention from the "normal" level and any potential time trends, the investor attention measure is standardized by the baseline level of investor attention to rule out any seasonality and day of week effects. The abnormal attention of a specific stock $AbAtt_{i,t}$ measured by the change in message volume $MsgVol_{i,t}$ is defined by Equation (1). $AbAtt_{i,t}$ is the difference between the message volume of stock i on day t and its average message volume over a 45-day window prior to 2 weeks before day t (t-60, t-15) scaled by the average. Drake, Roulstone and Thornock (2012) find that investors' information demanding activity through Google search increases about two weeks prior the earnings announcement. Consequently, I skip the most recent two weeks in the calculation of the benchmark to avoid potential spillover effects of the investor attention. As abnormal message volume on the announcement day measures the amount of increased discussion and posts about a firm, it provides a direct measure of investor attention to earnings announcements. This detrended measure removes time trends and seasonality. Also, the 45-day window captures the baseline level of attention so that these measures will provide a proxy for how much increased

attention investors are paying to earnings.

$$AbAtt_{i,t} = \frac{MsgVol_{i,t} - Average\ MsgVol_{i,(t-60,t-15)}}{Average\ MsgVol_{i,(t-60,t-15)}} \tag{1}$$

Consequently, this measure of attention indicates the deviation from the benchmark baseline level. For example, a “0.5” score captures a deviation of 50% of attention of a specific stock on a given day from the “normal” level.

Market level attention

I measure market-level attention by looking at the relevant messages about the board market. Specifically, I screened for messages containing the cashtags of $SPY, $ES_F, and $SPX and compute the daily message volume of these cashtags on StockTwits to measure the abnormal attention to board market on that day. The abnormal market attention $AbMktAtt$ measured by the change in message volume of board market $MktMsgVol$ is defined by Equation (2). $AbMktAtt$ is the difference between the message volume of board market on day t and the average message volume from day t-60 to day t-15, scaled by the average.

$$AbMktAtt_t = \frac{MktMsgVol_t - Average\ MktMsgVol_{(t-60,t-15)}}{Average\ MktMsgVol_{(t-60,t-15)}} \quad (2)$$

Earnings announcements

I obtain quarterly earnings announcement data from I/B/E/S from 2013 to 2018 and merge earnings announcement data and attention data from StockTwits and require non-missing values in both datasets. I decide the earnings announcement dates by comparing the dates reported by both Compustat and I/B/E/S. When there is discrepancy between the two sources, following DellaVigna and Pollet (2009), I take the earlier date of the two. Following Hirshleifer, Lim and Teoh (2009), my sample firms are limited to those that have I/B/E/S coverage so I expect accurate earnings announcement dates from my sample. Following DellaVigna and Pollet (2009), I measure earnings surprise (SUE) using Equation (3).   It is the difference between the announced actual EPS (Actual EPS) of the quarter as reported by I/B/E/S and the median of the most recent forecast

(Consensus Forecast) acquired from the I/B/E/S detail file divided by the stock price at the end of the corresponding quarter (Price QE). If an analyst made multiple forecasts in a given quarter, the consensus forecast used is the most recent one prior to the announcement. To keep the forecasts most up-to-date, I require the forecasts were issued in the last 60 calendar days before the earnings announcement. Also, I exclude observations: 1) when actual earning or forecast is larger in absolute value than the stock price, 2) when the stock price is less than $1, and 3) those with a missing earnings surprise. The final sample includes 48,765 earnings announcements for 2,814 unique stocks. I include full I/B/E/S earnings announcements data when I compute the number of competing announcements.

$$SUE = \frac{Actual\ EPS - Consensus\ Forecast}{Price\ QE} \tag{3}$$

It is believed that investors react in the direction of the SUE, i.e., positive response to positive SUE and negative response to negative SUE. Since investors can respond to announcements made during trading hours immediately, following Michaely, Rubin and Vedrashko (2013), if an announcement is made during trading hours, I count the earnings announcement and match it with attention measured on the same day. If an announcement is made after trading hours (i.e., after 16:00) or during a holiday, day "zero" is defined as the following trading day and I count the earnings announcement and match it with attention on that day.

Because the relationship between announcement-day abnormal returns and the raw earnings surprise is nonlinear (e.g., (Bernard and Thomas (1989); Kothari (2001)), I rank and sort SUE into quintiles from the most negative low $SUE1$ to the most positive $SUE5$ to mitigate the nonlinear relation following prior literature (e.g., (DellaVigna and Pollet (2009); Hirshleifer, Lim and Teoh (2009); Sheng (2019)). Then the relationship between CAR and the earnings surprise quintiles is almost linear.

Stock price response to earnings news is measured by cumulative abnormal return (CAR) for each stock. The CARs are calculated using the market model parameters estimated over the period between 300 and 46 days prior to the earnings announcement and adjusted by the CRSP value-weighted index return. For the immediate price response, I use CAR over the 2-trading-day window [0, 1] surrounding the earnings announcement. For post announcement drift, following DellaVigna and Pollet (2009), I use $CAR[2,75]$.[7] Stock return on day t are measured from the market close (16:00) on day t-1 to the market close (16:00) on day t.

Macroeconomic announcements

I obtain information for macro-news announcements from Bloomberg. I employ the full list of macroeconomic announcements from Bloomberg to count the number of macro-news announcements on a specific day. However, macro-news announcements have different impacts on investor attention allocation and the stock market. Based on the Bloomberg relevance index[8] during my sample period, I define a day to be an important macro-news day ($ImpMAday$) if one of the following macro-news announced on that day: the Federal Open Market Committee (FOMC) rate decision, nonfarm payrolls, ISM manufacturing index, initial jobless claims, CPI MoM and gross domestic product (GDP) growth. All these macroeconomic news announcements have a Bloomberg relevance score no less than 95. Since macro-news are announced before or during trading hours, I match macro-news announcements with $AbMktAtt$ and $AbAtt$ of the same day.

[7] Alternative choice of windows is also used.
[8] A measure of the importance of macro-economic news assigned by Bloomberg, ranging from 0 to 100.

Summary statistics

Table 2 reports summary statistics based on the full sample. Exploring the stock characteristics in the sample indicates that these are not small firms. The mean (median) size is about 8.6 (1.4) billion. The mean (median) institutional holdings make up about 70% (78%) of shares outstanding. The mean (median) number of analysts following a stock is 9 (7). On average, there are 171 earnings announcements and 8 macro-news announcements on a typical earnings announcement day. The mean immediate reaction to an earnings announcement ($CAR[0,1]$) is 0.08%, and the mean of the PEAD ($CAR[2,75]$) is -0.38%. The mean firm-level abnormal attention is 16.91 and the mean board market abnormal attention is 0.41 on a typical earnings announcement day. The standard deviation is 39.03 and 0.52, suggesting that there is considerable cross-sectional and time-series variation in both firm-level and market-level attention.

EMPIRICAL ANALYSIS

What determines the allocation of investor attention on a typical day or in a typical month?

Friday vs. other weekdays

Figure 1, Figure 2, and Table 3 present the day of week patterns of firm-level abnormal attention and the number of earnings announcements. In Table 3 Panel A, it shows that earnings announcements cluster by day of week and demonstrate a strong seasonal pattern. As documented in prior studies, the number of announcements is lowest on Friday (5,692) and higher on Tuesday, Wednesday, and Thursday (DellaVigna and Pollet (2009); Hirshleifer, Lim and Teoh (2009)). Monday has twice as many announcements as Friday has and the average number of announcements from Monday to Thursday is 20,630. The mean and median $AbAtt$ is also higher on Tuesday, Wednesday, and Tuesday. The difference of means test and the non-parametric median test show that the mean and median $AbAtt$ on Friday (0.212 and 0.217) is lower than on other weekdays (0.407 and 0.402) and the difference is significant at 1% level. Please note that weekend days have negative abnormal attention and the lowest number of announcements, suggesting that investors pay less attention to stocks during non-trading days.

In Panel B, I compare the mean and median $AbAtt$ on earnings announcement days with non-announcement days. It shows that on earnings announcement days, the mean and median $AbAtt$ on Friday (0.239 and 0.234) is lower than on other weekdays (0.437 and 0.422) and the difference is significant at 1% level. On days without earnings announcements, the mean and the median $AbAtt$ is negative on all weekdays and the mean and median $AbAtt$ drops the most on Thursday. The mean and median $AbAtt$ is higher on announcement days than on non-announcement days and the difference is significant, suggesting that investors pay more attention to stocks on days with earnings announcements. It is also worth noting that on non-announcement days, the mean and median $AbAtt$ on Friday (-0.459 and -0.373) is still lower than on other weekdays (-0.199 and -0.09) and the difference is statistically significant. The findings suggest that investors are generally less attentive on Friday either with or without earnings news released, which is consistent with DellaVigna and Pollet (2009).

Figure 3, Figure 4, and Table 4 present the day of week patterns of market-level abnormal attention and the number of macro-news announcements. In Table 4 Panel A, it shows that macroeconomic announcements are generally released during weekdays and the mean and median $AbMktAtt$ is lowest on weekends, suggesting that investors pay less attention to the board market during non-trading days. The number of announcements is lowest on Monday and higher on other weekdays. The mean and median $AbMktAtt$ is lowest on Monday and the mean and median $AbMktAtt$ on Friday is only slightly higher than on Monday. The mean and median $AbMktAtt$

on Friday (0.248 and 0.164) is lower than on other weekdays (0.389 and 0.286) and the difference is significant at 1% level.

In Panel B, I compare the mean and median $AbMktAtt$ on macro-news announcement days with non-announcement days. It shows that the mean and median $AbMktAtt$ is lower on non-announcement days than on announcement days, suggesting that investors pay less attention to board market on days without macro-news announcements. It is also worth noting that on macro-news announcement days, the mean and median $AbMktAtt$ on Friday (0.283 and 0.183) is lower than on other weekdays (0.435 and 0.309) and the difference is significant at 1% level, suggesting that investors pay less attention to macro-news announced on Friday.

Summer vs. other months

Figure 5, Figure 6, and Table 5 present the month of year patterns of firm-level abnormal attention and the number of earnings announcements. As documented in Hirshleifer, Lim and Teoh (2009), the number of announcements show a 3-month cycle, with the lowest number of announcements in March, June, September, and December. Accordingly, the mean $AbAtt$ in these months is negative and lower than in other months. It is also worth noting that the number of announcements in January is even lower than in March but the mean $AbAtt$ is much higher in January. In Panel A, it indicates that the mean and median $AbAtt$ in Summer (July and August) is higher than in other months and the difference is significant at 10% level. The finding differs from with Hong and Yu (2009) which finds that investors are less attentive during summer holidays.

In Panel B, I compare the mean and median $AbAtt$ on earnings announcement days with non-announcement days by month of year. On earnings announcement days, the mean $AbAtt$ in Summer is higher than in other months and the difference is significant at 5% level. It is also worth noting, in each month, the mean $AbAtt$ is positive on earnings announcement days and is negative on non-announcement days, and the difference is significant. The findings suggest that investors pay less attention to stocks on days without earnings announcements.

Figure 7, Figure 8, and Table 6 present the month of year patterns of market-level abnormal attention and the number of macro-news announcements. In Table 6 Panel A, it shows that the macro-news is released evenly among months and there is no significant difference between the mean and median $AbMktAtt$ in Summer and in other months. In Panel B, I compare the mean and median $AbMktAtt$ on macro-news announcement days with non-announcement days by month of year. In each month, the mean $AbMktAtt$ is positive on macro-news announcement days and negative on non-announcement days, and the difference is significant, suggesting that investors pay less attention to board market when there is no macro-news announced on that day.

What determines allocation of investor attention on earnings announcement days?

In this section, I explore a set of variables that are associated with abnormal firm-level investor attention on earnings announcement days. In order to examine whether macro-news announcements strengthen (Chen, Jiang and Zhu (2018); Sheng (2019)) or attenuate the attention (Huang, Huang and Lin (2018); Liu and Peng (2015); Peng and Xiong (2006)) to earnings announcements, I include a dummy variable $ImpMAday$. $ImpMAday$ is equal to 1 if a day is an announcement day for one of the important macroeconomic announcements (i.e., FOMC, GDP, ISM PMI, nonfarm payroll, initial jobless claims and CPI). To investigate the distracting effect of same-day announcements from other firms (Hirshleifer, Lim and Teoh (2009)), I include $NumEA$, which is the natural logarithm of number of same-day earnings announcements. Using the full list of macro-news announcements, I also include $NumMA$, which is the natural logarithm of number of same-day macro-news announcements. $AbsSUE$ is absolute earnings surprise. $LnSize$ is the natural logarithm of market capitalization. $LnBM$ is the is the natural logarithm of book to market ratio. $NumAnalyst$ is the natural logarithm of 1+ the number of analysts covering the stock. $InstOwn$ is institutional ownership which is the percentage of shares held by institutional investors by using the most recent information before the announcement date. $SDRet$ is the standard deviation of daily stock returns from day t-60 to day t-15. $AbTurnover$ is the stock's abnormal turnover. $ILLIQ$ is the logarithm of Amihud (2002) illiquidity. $AbMktAtt_t$ is the abnormal market-level attention on day t. I also include dummies $Friday$ and $Summer$ to address the seasonality of investor attention (DellaVigna and Pollet (2009); Hong and Yu (2009)).

I run the following regression:

$$
\begin{aligned}
&AbAtt_{i,t} \\
&= \alpha + \beta_1\ ImpMAday + \beta_2 NumEA_t + \beta_3 NumMA_t + \beta_4 AbMktAtt_t + \beta_5 AbsSUE + \beta_6 SDRet \\
&+ \beta_7 InstOwn + \beta_8 LnSize + \beta_9 LnBM + \beta_{10} ILLIQ + \beta_{11} NumAnalyst\ + \beta_2 AbTurnover_t \\
&+ \beta_{13} Friday + \beta_{14} Summer \\
&+ \varepsilon_{i,t} \qquad (4)
\end{aligned}
$$

The results are reported in Table 7. Motivated by the prior studies, in column (1), I examine attention allocation among concurrent competing information shocks ($NumEA$ and $NumMA$), on important macro-news announcement days, on Friday, and in summer. The constant is 48.96 and is statistically significant at 1% level, suggesting that the abnormal firm-level attention is significantly higher on earnings announcement days. The coefficients on $NumEA$ and $Friday$ are -6.40 and -3.65, both significant at 1% level. The findings suggest that investors are less attentive on Friday and days with high volume of concurrent competing news, which is consistent with prior studies (DellaVigna and Pollet (2009); Hirshleifer, Lim and Teoh (2009)). The coefficient on $ImpMAday$ is 1.16, statistically significant at 1% level, suggesting that macro-news announcements strengthen the attention to earnings announcements. The coefficient on $Summer$ is 1.04 and statistically significant at 5% level, suggesting that investors are not less attentive in summer holidays, which differs with Hong and Yu (2009). The coefficients on $AbMktAtt$ is -0.14, however is not statistically significant.

In column (2), I examine variables that are related to equilibrium outcomes and various firm characteristics. All variables except $LnSize$ are statistically significant. It shows that firms with high institutional ownership and the less liquid stocks with higher abnormal turnover are associated with higher abnormal firm-level attention on earnings announcement days. It shows that firms with greater analyst coverage are associated with less abnormal firm-level attention on earnings announcement days, which differs from prior studies (e.g., Ben-Rephael, Da and Israelsen (2017)); Liu and Peng (2015)). It also shows that investors pay more attention to the stocks with a higher magnitude of SUE. The negative coefficient on $SDRet$ is potentially driven by the fact that a high $SDRet$ likely correlates with high firm-level attention in the benchmark window (t-60, t-15).

In column (3), I regress abnormal firm-level attention on both categories of variables. The results are generally similar to those in column (1) and (2). Alternatively, controlling for the other variables, the coefficient on $AbMktAtt$ is -0.76 and becomes statistically significant at 5% level in the full regression, suggesting that investors assign their limited attention accordingly between firm-level information shocks and market-level information shocks. The coefficient on $ImpMAday$ is 0.65 and is significant at 10% level in the full regression, suggesting that firm-level investor attention is higher on days with important macro-news. Prior literature suggests that investors prioritize their limited attention to market-level information over firm-specific information, therefore investors allocate less attention to firms' earnings news announced on days with important macro news than on other days (Chen, Jiang and Zhu (2018); Huang, Huang and Lin (2018); Liu and Peng (2015); Peng and Xiong (2006)). Chen, Jiang and Zhu (2018) and Sheng (2019) find that the immediate price response is higher and the drift is lower for earnings announcements with concurrent macro-news announcements but they failed to find the evidence of increased firm-level retail investor attention on macro-news days by using different measures of investor attention from mine. Sheng (2019) employs the ticker-searching activity captured by Google Search Volume Index as a proxy of retail investor attention and finds that retail investor attention is lower on macro-news days. Chen, Jiang and Zhu (2018) use excess trading volume and absolute market return as proxies for investor attention and find that firm-level attention is lower on macro-news days. By using the novel direct measures for both market-level and firm-level attention, I am be able to distinguish the limited attention disproportionately assigned between market level and firm level and separate the attention from equilibrium outcomes such as trading volume that reflects economic dynamism other than investor attention. I find that investors pay more attention to earnings announcements when important macro-news is released on the same day, suggesting that firm-level attention is strengthened rather than weakened with concurrent market-level information shocks. The presence of important macro-news on earnings announcement days actually leads investors to learn the firms' earnings announcements more intensively. Therefore, my evidence is consistent with Sheng (2019) which finds that the relationship between macro news and earnings news is complementary.

Investor attention, price response to earnings announcements and PEAD

Investors have limited attention and such limited attention leads to underreaction to earnings announcements and a voluminous literature suggests that investor (in)attention affects the pricing of earnings and causes the post announcement drift (PEAD). In this section, I examine the impact of firm-level investor attention on the pricing of earnings. I investigate whether firm-level investor attention on the announcement day facilitates faster information incorporation and alleviates price underreaction to earnings news by examining returns around, and following earnings announcements. If firm-level investor attention facilitates information incorporation on the earnings announcement day t, then I expect that the immediate reaction to earnings surprises will be positively associated with the amount of allocated firm-level investor attention. More importantly, the amount of allocated firm-level investor attention would result in less drift over subsequent days. Therefore, abnormal firm-level investor attention $AbAtt$ is expected to be positively associated with immediate reaction to earnings surprises and negatively related to PEAD.

Univariate tests

I rank $AbAtt$ into quintiles from the lowest attention group $ATT1$ to the highest attention group $ATT5$. In the highest attention quintile $ATT5$ and the lowest attention quintile $ATT1$, I calculate the mean $CAR[0,1]$ and $CAR[2,75]$ across each earnings surprise quintile from the most positive $SUE5$ to the most negative $SUE1$. The spread in CAR between the two extreme earnings surprise quintiles ($SUE5 - SUE1$) measures the immediate stock price response and the investor inattention to earnings news as reflected in PEAD. A large spread in $CAR[0,1]$ indicates a stronger immediate price reaction to earnings news and a larger spread in $CAR[2,75]$ indicates a stronger post-announcement drift. I expect a larger $CAR[0,1]$ spread and a smaller $CAR[2,75]$ spread for the highest attention group $ATT5$ compared to the lowest attention group $ATT1$.

In Figure 9, the abnormal announcement return $CAR[0,1]$ is plotted against SUE quintiles separately for the highest attention group $ATT5$ and the lowest attention group $ATT1$. The investor attention on the announcement day facilitates faster information incorporation and leads to stronger price reaction to earnings news, which is reflected by a steep slope of line $ATT5$ in the graph. In Figure 10, it plots the in-quintile spread ($SUE5-SUE1$) for the highest abnormal attention quintile $ATT5$ and the lowest abnormal attention quintile $ATT1$ at alternative horizons. It shows that the highest abnormal firm-level attention quintile $ATT5$ has the larger spread ($SUE5-SUE1$) in $CAR[0,1]$ and then the spread diminishes subsequently. In contrast, the spread ($SUE5-SUE1$) for the lowest abnormal firm-level attention quintile $ATT1$ is significantly smaller in $CAR[0,1]$ and then grows from 30 days following the announcement day and the spread becomes substantial subsequently. The findings suggest that the immediate price reaction is stronger (weaker) for the highest (lowest) abnormal attention quintile $ATT5$ ($ATT1$) and the post-announcement drift is stronger (weaker) for the lowest (highest) abnormal attention quintile $ATT1$ ($ATT5$). Prior studies suggest that abnormal returns to PEAD are concentrated in the period surrounding the earnings announcement day. For example, Bernard and Thomas (1989) report that most of the drift occurs during the first 60 trading days after the announcement day. However, I find that the drift is getting substantial from day t+61.

Next, I calculate the mean $CAR[0,1]$ and $CAR[2,75]$ across earnings surprise quintiles by the extreme attention quintiles $ATT5$ and $ATT1$. Table 8 reports the result. The in-quintile spread ($SUE5-SUE1$) in $CAR[0,1]$ is 15.73% for $ATT5$ and 3.26% for $ATT1$, both significant at 1% level. The spread ($SUE5-SUE1$) in $CAR[2,75]$ is 2.71% (significant at 5% level) for $ATT1$ and 0.15 % (not statistically significant) for $ATT5$. The results indicate that the immediate price reaction (drift) is stronger with higher (lower) level of firm-level abnormal attention.

Multivariate tests

In this section, I conduct multivariate regression analysis to control for the effect of firm characteristics on the relation between short-window abnormal return $CAR[0,1]$ or long-window abnormal return $CAR[2,75]$ and earnings surprise SUE. I examine whether abnormal firm-level investor attention enhances the immediate price reaction to a firm's earnings surprise and alleviates the post announcement drift (PEAD). I estimate the following regression:

$$CAR = \alpha + \beta_1 SUE + \beta_2 AbAtt + \beta_3 AbMktAtt + \beta_4 ImpMAday + \beta_5 SUE \times AbAtt + \beta_6 SUE \times AbMktAtt + \beta_7 SUE \times ImpMAday + \sum_{i=1}^{n} \gamma_i X_i + \varepsilon \quad (5)$$

Where CAR is either $CAR[0,1]$ for immediate reaction, or $CAR[2,75]$ for PEAD. X_i are the control variables. I include $LnSize$, $LnBM$, $NumAnalyst$, $CAR[-202,-3]$, and $SDRet$ to control for possible sources of variation in the relation between CAR and SUE. $CAR[-202,-3]$ is the past cumulative abnormal returns over the 200-day window prior to 3 days before day t, used as a proxy of stock price momentum. $AbMktAtt$ is also ranked into quintiles from the lowest attention group $MktATT1$ to the highest attention group $MktATT5$. If abnormal firm-level investor attention $AbAtt$ is positively associated with immediate reaction to earnings surprises and negatively related to PEAD, then I expect that $\beta_5 > 0$ for $CAR[0,1]$ and $\beta_5 < 0$ for $CAR[2,75]$. Peng and Xiong (2006) suggests that investors allocate their limited attention accordingly between market-level and firm-level information shocks and the results from Table 7 show that market-level attention is negatively associated with firm-level attention, then higher market-level attention is associated with weaker immediate reaction and stronger PEAD. Therefore, I expect that $\beta_6 < 0$ for $CAR[0,1]$ and $\beta_6 > 0$ for $CAR[2,75]$. Chen, Jiang and Zhu (2018) and Sheng (2019) find that the earnings announcements announced on macro-news days have stronger immediate price reaction and weaker drift than on other days. The results from Table 7 show that the presence of important macro-news on earnings announcement days actually leads investors to pay more attention to firms' earnings announcements. Therefore, I expect that $\beta_7 > 0$ for $CAR[0,1]$ and $\beta_7 < 0$ for $CAR[2,75]$.

Table 9 reports the results. For the immediate price reaction, column (1) represents the result from a parsimonious specification without including any control variables, column (2) is the full regression with controls. In both columns, the coefficients on the interaction terms $SUE \times AbAtt$ and $SUE \times ImpMAday$ are both positive and statistically significant at 1% level, suggesting that the immediate price reaction to earnings announcements is stronger when investors pay more attention to the earnings announcements and when there is important macro-news announced on the same day. The coefficient on the interaction term $SUE \times AbMktAtt$ is negative and significant at 1% level as well. This suggests that investors allocate their limited attention accordingly between market-level and firm-level therefore investors have more muted initial reactions to earnings announcements if they pay more attention to board market.

For the drift, column (3) is the parsimonious specification without including any control variables and column (4) is the full regression with control variables. In both columns, the coefficients on the interaction terms $SUE \times AbAtt$ and $SUE \times ImpMAday$ are both negative and statistically significant, suggesting that higher firm-level abnormal attention and concurrent important macro-news announcements alleviate initial underreactions to earnings surprises therefore attenuate the post-announcement drift. The coefficient on the interaction term $SUE \times AbMktAtt$ is positive as expected but not statistically significant.

Investor attention and volume reaction

In this section, I test the impact of investor attention on trading activities. Investor attention often triggers trading and it is believed that the magnitude of reaction to earnings news can also be measured by trading volume in response to the earnings announcement (Hirshleifer, Lim and Teoh (2009)). Therefore, if $AbAtt$ truly captures abnormal firm-level attention, I would expect a strong concurrent correlation between $AbAtt$ and investor trading, i.e., a higher trading volume response with a higher level of abnormal firm-level attention. The stock's abnormal trading volume $AbVol$ is calculated similarly to Barber and Odean (2008) as the stock's daily volume on day t divided by the average trading volume from day t-252 to day t-15.

Table 10 reports the results. Column (1) is the parsimonious specification without including any control variables and column (2) is the full regression with control variables. Both columns show that the coefficient on $AbAtt$ is positive and statistically significant in both columns. On the other hand, I find no evidence that the abnormal trading volume is higher for firms that announce earnings on days with important macro-news announcements. The coefficient on $ImpMAday$ is positive but not statistically significant in both columns. It is also worth noting that controlling for the other variables, the coefficient on $AbMktAtt$ is positive and becomes statistically significant at 5% level in the full regression, suggesting that the stock's abnormal trading volume is higher with higher level of abnormal market-level attention. Since both market-level and firm-level attention trigger trading, using trading volume as a proxy of attention may conflate the different effects of market-level and firm-level attention on earnings pricing.

Robustness

Figure 10 shows that the drift becomes substantial from 75 trading days following the earnings announcement day, to examine whether the findings in Table 9 depend on choice of window to measure the drift, I run the same examination by using alternative drift windows, i.e. CAR[2,90] and CAR[2,105]. Table 11 presents the results and indicates that higher firm-level abnormal attention and important macro-news released on the earnings announcement day dampens the post-announcement drift, which is similar to the main findings in Table 9.

I further examine whether the results from Table 9 are robust to alternative measures of earnings surprise quintiles. I rank firms with negative surprise equally to quintile 1 and 2, and firms with positive surprise equally to quintile 4 and 5. Firms with zero surprise are assigned to quintile 3. I then re-estimate Equation (5) with the re-assigned earnings surprise quintiles. Table 12 reports the results. For the immediate price reaction, column (1) represents the result from a parsimonious specification without including any control variables, column (2) is the full regression with controls. In both columns, the coefficients on the interaction terms $SUE \times AbAtt$, $SUE \times AbMktAtt$, and $SUE \times ImpMAday$ have the expected signs, all significant at 1% level. For the drift, column (3) is the parsimonious specification without including any control variables and column (4) is the full regression with control variables. The coefficient on the interaction term $SUE \times AbAtt$ is negative as expected, significant at 10% level. Overall, the impact of firm-level and market-level attention on earnings pricing is robust to alternative measures of earnings surprise quintiles.

CONCLUSION

In this paper, I develop direct measures for both market-level and firm-level attention. By using such measures, I am be able to distinguish the limited attention strategically assigned between market level and firm level and separate attention from equilibrium outcomes such as trading volume that reflects economic dynamism other than investor attention. I provide direct evidence that firm-level attention is strengthened rather than weakened with concurrent market-level information shocks, which differs from existing theories. I find that market-level attention is negatively associated with firm-level attention and they have different effects on earnings pricing. Investors allocate their limited attention accordingly between market-level and firm-level therefore investors have more muted initial reactions to earnings announcements if they pay more attention to board market. On the other hand, higher firm-level investor attention and concurrent important macro-news enhances the immediate price reaction to a firm's earnings surprise and alleviates the post-announcement drift (PEAD).

Similar to my findings, Chen, Jiang and Zhu (2018) and Sheng (2019) find the complementary relationship between macro news and earnings news. Chen, Jiang and Zhu (2018) hypothesize that the higher combined total attention helps investors have a better understanding of earnings surprises. Sheng (2019) suggests an extension to existing theories to include investor attention allocated beyond the stock market. This study suggests that employment of big data in construction of direct measures of attention is a promising addition to this line for future research.

FIRM-LEVEL SENTIMENT, THE JOINT EFFECT OF SENTIMENT AND ATTENTION, AND EARNINGS PRICING

INTRODUCTION

Evidence from prior studies in behavioral finance suggests that investor sentiment drives stock price away from fundamental value and that arbitraging against sentiment-driven noise traders can be costly and risky e.g., (Baker and Wurgler (2006); Barberis, Shleifer and Vishny (1998); Brown and Cliff (2005); Daniel, Hirshleifer and Subrahmanyam (1998); De Long, Shleifer, Summers and Waldmann (1990); Hirshleifer and Teoh (2003)). Underlying the prior studies is the notion that the erroneous expectations about future payoffs of sentiment-driven noise traders lead to overvaluation (undervaluation) that reverse in the future. This notion challenges efficient market hypothesis (EMH) and proposes the factor of investor sentiment as a source of market volatility and anomalies.

A major empirical challenge is how to measure investor sentiment and quantify its influence because it is not directly observable (Baker and Wurgler (2007)). Market-based measures are extensively adopted in prior literature such as mutual funds flow (Ben-Rephael, Kandel and Wohl (2012)); overnight (close-to-open) return (Aboody, Even-Tov, Lehavy and Trueman (2018)), and the most widely used BW index (Baker and Wurgler (2006)). The main drawback of market-based measure is that such equilibrium outcome cannot guarantee a natural connection to investor sentiment because it can be driven by other economic factors (Da, Engelberg and Gao (2015)).

Survey-based measures are frequently used as well such as the University of Michigan Consumer Sentiment Index (Antoniou, Doukas and Subrahmanyam (2015); Bergman and

Roychowdhury (2008); Li and Luo (2016); Seybert and Yang (2012)); the Conference Board Index of Consumer Confidence (Antoniou, Doukas and Subrahmanyam (2013); Charoenrook (2005); Lemmon and Portniaguina (2006)); and Investor Intelligence (Brown and Cliff (2005); Fisher and Statman (2000); Kurov (2010); Lee, Jiang and Indro (2002)). However, as addressed by Da, Engelberg and Gao (2015), macro surveys are not available at a highly disaggregate temporal level (days, hours, minutes) and are less reliable when the incentive of telling truth is low.

Non-economic events such as weather conditions (Hirshleifer and Shumway (2003); Jiang, Norris and Sun (2018)) are also employed to examine sentiment and show such sentiment-changing events have impact on asset prices.

More recently, direct measures constructed from big data of users' online activities are employed to explore the effect of investor sentiment on asset price. [9] Da, Engelberg and Gao (2015) employ Google queries as a sentiment indicator and construct the Financial and Economic Attitudes Revealed by Search (FEARS) index, showing that FEARS predicts return reversals, temporary market volatility and mutual funds flow from equity funds to bond funds. However, Da, Engelberg and Gao (2015) focus on aggregate stock market indices rather than individual stocks.

Today, investors are increasingly utilizing the highly interactive social media platforms to create, modify and share user-generated content (UGC) (Kietzmann, Hermkens, McCarthy and Silvestre (2011)). In the field of behavioral finance, social media detailed data provide insights on the investors' perceptions, interactions and behavior, the trends on the market, and the associations between investors and capital markets. In this paper, I employ social media data in a traditional event-study framework. I use the proprietary StockTwits official sentiment scores to investigate

[9] Google queries are considered in this paper as big data since it offers insight about the interest of investors in the searched topic.

the impact of investor sentiment on earnings pricing. I also examine the joint effect of sentiment and attention on earning pricing.

StcokTwits has granted me access to their firehose for research purposes. [10] I use StockTwits as my real-world laboratory because it provides an ideal setting to measure investor sentiment for several reasons:

First, StockTwits is an investor community specifically dedicated to discussing investment related topics. As of July 2016, StockTwits attracts more than 1.5 million monthly active users, most of them are young professionals, 60% of its users under 44. [11] The ever-growing users on StockTwits are active and involved. StockTwits users post about 220 messages a minute during the trading day and spend an average of 51 minutes a day on StockTwits' website.[12] Therefore StockTwits is likely to be truly representative of the entire market.

Second, the cashtagging by "$" makes it easier for investors to identify the tweets on individual stocks in real time and the time stamp of each tweet makes it easier to connect investor reactions to market events. In real life, investors all probe the "temperature" of other market participants to moderate, modify or reinforce their own beliefs. In this sense, StockTwits provides an inherently precise sampling of perceptions of market participants at a highly disaggregate temporal level.

Third, StockTwits allows users to tag their content as bullish or bearish. But only about 20%-30% of all content is generally tagged and the tags have a slightly bullish bias.[13] More

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[10] I would like to thank StockTwits for their generous support and provision of proprietary data for use in this research.
[11] https://techcrunch.com/2016/07/06/stocktwits-raises-funding-gets-new-ceo/
[12] https://xconomy.com/san-diego/2017/01/24/new-stocktwits-ceo-looks-to-expand-share-of-investor-community/
[13] http://breakthroughanalysis.com/2018/02/26/stocktwits-social-data-science/

recently, StockTwits adopted a proprietary real-time market sentiment model to bring a full coverage to all messages posted on StockTwits and to assign a real-time investor-sentiment score to each message. This allows me to quantify sentiment in a more precise way, revealing its strong association with stock market dynamics such as direction and volatility.

Fourth, there is a growing number of studies employing crowd-sourced data generated by StockTwits and we are witnessing more and more evidences that show efficacy of this data.[14] Giannini, Irvine and Shu (2019) study a set of StockTwits posts to investigate the change in investor disagreement around earnings announcements. They find that investor disagreement is associated with higher earnings announcement returns. Liew and Budavari (2016) directly employ the tagged self-identified commentary sentiment data for the period 2012 to 2015 and conclude that Social Media Factor should be considered as the sixth factor of the Fama-French five-factor model. Renault (2017) use labeled self-identified commentary sentiment data as training data to derive investor sentiment from messages posted on StockTwits and find evidence that investor sentiment predicts intraday stock index returns.

By using direct measures for both firm-level sentiment and firm-level attention, I first explore the determinants on firm-level sentiment on earnings announcement days. I find that firm-level sentiment is positively related to market-level sentiment and negatively associated with firm-level attention, i.e., bullish sentiment is moderated by attention.

Then, I explore the impact of firm-level sentiment on earnings pricing. I find that good news is actually punished with bullish sentiment but bad news is punished significantly more with

[14] Several studies employ the sentiment data from third party data analytics providers such as Market IQ and PsychSignal (Argarwal, Azar, Lo and Singh (2018); Karagozoglu and Fabozzi (2017); Karampatsas, Malekpour and Mason (2017)). These commercial data providers extract and analyze stock-related messages from Twitter and StockTwits to build their own sentiment data.

bearish sentiment. Good news is rewarded the most with bearish sentiment. The findings suggest that investors do not overreact to good news with bullish sentiment but overreact to bad news with bearish sentiment. I document that both firm-level and market-level sentiment are negatively associated with the immediate price reaction to earnings news, i.e., the more bullish sentiment is, the weaker is the immediate price reaction to earnings news. For the drift, I find that drift is stronger following bullish sentiment.

Last, I examine the joint effect of sentiment and attention on earnings pricing. I find that good news is rewarded more with high attention when sentiment is either bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. Bad news is considerably punished with high attention when sentiment is bearish. The immediate price reaction is strengthened with high attention when sentiment is either bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. For the drift, I find that the post-announcement drift is weaker with high attention following bullish sentiment. It is worth noting that good news with bearish sentiment and high attention has both stronger immediate response and post-announcement drift.

This paper proposes promising big-data-based direct measures for both market-level and firm-level sentiment and provides direct evidence that both firm-level and market-level sentiment are negatively associated with the immediate price reaction to earnings news. This paper also provides new evidence for the associations between investors' perceptions, interactions and behavior and capital markets. In particular, this study extends the evolving literature which studies the influence of investor behavior and belief on assets (mis)pricing by connecting the sentiment-related (mis)pricing of earnings to the attention-related (mis)pricing of earnings.

LITERATURE REVIEW

Investor sentiment and earnings pricing

Earnings announcements are recurring, salient events which are naturally attention-grabbing, and scrutinized closely by investors. Ball and Brown (1968) first document the post-earnings price drifts, known as PEAD (post-earnings announcement drift) or earnings momentum. They find that prices continue to drift in the direction of the earnings news over a period after the announcement. Bernard and Thomas (1989) conclude that only a small portion of the earnings momentum could be explained by risk. Among the continuing stream of studies that has attempted to explain the price reaction to earnings announcements, a large body of literature on the effect of investor attention on earnings pricing has established that investor attention enhances the immediate price reaction to a firm's earnings surprise and alleviates the post-announcement drift (PEAD) (Ben-Rephael, Da and Israelsen (2017); Chen, Jiang and Zhu (2018); DellaVigna and Pollet (2009); Hirshleifer, Lim and Teoh (2009); Sheng (2019)). However, there is limited prior research on the influence of investor sentiment on earnings pricing and mixed evidence is usually presented. Both using the BW index (Baker and Wurgler (2006)), Livnat and Petrovits (2009) and Mian and Sankaraguruswamy (2012) investigate the effect of investor sentiment on earnings pricing and they get mixed results. Mian and Sankaraguruswamy (2012) find that the stock price sensitivity to good (bad) earnings news is higher during high (low) sentiment periods than during periods of low (high) sentiment. The result indicates that investors overreact (underreact) to good earnings news and underreact (overreact) to bad news during bullish (bearish) times. However, Livnat and Petrovits (2009) document that the price reaction is greater to extremely good (bad) earnings news during low (high) sentiment periods. For the drift, Mian and Sankaraguruswamy (2012) find that the upward drift for good news is stronger following high sentiment and Livnat and Petrovits (2009) find the drift for good news is greater following low sentiment. The contradictory evidence from the prior studies suggests further research is warranted to understand how investor sentiment influences earnings pricing.

Livnat and Petrovits (2009) and Mian and Sankaraguruswamy (2012) measure investor sentiment at the market level. Market-wide sentiment roughly aligns with peaks and troughs in the market (Baker and Wurgler (2006)) but can have different effects on (mis)pricing cross-sectionally. Investors react to firm-specific or market-wide events by different width and depth. Hence, firm-specific sentiment can have an effect on the (mis)pricing of earnings directly. More recently, the development of measures of firm-specific investor sentiment enables researchers to focus on the effect of sentiment at the individual firm level. Several studies employ measures of firm-specific investor sentiment to investigate the impact of sentiment on the price reaction to earnings news. Cahan, Chen and Nguyen (2013) employ a measure of firm-specific sentiment constructed by data from Thomson Reuter's News Analytics (TRNA) and they find that investors overreact to positive (negative) earnings surprises when sentiment is positive (negative), which is consistent with Mian and Sankaraguruswamy (2012). Aboody, Even-Tov, Lehavy and Trueman (2018) use overnight returns as a proxy for firm-specific investor sentiment and find that the more positive investor sentiment is, the lower is the price response to earnings announcements. In this paper, I use the StockTwits official sentiment scores for individual stocks to investigate the impact of firm-level investor sentiment on earnings pricing.

The interplay of investor attention and sentiment

Within prior behavioral research, a number of studies have already examined the impact of investor sentiment and investor attention on the price reactions to earnings announcements separately. But to the best of my knowledge, previous studies have neglected the interplay between investor sentiment and investor attention as well as its influence on the price response to earnings announcements. Nevertheless, it seems intuitive to take the interaction of attention and sentiment into account: bounded rationality of investors such as underreaction or overreaction must be led by the attention actually paid to specific information and investors are influenced by sentiment as long as they actually notice the earnings announcements. In this context, investors who pay attention to the earnings announcements are also confronted with the corresponding sentiment. Investor sentiment is a belief about future cash flows (Baker and Wurgler (2007)), when investors pay more attention to the incremental cash flows embedded in earnings announcements, they may modify or reinforce their beliefs. As a result, it is more likely that their trading decisions and behavior are affected by both attention and sentiment. Hence, I expect a joint effect of investor attention and sentiment on earnings pricing. However, it is still an open empirical question how, if at all, the interplay of investor attention and sentiment affects earnings pricing. Therefore, the purpose of this paper is not to test any particular behavioral theories. Instead, my objective is to evaluate whether the interaction of attention and sentiment influences the earnings pricing relative to the null hypothesis that the interaction has no influence.

DATA AND RESEARCH DESIGN

StockTwits sentiment score

StockTwits provides real-time streaming of investor sentiment towards individual stocks and assign a unique sentiment score to each message to indicate the direction and strength of sentiment. A typical message from the sentiment stream contains a unique message id, timestamp of the message creation, sentiment score, and symbols. Symbols include the ticker representing the stock and other information such as stock id and the exchange this stock is listed. The score ranges between −1 and 1, with −1 representing completely bearish sentiment, 0 representing neutral sentiment, and 1 representing completely bullish sentiment. The sentiment score is not binary, so a slightly bearish message will be −0.25, and inversely, a slightly bullish message will be 0.25. For messages with multiple symbols, I attribute the same sentiment score to all symbols in the message. I measure investor sentiment by using the mean daily sentiment score (DSS). I rank $DSS_{i,t}$ into quintiles from the most bearish sentiment group (DSS1) to the most bullish sentiment group (DSS5). I use the mean daily sentiment scores of $SPY from StockTwits to measure market-level sentiment.

Firm-level investor attention

I measure daily investor attention to a specific stock by using unique dynamic analytics from StockTwits. Specifically, I compute the daily message volume of a specific stock on StockTwits to measure the abnormal attention of this stock on that day. To capture the deviation of investor attention from the "normal" level and any potential time trends, the investor attention measure is standardized by the baseline level of investor attention to rule out any seasonality and day of week effects. The abnormal attention of a specific stock ($AbAtt_{i,t}$) measured by the change in message volume ($MsgVol_{i,t}$) is defined by Equation (3). ($AbAtt_{i,t}$) is the difference between the message volume of stock i on day t and its average message volume over a 45-day window prior to 2 weeks before day t (t-60, t-15) scaled by the average. Drake, Roulstone and Thornock (2012) find that investors' information demanding activity through Google search increases about two weeks prior the earnings announcement. Consequently, I skip the most recent 2 weeks in the calculation of the benchmark to avoid potential spillover effects of the investor attention. As abnormal message volume on the announcement day measures the amount of increased discussion and posts about a firm, it provides a direct measure of investor attention to earnings announcements. This detrended measure removes time trends and seasonalities. Also, the 45-day window captures the baseline level of attention so that these measures will provide a proxy for how much increased attention investors are paying to earnings.

$$AbAtt_{i,t} = \frac{MsgVol_{i,t} - Average\ MsgVol_{i,(t-60,t-15)}}{Average\ MsgVol_{i,(t-60,t-15)}} \quad (1)$$

I rank $AbAtt$ into quintiles from the lowest attention group ($ATT1$) to the highest attention group ($ATT5$).

Earnings news

I obtain earnings announcements dates by comparing the dates reported by both Compustat and I/B/E/S. When there is discrepancy between the two sources, following DellaVigna and Pollet (2009), I take the earlier date of the two. Following DellaVigna and Pollet (2009), I measure earnings surprise (SUE) using Equation (4). It is the difference between the announced actual EPS (Actual EPS) of the quarter as reported by I/B/E/S and the median of the most recent forecast (Consensus Forecast) acquired from the I/B/E/S detail file divided by the stock price at the end of the corresponding quarter (Price QE). If an analyst made multiple forecasts in a given quarter, the consensus forecast used is the most recent one prior to the announcement. To keep the forecasts most up-to-date, I require the forecasts were issued in the last 60 calendar days before the earnings announcement. Also, I exclude observations: 1) when actual earning or forecast is larger in absolute value than the stock price, 2) when the stock price is less than $1, and 3) those with a missing earnings surprise.

$$SUE = \frac{Actual\ EPS - Consensus\ Forecast}{Price\ QE} \quad (2)$$

It is believed that investors react in the direction of the SUE, i.e., positive response to positive SUE and negative response to negative SUE. Because the relationship between announcement-day abnormal returns and the raw earnings surprise is nonlinear (e.g., (Bernard and Thomas (1989); Kothari (2001)), I rank and sort SUE into quintiles from the most negative low ($SUE1$) to the most positive ($SUE5$) to mitigate the nonlinear relation following prior literature e.g., (DellaVigna and Pollet (2009); Hirshleifer, Lim and Teoh (2009); Sheng (2019)). Then the relationship between CAR and the earnings surprise quintiles is almost linear.

I use the announcement day (day 0) sentiment to examine the effect of sentiment on the return of short window [0, 1] and PEAD. Following Michaely, Rubin and Vedrashko (2013), if an announcement is made before or during trading hours (i.e., 0:00-15:59), I match it with sentiment measured on the same day. If an announcement is made after trading hours (i.e., 16:00-23:59) or during a holiday, day 0 is defined as the next trading day and I match it with sentiment on that day.

Stock price response to earnings news is measured by cumulative abnormal return (CAR) for each stock. The CARs are calculated using the market model parameters estimated over the period between 300 and 46 days prior to the earnings announcement and adjusted by the CRSP value-weighted index return. For the immediate price response, I use CAR over the short window [0,1] surrounding the earnings announcement. For post announcement drift, I use $CAR[2,90]$. The spread in CAR between the two extreme earnings surprise quintiles ($SUE5- SUE1$) measures the immediate stock price response and the investor inattention to earnings news as reflected in PEAD. Therefore, a large spread in $CAR[0,1]$ indicates a stronger immediate price reaction to earnings news and a larger spread in $CAR[2,90]$ indicates a stronger post-announcement drift. Stock return on day t are measured from the market close (16:00) on day t-1 to the market close (16:00) on day t.

EMPIRICAL ANALYSIS

What drives investor sentiment on earnings announcement days?

In this section, I explore a set of variables that are associated with firm-level investor sentiment on earnings announcement days. In order to investigate the impact of market-wide sentiment on firm-level sentiment, I use the University of Michigan Consumer Sentiment Index (CSI) as a proxy for monthly market sentiment, and the daily sentiment scores of $SPY extracted from StockTwits ($MktDSS$) as a proxy for daily market sentiment. I control for the impact of investor attention (ATT) on investor sentiment and also include a dummy $Friday$ to address the possible seasonality of investor sentiment. I also control for the impact of earnings surprises (SUE) and other possible sources of variation in the relation between DSS and SUE. $NumAnalyst$ is the natural logarithm of 1+ the number of analysts covering the stock. $LnSize$ is the natural logarithm of market capitalization. $LnBM$ is the natural logarithm of book to market ratio. $InstOwn$ is the percentage of shares outstanding held by institutional investors. I run the following regression:

$$DSS_{i,t} = \alpha + \beta_1 SUE + \beta_2 ATT_{i,t} + \beta_3 MktDSS_t + \beta_4 CSI + \beta_5 LnSize + \beta_6 LnBM + \beta_7 NumAnalyst + \beta_8 InstOwn + \beta_9 Friday + \varepsilon_{i,t} \qquad (3)$$

The results are reported in Table 13. Column (1) presents the results from parsimonious specification examining the impact of earnings surprises (SUE), investor attention (ATT), and market-level sentiment on firm-level investor sentiment. The coefficient on earnings surprises (SUE) is 0.21, statistically significant at 1% level, indicating that investor sentiment is positively associated with earnings surprise, i.e., more positive earnings surprise, more bullish sentiment on earnings announcement days. For the market-level sentiment measures, the coefficients on CSI and $MktDSS$ are both positive and statistically significant, suggesting that firm-level sentiment is positively associated with market-level sentiment. It is worth noting that the coefficient on investor attention (ATT) is negative (-0.02) and statistically significant at 1% level, suggesting that bullish sentiment is moderated by investor attention.

Column (2) presents the results of the full regression controlling for various firm characteristics. The results are generally similar to those in the column (1). The coefficients on earnings surprise (SUE), investor attention (ATT), and market-level sentiment keep the same signs, all statistically significant. It shows that larger firms with higher institutional ownership and lower B/M ratio, followed by more analysts have more bullish investor sentiment on earnings announcement days. It is worth noting that the coefficient on dummy $Friday$ is negative and significant at 1% level, suggesting that investors are less bullish to earnings announced on Fridays.

Sentiment and immediate price response to earnings announcements

Figure 11 shows that the most bullish sentiment line (DSS5) is above the most bearish sentiment line (DSS1), suggesting that the price reaction to all earnings surprise quintiles is more positive when sentiment is more bullish. The extreme bearish sentiment line (DSS1) approaches to the extreme bullish sentiment line (DSS5) at the side of the most positive earnings surprise quintile (SUE5), but plunges at the side of the most negative earnings surprise quintile (SUE1), suggesting that bad news is punished significantly more when investor sentiment is bearish.

Table 14 Panel A shows the mean $CAR[0,1]$ across earnings surprise quintiles by the extreme sentiment quintiles. The difference between the two extreme sentiment quintiles DSS5 and DSS1 across all earnings surprise quintiles is positive and significant at 1% level, increasing monotonically from the most positive (SUE5) to the most negative (SUE1), suggesting that investors react more positively to earnings news with bullish sentiment and bad news receives more negative price reaction when investors are bearish. In the most bullish sentiment quintile (DSS5), the mean CAR[0,1] is only negative for the most negative earnings surprise quintile (SUE1) and positive for all other earnings surprise quintiles. The most positive earnings surprise quintile (SUE5) has an average CAR of 4.09% and the most negative earnings surprise quintile (SUE1) has an average CAR of −0.51% and the spread (SUE5-SUE1) is 4.60%, which is statistically significant at 1% level.

In the most bearish sentiment quintile (DSS1), the mean CAR[0,1] is only positive for the most positive earnings surprise quintile (SUE5) and negative for all other earnings surprise quintiles. The most positive earnings surprise quintile (SUE5) has an average CAR of 2.98% and the most negative earnings surprise quintile (SUE1) has an average CAR of −8.45% and the spread (SUE5-SUE1) is 11.43%, which is statistically significant at 1% level.

So far, Table 13 Panel A indicates that good news is barely rewarded when sentiment is bullish but bad news is significantly punished when sentiment is bearish and the spread (SUE5-SUE1) is much larger for the bearish sentiment quintile than for the bullish sentiment quintile. To verify that the different effects of bullish and bearish sentiment on the immediate price reaction to good and bad earnings news are statistically meaningful, I estimate the following regression:

$$CAR[0,1] = \alpha + \beta_1 SUE5 + \beta_2 SUE1 + \beta_3 DSS1 + \beta_4 DSS5 + \beta_5 SUE5 \times DSS5 + \beta_6 SUE1 \times DSS5 + \beta_7 SUE5 \times DSS1 + \beta_8 SUE1 \times DSS1 + \varepsilon \quad (4)$$

$SUE5$ ($SUE1$) is a dummy that is equal to 1 for the top (bottom) earnings surprise quintile. $DSS5$ ($DSS1$) is an indicator variable that is equal to 1 for the most bullish (bearish) quintile. Thus, the coefficients on the interaction terms β_5 to β_8 examine different effects of bullish and bearish sentiment on the immediate reaction to good and bad earnings news.

Table 15 reports the results. The coefficients on $SUE5$ ($SUE1$) and $DSS5$ ($DSS1$) all have the expected signs, significant at 1% level, suggesting that investors react in the direction of SUE and DSS. It is worth noting that the coefficient on the interaction terms $SUE5 \times DSS5$ is −0.015 (t = −6.01), significant at 1% level, suggesting that good news is actually punished when sentiment is bullish. The finding is similar to Aboody, Even-Tov, Lehavy and Trueman (2018) which finds that investors react less positively to earnings when they are bullish than when they are bearish. The coefficient on $SUE5 \times DSS1$ is 0.029 (t = 6.98) and significant at 1% level, suggesting that good news is rewarded the most when sentiment is bearish. This finding is in consistency with Livnat and Petrovits (2009) which finds that good news is rewarded more when sentiment is low. The coefficient on $SUE1 \times DSS1$ is −0.023 (t = −8.45) and significant at 1% level, suggesting that bad news is punished significantly more when sentiment is bearish. Prior studies such as Cahan, Chen and Nguyen (2013) and Mian and Sankaraguruswamy (2012) find that investors overreact to good news (bad news) when sentiment is high (low). My evidence suggests that investors do not overreact to good news when sentiment is high (bullish) but overreact to bad news when sentiment is low (bearish).

To examine whether the difference between in-quintile spread ($SUE5{-}SUE1$) of the most bearish sentiment quintile ($DSS1$) and the most bullish sentiment quintile ($DSS5$) is statistically meaningful, I estimate the following regression:

$$CAR[0,1] = \alpha + \beta_1 SUETOP + \beta_2 DSS5 + \beta_3 DSS1 + \beta_4 SUETOP \times DSS5 + \beta_5 SUETOP \times DSS1 + \varepsilon \quad (5)$$

$SUETOP$ is a dummy that is equal to 1 for the top earnings surprise quintile and 0 for the bottom earnings surprise quintile. $DSS5$ ($DSS1$) is an indicator variable that is equal to 1 for the most bullish (bearish) quintile. Thus, the coefficients β_4 and β_5 test the different effects of bullish and bearish sentiment on CAR spreads between good and bad earnings news firms for $CAR[0,1]$.

Table 15 column (1) reports the results. The coefficients on the interaction terms $SUETOP \times DSS5$ and $SUETOP \times DSS1$ is −0.017 (t=−5.04) and 0.052 (t=11.34), suggesting that the immediate price reaction is weaker (stronger) when sentiment is bullish (bearish), i.e., investor sentiment is negatively associated with the immediate price reaction to earnings news.

Then I examine how sentiment affects investors' reaction to earnings news across all sentiment and earnings surprises quintiles. I estimate the following regression:

$$CAR[0,1] = \alpha + \beta_1 SUE + \beta_2 DSS + \beta_3 MktDSS + \beta_4\, SUE \times DSS + \beta_5\, SUE \times MktDSS + \sum_{i=1}^{n} \gamma_i X_i + \varepsilon \quad (6)$$

X_i are the control variables. I include $LnSize$, $LnBM$, and $CAR[-202,-3]$ to control for the known risk measures of size, book-to-market ratio, and momentum. $CAR[-202,-3]$ is the past cumulative abnormal returns over the 200-day window prior to 3 days before day 0, used as a proxy of stock price momentum. Extant literature suggests that investor sentiment has a greater effect on stocks that are hard to value and difficult to arbitrage (Baker and Wurgler (2007); Cahan, Chen and Nguyen (2013); Mian and Sankaraguruswamy (2012)). For those 'speculative' stocks, investors are more likely to be influenced by sentiment because they have less hard information (Engelberg (2008)) to rely on. Therefore, I include $NumAnalyst$, $InstOwn$, $ILLIQ$, and $SDRet$ to control cross-sectional variation for hard to value and difficult to arbitrage stocks. Daily market-level sentiment ($MktDSS$) is also ranked into quintiles from the most bearish market-level sentiment group ($MktDSS1$) to the most bullish market-level sentiment group ($MktDSS5$). Because the previous result shows that firm-level investor sentiment is negatively associated with immediate price reaction to earnings news, I expect that $\beta_4 < 0$ for $CAR[0,1]$.

Table 16 Column (2) and (3) report the results. Column (2) presents the result from a parsimonious specification without including any control variables, column (3) is the full regression with controls. In both columns, the coefficients on the interaction terms $SUE \times DSS$ and $SUE \times MktDSS$ are negative and statistically significant, suggesting that sentiment is negatively related to the immediate price reaction to earnings news, i.e., the more bullish sentiment is, the weaker is the immediate price reaction to earnings news. These findings differ from Mian and Sankaraguruswamy (2012) which finds that the Earnings Response Coefficients (ERCs) for firms with good news are higher (lower) when market sentiment is high (low).

Sentiment and post-announcement drift

Mian and Sankaraguruswamy (2012) suggests that the impact of sentiment on price reaction to earnings news extends to several months following the announcement day. Livnat and Petrovits (2009) provides evidence that investor sentiment influences the abnormal returns following the announcement day. In this section, I examine whether the impact of sentiment on the earnings pricing is temporary or continues into the near future.

Figure 12 plots the spread in average cumulative abnormal returns between the extreme earnings surprise quintiles (SUE5−SUE1) by the extreme investor sentiment quintiles (DSS5 and DSS1) over alternative windows. It shows that the immediate price reaction to earnings news is stronger for the most bearish sentiment quintile (DSS1) than for the most bullish sentiment quintile (DSS5). The post-announcement drift is stronger for the most bullish sentiment quintile (DSS5) than for the most bearish sentiment quintile (DSS1), which is getting substantial from 75 days following the announcement day.

Table 13 Panel B shows the mean $CAR[2,90]$ across earnings surprise quintiles by the extreme sentiment quintiles. It shows that the strongest reverse (-8.45% to 2.13%) occurs for the most negative earnings surprise following bearish sentiment. It also can be seen that the spread in average CAR between the extreme earnings surprise quintiles (SUE5−SUE1) is 3.56% for the most bullish sentiment quintile (DSS5), which is statistically significant at 5% level. The spread (SUE5−SUE1) is 2.13% for the most bearish sentiment quintile (DSS1), which is statistically significant at 10% level. Taking into account of the evidence from Figure 12, it indicates that the strongest reverse for the most negative earnings surprise following bearish sentiment is the reason of the weaker post-announcement drift for the most bearish sentiment quintile (DSS1).

To test the different effects of bullish and bearish sentiment on CAR spreads between good and bad earnings news firms for $CAR[2,90]$, I re-estimate Equation (5) for post-announcement drift $CAR[2,90]$.

Table 17 reports the results. The coefficient on $SUETOP \times DSS5$ is 0.026 (t=1.77) and the coefficient on $SUETOP \times DSS1$ is positive but not statistically significant, suggesting that the post-announcement drift is greater following bullish sentiment.

The joint effect of sentiment and attention on earnings pricing

The immediate price response to earnings news

The results from previous sections suggest that sentiment is negatively related to both attention and the immediate price reaction to earnings news. Attention is documented to be positively related to the immediate reaction to earnings surprises, therefore the joint effect of sentiment and attention on the immediate reaction to earnings news is a question of interest.

The Figure 13 plots the average CAR[0,1] against the extreme earnings surprise quintiles (SUE5 and SUE1) by the extreme sentiment quintiles (DSS5 and DSS1) with the effect of the extreme attention quintiles (ATT5 and ATT1). The dash line plots the mean CAR[0,1] that is without the impact of attention, which is taken as a base line. It shows that for the highest (lowest) attention quintile ATT5 (ATT1), the line segments D5S5D5S1 and D1S5D1S1 become steeper (flatter) than the dash line (without the impact of attention), suggesting that the in-quintile spread (SUE5−SUE1) for both sentiment quintiles (DSS5 and DSS1) turns out to be larger (smaller) than the base level. Therefore, for the highest (lowest) attention quintile ATT5 (ATT1), the immediate price reaction to earnings news is stronger (weaker) for both bullish and bearish quintiles (DSS5 and DSS1) than the base level.

The Figure 14 plots the average CAR[2,90] against the extreme earnings surprise quintiles (SUE5 and SUE1) by the extreme sentiment quintiles (DSS5 and DSS1) with the effect of the extreme attention quintiles (ATT5 and ATT1). As it can be seen, for the lowest attention quintile ATT1, both line segments D5S5D5S1 and D1S5D1S1 become steeper than the base line (without the impact of attention), suggesting that the in-quintile spread (SUE5−SUE1) for both bullish and bearish sentiment quintiles (DSS5 and DSS1) turns out to be larger than the base level. Therefore, the post-announcement drift is stronger for both bullish and bearish sentiment quintiles (DSS5 and

DSS1) with low attention. It shows that for the highest attention quintile ATT5, line segment D5S5D5S1 becomes flatter than the base line (without the impact of attention), suggesting that the spread (SUE5−SUE1) for the bullish sentiment quintile DSS5 turns out to be smaller than the base level. It is also worth noting that for the highest attention quintile ATT5, line segment D1S5D1S1 becomes steeper than the base line (without the impact of attention), suggesting that the spread (SUE5−SUE1) for the bearish sentiment quintile DSS1 is larger than the base level. Therefore, the post-announcement drift is weaker (stronger) for the bullish (bearish) sentiment quintile DSS5 (DSS1) with high attention.

Take a look at both Figure 13 and Figure 14, we can find that for the highest attention quintile (ATT5), the line segment D1S5D1S1 is much steeper than the line segment D5S5D5S1 in both figures, suggesting that the immediate price reaction and the post-announcement drift are both stronger for the bearish sentiment quintile (DSS1) with higher attention.

Table 18 presents the numeric evidence of the impact of attention on the CARs across the earnings surprise quintiles by the extreme investor sentiment quintiles (DSS5 and DSS1). It is worth noting that with high attention, the mean CAR[0,1] for good news (SUE5) changes from 4.09% to 8.09% for the bullish sentiment quintile (DSS5) and from 2.98% to 9.21% for the bearish sentiment quintile (DSS1). The mean CAR[0,1] for bad news (SUE1) changes from −8.45% to −11.69% for the bearish sentiment quintile (DSS1) with high attention, suggesting that the overreaction to bad news (SUE1) with bearish sentiment is amplified by high attention.

So far, it shows that the effect of investor attention is different across the extreme sentiment quintiles and earnings surprise quintiles. To verify that these differences are statistically meaningful, I estimate the following model:

$$CAR[0,1] = \alpha + \beta_1 SUE5 + \beta_2 SUE1 + \beta_3 DSS5 + \beta_4 DSS1 + \beta_5 ATT5 + \beta_6 ATT1 + \beta_7 SUE5 \times DSS5 + \beta_8 SUE1 \times DSS5 + \beta_9 SUE5 \times DSS1 + \beta_{10} SUE1 \times DSS1 + \beta_{11} SUE5 \times DSS5 \times ATT5 + \beta_{12} SUE5 \times DSS1 \times ATT5 + \beta_{13} SUE1 \times DSS5 \times ATT5 + \beta_{14} SUE1 \times DSS1 \times ATT5 + \beta_{15} SUE5 \times DSS5 \times ATT1 + \beta_{16} SUE5 \times DSS1 \times ATT1 + \beta_{17} SUE1 \times DSS5 \times ATT1 + \beta_{18} SUE1 \times DSS1 \times ATT1 + \varepsilon \quad (7)$$

$SUE5$ ($SUE1$) is an indicator variable that is equal to 1 for the top (bottom) quintile of earnings surprise. $DSS5$ ($DSS1$) is an indicator variable that is equal to 1 for the top (bottom) quintile of sentiment. $ATT5$ ($ATT1$) is an indicator variable that is equal to 1 for the top (bottom) attention quintile. Thus, the coefficients of interest β_{11} to β_{18} examine the different impact of high and low attention across both top and bottom sentiment and earnings surprise quintiles.

Table 18 reports the results. The coefficients on the interaction terms $SUE5 \times DSS5 \times ATT5$ and $SUE5 \times DSS1 \times ATT5$ are positive 0.024 (t = 4.78) and 0.059 (t = 5.93), both significant at 1% level. The evidence suggests that with high attention, good news is rewarded more when sentiment is either most bullish or most bearish, whereas the effect of attention is more pronounced when sentiment is bearish. The coefficient on the interaction term $SUE1 \times DSS1 \times ATT5$ is negative −0.054 (t= −9.67), significant at 1% level, suggesting that when sentiment is most bearish, bad news is considerably punished with high attention. The coefficients on the interaction terms $SUE5 \times DSS5 \times ATT1$ and $SUE5 \times DSS1 \times ATT1$ are negative −0.016 (t=−4.37) and −0.025 (t =−3.64), both significant at 1% level, suggesting that investors underreact to good news (SUE5) with low attention when sentiment is either most bullish or most bearish. The coefficient on the interaction term $SUE1 \times DSS1 \times ATT1$ is positive 0.042 (t=9.85), significant at 1% level, suggesting that investors underreact to bad news (SUE1) with low attention when sentiment is most bearish. The results are consistent with the evidence from Figure 13 and Table 18.

As it can be seen from Figure 13 and Table 18, the spread (SUE5−SUE1) becomes significantly larger than the base level for both bullish and bearish sentiment quintiles with high attention, suggesting that the immediate price reaction to earnings news is strengthened with high attention no matter whether sentiment is most bullish or most bearish. To verify that these differences are statistically meaningful, I estimate the following model:

$$\begin{aligned} CAR[0,1] &\\ = \alpha + \beta_1 SUETOP + \beta_2 DSS5 + \beta_3 DSS1 + \beta_4 ATTTOP + \beta_5 SUETOP \times DSS5 &\\ + \beta_6 SUETOP \times DSS1 + \beta_7 SUETOP \times DSS5 \times ATTTOP + \beta_8 SUETOP \times DSS1 \times ATTTOP &\\ + \varepsilon & \qquad (8) \end{aligned}$$

$ATTTOP$ is a dummy that is equal to 1 for the top attention quintile and 0 for the bottom attention quintile. Thus, the coefficients of interest β_7 and β_8 test whether the in-quintile spread (SUE5−SUE1) for bullish and bearish sentiment quintiles is significantly different with high attention.

Table 20 presents the results. The coefficients on the interaction terms $SUETOP \times DSS5 \times ATTTOP$ and $SUETOP \times DSS1 \times ATTTOP$ are both positive 0.043 (t=7.06) and 0.087 (t=8.02), significant at 1% level, suggesting that the immediate price reaction to earnings news is strengthened with high attention when sentiment is either bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. The results are consistent with the evidence from Figure 13 and Table 18.

Next I examine the joint effect of investor sentiment and attention on the immediate price reaction to earnings news across all sentiment, attention and earnings surprise quintiles. To empirically examine the joint effect of sentiment and attention, I estimate the following regression:

$$CAR[0,1] = \alpha + \beta_1 SUE + \beta_2 DSS + \beta_3 ATT + \beta_4 MktDSS + \beta_5 SUE \times DSS + \beta_6 SUE \times ATT + \beta_7 SUE \times MktDSS + \beta_8 SUE \times DSS \times ATT + \sum_{i=1}^{n} \gamma_i X_i + \varepsilon \tag{9}$$

X_i are the control variables. I include $LnSize$, $LnBM$, and $CAR[-202,-3]$ to control for the known risk measures of size, book-to-market ratio, and momentum. From the results of previous section, firm-level sentiment and market-level sentiment are both negatively related to the immediate price reaction, therefore I expect that β_5 and β_7 are < 0 for $CAR[0,1]$. Firm-level attention is documented to be positively associated with the immediate price reaction to earnings news, e.g., (Hirshleifer, Lim and Teoh (2009)), thus I expect that $\beta_6 > 0$ for $CAR[0,1]$. Table 20 shows that the immediate price reaction to earnings news is strengthened with high attention no matter whether sentiment is bullish or bearish, therefore I expect that $\beta_8 > 0$ for $CAR[0,1]$.

Table 21 reports the results. Column (1) presents the results from parsimonious specification examining the impact of sentiment, and the joint effect of sentiment and attention on the immediate price response to earnings news. Column (2) presents the results of the full regression with control variables. As it can be seen in both columns, the coefficients β_5 and β_7 are both negative and significant at 1% level, suggesting that sentiment is negatively associated with the immediate price reaction to earnings news, i.e., the more bullish sentiment is, the weaker is the immediate reaction. The coefficient β_6 is positive and significant at 1% level, suggesting that attention is positively related to the immediate reaction to earnings news, i.e., the higher attention is, the stronger is the immediate response. The coefficient β_8 is positive and significant at 1% level, suggesting that the immediate price reaction is generally strengthened with highe attention across sentiment quintiles.

The post-announcement drift

Since I have taken into account both investor sentiment and investor attention in the previous investigation of their joint effect on the abnormal returns around announcement, in this section I examine how the interaction of sentiment and attention influences the well-documented post-announcement drift.

Figure 15 plots the mean CAR against the extreme sentiment quintiles (DSS5 and DSS1) and earnings surprise quintiles (SUE5 and SUE1) with low attention (ATT1) at different horizons. It shows that with low attention, prices continue to drift in the direction of the earnings news over a period after the announcement, which is in consistency with prior literature. Figure 16 plots the mean CAR against the extreme sentiment quintiles (DSS5 and DSS1) and earnings surprise quintiles (SUE5 and SUE1) with high attention (ATT5) at different horizons. As it can be seen, with high attention, the drift is generally weaker but the drift is stronger for good news following bearish sentiment. To verify that these differences are statistically meaningful, I re-estimate Equation (7) for the post-announcement drift $CAR[2,90]$.

Table 22 reports the results. The coefficient on the three-way interaction term $SUE5 \times DSS1 \times ATT5$ is positive 0.037 (t=1.86) and significant at 5% level, indicating that the drift is stronger for good news following bearish sentiment with high attention. The finding is consistent with the evidence from Figure 16.

Figure 17 plots the in-quintile spread (SUE5−SUE1) by the extreme sentiment (DSS5 and DSS1) and attention (ATT5 and ATT1) quintiles at different horizons. It shows that the spread in drift is larger with low attention for both bullish and bearish sentiment quintiles (A1D5 and A1D1). It is not surprising to see the spread is also larger with high attention for the bearish sentiment quintile (A5D1) as the result from Table 22 shows that the drift is stronger for good news following bearish sentiment with high attention. It is worth noting that the spread in drift is the smallest with high attention following bullish sentiment (A5D5). To verify that these differences are statistically meaningful, I re-estimate Equation (8) for the post-announcement drift $CAR[2,90]$.

Table 23 reports the results. The coefficient on the three-way interaction term $SUETOP \times DSS5 \times ATTTOP$ is negative −0.04 (t=−1.67) and significant at 10% level, suggesting that the post-announcement drift is weaker with high attention following bullish sentiment. The coefficient on the three-way interaction term $SUETOP \times DSS1 \times ATTTOP$ is positive 0.032 but not statistically significant.

Last, I examine the joint effect of investor sentiment and attention on the post-announcement drift across all sentiment, attention and earnings surprise quintiles. To empirically examine the joint effect, I re-estimate Equation (9) for the drift $CAR[2,90]$.

Table 24 presents the results. Column (1) presents the results from parsimonious specification examining the impact of sentiment, and the joint effect of sentiment and attention on the post-announcement drift. Column (2) presents the results of the full regression with control variables. In Column (1), the coefficient of the three-way interaction term $SUE \times DSS \times ATT$ is negative −0.0003 (t=−1.51) but not statistically significant. This is perhaps not surprising given that investigation of long-term abnormal return is treacherous (Lyon, Barber and Tsai (1999)) and the earnings news may be a noisy proxy for all the firm-specific news announced during the year as suggested by Mian and Sankaraguruswamy (2012). In Column (2), the coefficient of the three-way interaction term $SUE \times DSS \times ATT$ is negative −0.0006 (t=−2.83) and significant at 1% level, suggesting that the post-announcement drift is weaker with high attention following bullish sentiment.

CONCLUSION

In this paper, I employ social media data in a traditional event-study framework. I use the proprietary StockTwits official sentiment score as a direct measure of firm-level sentiment to investigate the impact of investor sentiment on earnings pricing. I report evidence that good news is punished (rewarded) when sentiment is bullish (bearish) and bad news is punished significantly more when sentiment is bearish. My evidence suggests that investors do not overreact to good news when sentiment is high (bullish) but overreact to bad news when sentiment is low (bearish). For the immediate response, I find that the immediate price reaction to earnings news is weaker when sentiment is bullish. For the drift, I find that the post-announcement drift is stronger following bullish sentiment.

In particular, this study extends the evolving literature which studies the influence of investor behavior and belief on assets (mis)pricing by connecting the sentiment-related (mis)pricing of earnings to the attention-related (mis)pricing of earnings. I employ direct measures of firm-level attention and sentiment to explore the joint effect of attention and sentiment on earnings pricing. I find that good news is rewarded more with high attention no matter whether sentiment is bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. The evidence also suggests that bad news is considerably punished with high attention when sentiment is bearish. For the immediate response, I find that the immediate price reaction is strengthened with high attention no matter whether sentiment is bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. For the drift, I find that the post-announcement drift is weaker with high attention following bullish sentiment. It is worth noting that good news with bearish sentiment and high attention has both stronger immediate response and post-announcement drift. Existing literature, however, suggests that high investor attention is associated with stronger immediate price reactions and weaker post announcement price drifts to firms' earnings announcements. Thus, my findings reflect the joint effect of attention and sentiment and provide new evidence that investor attention and sentiment do jointly affect the source of excess returns documented in the prior earnings-based market anomaly literature. This finding furthers our understanding of the influence of investor behavior and belief on assets (mis)pricing.

REFERENCES

Aboody, David, Omri Even-Tov, Reuven Lehavy, and Brett Trueman, 2018, Overnight returns and firm-specific investor sentiment, *Journal of Financial and Quantitative Analysis* 53, 485-505.

Aboody, David, Reuven Lehavy, and Brett Trueman, 2009, Limited attention and the earnings announcement returns of past stock market winners, *Review of Accounting Studies* 15, 317-344.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Antoniou, Constantinos, John A. Doukas, and Avanidhar Subrahmanyam, 2013, Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245-275.

Antoniou, Constantinos, John A. Doukas, and Avanidhar Subrahmanyam, 2015, Investor sentiment, beta, and the cost of equity capital, *Management Science* 62, 347-367.

Argarwal, Shreyash, Pablo Azar, Andrew W Lo, and Taranjit Singh, 2018, Momentum, mean-reversion and social media: Evidence from stocktwits and twitter.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *The Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129-151.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-178.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785-818.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen, 2017, It depends on where you search: Institutional investor attention and underreaction to news, *The Review of Financial Studies* 30, 3009-3047.

Ben-Rephael, Azi, Shmuel Kandel, and Avi Wohl, 2012, Measuring investor sentiment with mutual fund flows, *Journal of Financial Economics* 104, 363-382.

Bergman, Nittai K., and Sugata Roychowdhury, 2008, Investor sentiment and corporate disclosure, *Journal of Accounting Research* 46, 1057-1083.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium?, *Journal of Accounting Research* 27, 1-36.

Brown, Gregory W., and Michael T. Cliff, 2005, Investor sentiment and asset valuation, *Journal of Business* 78, 405-440.

Cahan, Steven, Chen Chen, and Nhut H Nguyen, 2013, Media sentiment, investor sentiment, and stock price sensitivity to earnings, Auckland Region Accounting Conference. Available at: https://www. uts. edu. au/sites/default/files/ACC_conf14_CChen. pdf.

Chapman, Kimball, 2018, Earnings notifications, investor attention, and the earnings announcement premium, *Journal of Accounting and Economics* 66, 222-243.

Charoenrook, Anchada, 2005, Does sentiment matter, *Unpublished working paper. Vanderbilt University*.

Chemmanur, Thomas J. , and An Yan, 2009, Advertising, attention, and stock returns, *SSRN 1340605*.

Chen, Linda H., George J. Jiang, and Kevin X. Zhu, 2018, Total attention: The effect of macroeconomic news on market reaction to earnings news, *Journal of Banking & Finance* 97, 142-156.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *The Journal of Finance* 63, 1977-2011.

Curtis, Asher, Vernon J. Richardson, Roy Schmardebeck, 2014, Investor attention and the pricing of earnings news, *Available at SSRN 2467243*.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *The Journal of Finance* 66, 1461-1499.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2015, The sum of all fears investor sentiment and asset prices, *The Review of Financial Studies* 28, 1-32.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *The Journal of Finance* 53, 1839-1885.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

deHaan, Ed, Terry Shevlin, and Jacob Thornock, 2015, Market (in)attention and the strategic scheduling and timing of earnings announcements, *Journal of Accounting and Economics* 60, 36-55.

DellaVigna, Stefano, and Joshua M. Pollet, 2009, Investor inattention and friday earnings announcements, *The Journal of Finance* 64, 709-749.

Drake, Michael S., Darren T. Roulstone, and Jacob R. Thornock, 2012, Investor information demand: Evidence from google searches around earnings announcements, *Journal of Accounting Research* 50, 1001-1040.

Engelberg, Joseph, 2008, Costly information processing: Evidence from earnings announcements, AFA 2009 San Francisco Meetings Paper.

Fisher, Kenneth L., and Meir Statman, 2000, Investor sentiment and stock returns, *Financial Analysts Journal* 56, 16-23.

Giannini, Robert, Paul Irvine, and Tao Shu, 2019, The convergence and divergence of investors' opinions around earnings news: Evidence from a social network, *Journal of Financial Markets* 42, 94-120.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *The Journal of Finance* 64, 2289-2325.

Hirshleifer, David, and Tyler Shumway, 2003, Good day sunshine: Stock returns and the weather, *The Journal of Finance* 58, 1009-1032.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337-386.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337-386.

Hong, Harrison, and Jialin Yu, 2009, Gone fishin': Seasonality in trading activity and asset prices, *Journal of Financial Markets* 12, 672-702.

Hou, Kewei, Wei Xiong, and Lin Peng, 2009, A tale of two anomalies: The implications of investor attention for price and earnings momentum, *SSRN 976394*.

Huang, Shiyang, Yulin Huang, and Tse-Chun Lin, 2018, Attention allocation and return co-movement: Evidence from repeated natural experiments, *Journal of Financial Economics*.

Huberman, Gur, and Tomer Regev, 2001, Contagious speculation and a cure for cancer: A nonevent that made stock prices soar, *The Journal of Finance* 56, 387-396.

Jiang, Danling, Dylan Norris, and Lin Sun, 2018, Weather, institutional investors, and earnings news.

Kahneman, Daniel, 1973. *Attention and effort* (Citeseer).

Karagozoglu, Ahmet K, and Frank J Fabozzi, 2017, Volatility wisdom of social media crowds, *Journal of Portfolio Management* 43, 136.

Karampatsas, Nikolaos, Soheila Malekpour, and Andrew Mason, 2017, Beyond market mood: Stock sentiment and the response to corporate earnings announcements, *SSRN*.

Kietzmann, Jan H., Kristopher Hermkens, Ian P. McCarthy, and Bruno S. Silvestre, 2011, Social media? Get serious! Understanding the functional building blocks of social media, *Business Horizons* 54, 241-251.

Kothari, S. P., 2001, Capital markets research in accounting, *Journal of Accounting and Economics* 31, 105-231.

Kurov, Alexander, 2010, Investor sentiment and the stock market's reaction to monetary policy, *Journal of Banking & Finance* 34, 139-149.

Lee, Wayne Y., Christine X. Jiang, and Daniel C. Indro, 2002, Stock market volatility, excess returns, and the role of investor sentiment, *Journal of Banking & Finance* 26, 2277-2299.

Lemmon, Michael, and Evgenia Portniaguina, 2006, Consumer confidence and asset prices: Some empirical evidence, *Review of Financial Studies* 19, 1499-1529.

Li, Xiafei, and Di Luo, 2016, Investor sentiment, limited arbitrage, and the cash holding effect, *Review of Finance*.

Liew, Jim Kyung-Soo, and Tamas Budavari, 2016, The'sixth'factor--social media factor derived directly from tweet sentiments, *Available at SSRN 2711825*.

Liu, Hongqi, and Lin Peng, 2015, Investor attention: Seasonal patterns and endogenous allocations, (Working paper).

Livnat, Joshua, and Christine Petrovits, 2009, Investor sentiment, post-earnings announcement drift, and accruals.

Loh, Roger K., 2010, Investor inattention and the underreaction to stock recommendations, *Financial Management* 39, 1223-1252.

Lou, Dong, 2014, Attracting investor attention through advertising, *The Review of Financial Studies* 27, 1797-1829.

Lyon, John D., Brad M. Barber, and Chih-Ling Tsai, 1999, Improved methods for tests of long-run abnormal stock returns, *The Journal of Finance* 54, 165-201.

Mian, G. Mujtaba, and Srinivasan Sankaraguruswamy, 2012, Investor sentiment and stock market response to earnings news, *Accounting Review* 87, 1357-1384.

Michaely, Roni, Amir Rubin, and Alexander Vedrashko, 2013, Corporate governance and the timing of earnings announcements*, *Review of Finance* 18, 2003-2044.

Michaely, Roni, Amir Rubin, and Alexander Vedrashko, 2016, Are friday announcements special? Overcoming selection bias, *Journal of Financial Economics* 122, 65-85.

Peng, Lin, 2005, Learning with information capacity constraints, *Journal of Financial and Quantitative Analysis* 40, 307-329.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563-602.

Peress, Joel, and Daniel Schmidt, 2018, Glued to the tv: Distracted noise traders and stock market liquidity, (Discussion paper, INSEAD).

Renault, Thomas, 2017, Intraday online investor sentiment and return patterns in the u.S. Stock market, *Journal of Banking & Finance* 84, 25-40.

Seasholes, Mark S., and Guojun Wu, 2007, Predictable behavior, profits, and attention, *Journal of Empirical Finance* 14, 590-610.

Seybert, Nicholas, and Holly I. Yang, 2012, The party's over: The role of earnings guidance in resolving sentiment-driven overvaluation, *Management Science* 58, 308-319.

Sheng, Jinfei, 2019, Macro news, micro news, and stock prices, *SSRN 2890864*.

Yantis, S., 1998, Control of visual attention, 1, 223.

Yung, Kenneth, and Nadia Nafar, 2017, Investor attention and the expected returns of reits, *International Review of Economics & Finance* 48, 423-439.

CONCLUSION

In this dissertation, I develop direct measures for both market-level and firm-level attention and sentiment. In the first essay, I provide direct evidence that firm-level attention is strengthened rather than weakened with concurrent market-level information shocks, which differs from existing theories. I find that market-level attention is negatively associated with firm-level attention and they have different effects on earnings pricing. Investors allocate their limited attention accordingly between market-level and firm-level therefore investors have more muted initial reactions to earnings announcements if they pay more attention to board market. On the other hand, higher firm-level investor attention and concurrent important macro-news enhances the immediate price reaction to a firm's earnings surprise and alleviates the post-announcement drift (PEAD).

In the second essay, I report evidence that good news is punished (rewarded) when sentiment is bullish (bearish) and bad news is punished significantly more when sentiment is bearish. My evidence suggests that investors do not overreact to good news when sentiment is high (bullish) but overreact to bad news when sentiment is low (bearish). For the immediate response, I find that the immediate price reaction to earnings news is weaker when sentiment is bullish. For the drift, I find that the post-announcement drift is stronger following bullish sentiment.

I employ direct measures of firm-level attention and sentiment to explore the joint effect of attention and sentiment on earnings pricing. I find that good news is rewarded more with high attention no matter whether sentiment is bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. The evidence also suggests that bad news is considerably punished with high attention when sentiment is bearish. For the immediate response, I find that the immediate price reaction is strengthened with high attention no matter whether sentiment is bullish or bearish, whereas the effect of attention is more pronounced when sentiment is bearish. For the drift, I find that the post-announcement drift is weaker with high attention following bullish sentiment. It is worth noting that good news with bearish sentiment and high attention has both stronger immediate response and post-announcement drift. Existing literature, however, suggests that high investor attention is associated with stronger immediate price reactions and weaker post announcement price drifts to firms' earnings announcements. Thus, my findings reflect the joint effect of attention and sentiment and provide new evidence that investor attention and sentiment do jointly affect the source of excess returns documented in the prior earnings-based market anomaly literature.

In conclusion, this dissertation suggests that employment of big data in construction of direct measures of attention and sentiment is a promising addition to this line for future research. The findings further our understanding of the influence of investor behavior and belief on assets (mis)pricing.

Table 1 Variable definitions and sources

Variable	Definition	Source
$AbAtt_{i,t}$	The difference between the message volume of stock i on day t and its average message volume over a 45-day window prior to 2 weeks before day t (t-60, t-15) scaled by the average.	StockTwits
$AbMktAtt$	The difference between the message volume of board market on day t and the average message volume from day t-60 to day t-15, scaled by the average.	StockTwits
SUE	The difference between the announced actual EPS and the median of the most recent forecast, divided by the stock price at the end of the corresponding quarter.	I/B/E/S
$ImpMAday$	Dummy is equal to 1 if a day is an announcement day for one of the important macroeconomic announcements (i.e., FOMC, GDP, ISM PMI, nonfarm payroll, initial jobless claims and CPI).	Bloomberg
CAR	CARs are calculated using the market model parameters estimated over the period between 300 and 46 days prior to the earnings announcement and adjusted by the CRSP value-weighted index return.	CRSP
BM	The book value of equity divided by the market value of equity in the year prior the earnings announcement.	Compustat
$Size$	The market capitalization in the year prior the earnings announcement.	Compustat
$NumEA$	The natural logarithm of number of earnings announcements on day t. Earnings announcements made during after-hours or holidays are counted in the following trading day.	I/B/E/S
$NumMA$	The natural logarithm of number of macro-news announcements on day t.	Bloomberg
$AbTurnover$	The stock's abnormal turnover calculated as the stock's daily turnover on day t divided by the average turnover from day t-252 to day t-15.	CRSP
$ILLIQ$	The natural logarithm of Amihud (2002) illiquidity which is measured as the average ratio of the absolute daily return to the daily dollar trading volume over the period from day t-252 to day t-15.	CRSP
$NumAnalyst$	The natural logarithm of 1+ the number of analysts covering the stock using the most recent information.	I/B/E/S
$InstOwn$	The percentage of shares outstanding held by institutional investors.	WRDS Thomson Reuters (13f)
$AbVol$	The stock's abnormal trading volume calculated as the stock's daily volume on day t divided by the average trading volume from day t-252 to day t-15.	CRSP
$SDRet$	The standard deviation of daily stock returns from day t-60 to day t-15.	CRSP

Table 2 Summary statistics of key variables

This table reports summary statistics: abnormal attention(AbAtt), abnormal market attention(AbMktAtt), cumulative abnormal returns (CARs), standardized unexpected earnings (SUE), book-to-market ratio (BM), firms size (Size), abnormal turnover (AbTurnover) as well as the number of earnings announcements per day (#EA), the number of macroeconomic announcements (#MA), the number of analysts following the firm (#Analyst), the logarithm of Amihud (2002) illiquidity (ILLIQ), the standard deviation of daily stock returns (SDRet), the percentage of shares held by institutional investors (InstOwn), abnormal trading volume (AbVol), daily sentiment score (DSS) and market daily sentiment score (MktDSS). See Appendix A for detailed definitions of the variables. The sample includes stocks that are traded on the NYSE and NASDAQ over the period of 2013-2018. All variables are except the log transformed variables winsorized at 1% and 99% level.

	Count	Mean	SD	P25	P50	P75
AbAtt	48669	16.91	39.03	4.05	9.31	18.93
AbMktAtt	48669	0.41	0.52	0.06	0.28	0.61
SUE	48669	-0.09	15.13	-0.08	0.04	0.21
# MA	47588	7.89	4.51	4	8	11
# EA	48669	171.48	111.98	82	162	254
# Analyst	48669	9.10	7.44	4	7	13
ILLIQ	45544	-6.46	2.42	-8.25	-6.55	-4.81
BM	47268	0.50	14.26	0.21	0.40	0.66
Size	47270	8605.24	30311.09	407.83	1363.41	4765.55
InstOwn	35837	0.70	0.28	0.59	0.78	0.90
SDRet	48669	0.02	0.015	0.013	0.018	0.026
AbTurnover	46394	2.89	9.08	1.33	2.08	3.33
AbVol	46394	2.93	9.18	1.36	2.11	3.38
CAR[0,1]%	48669	0.08	9.05	-3.96	0.03	4.03
CAR[2,75]%	48655	-0.38	24.61	-11.01	-0.49	10.21
CAR[2,90]%	48655	-0.18	27.69	-11.95	-0.26	11.59
CAR[-202,-3]%	48669	-1.10	30.03	-11.61	-0.60	10.37
DSS	48669	0.07	0.18	0.00	0.06	0.17
MktDSS	48669	0.015	0.03	-0.007	0.015	0.03

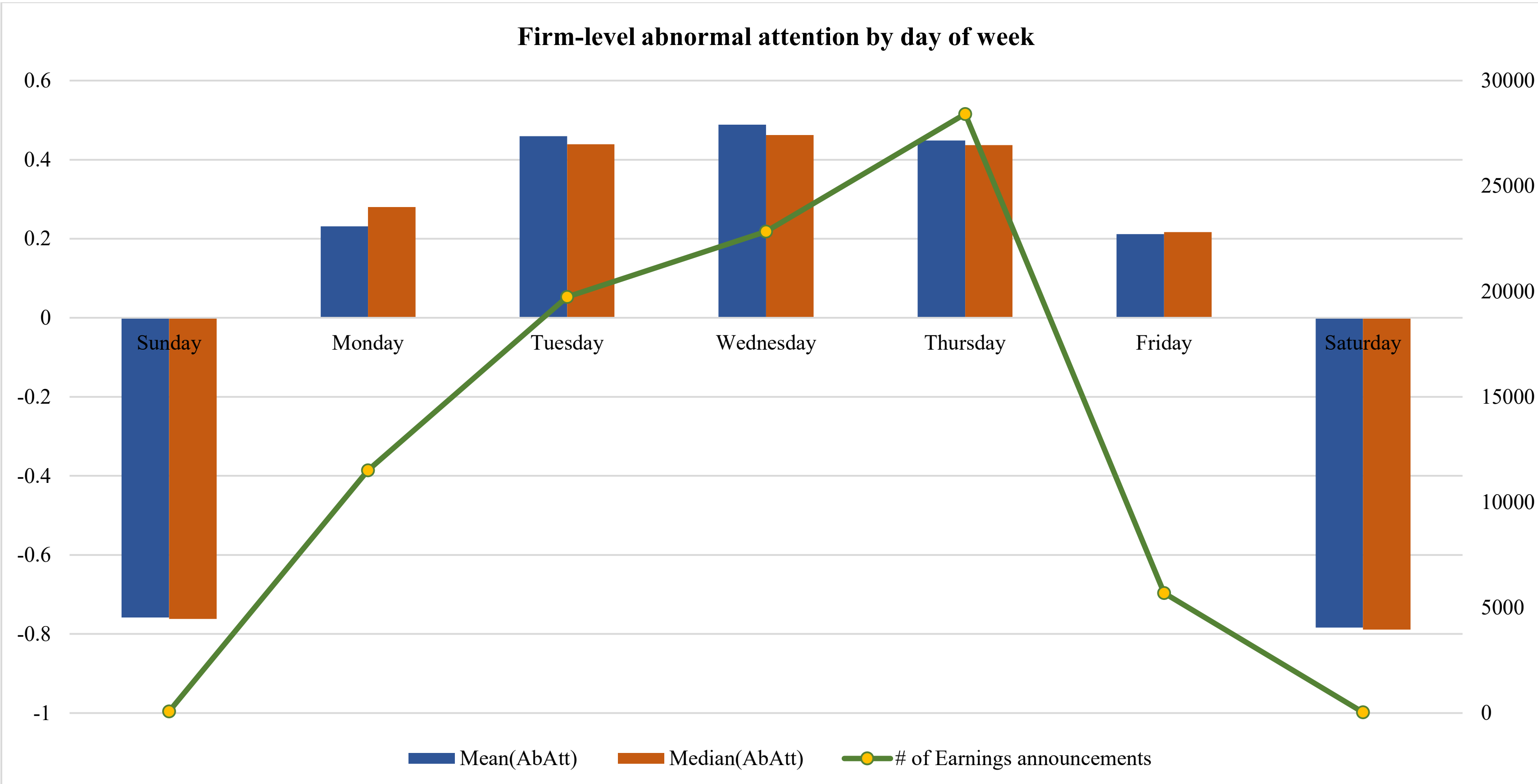

Figure 1 **Firm-level abnormal attention by day of week**

Abnormal attention on each day of week is calculated as the mean (median) AbAtt of all firm-days on that day of week. The detailed numbers in this figure are presented in Table 2 Panel A.

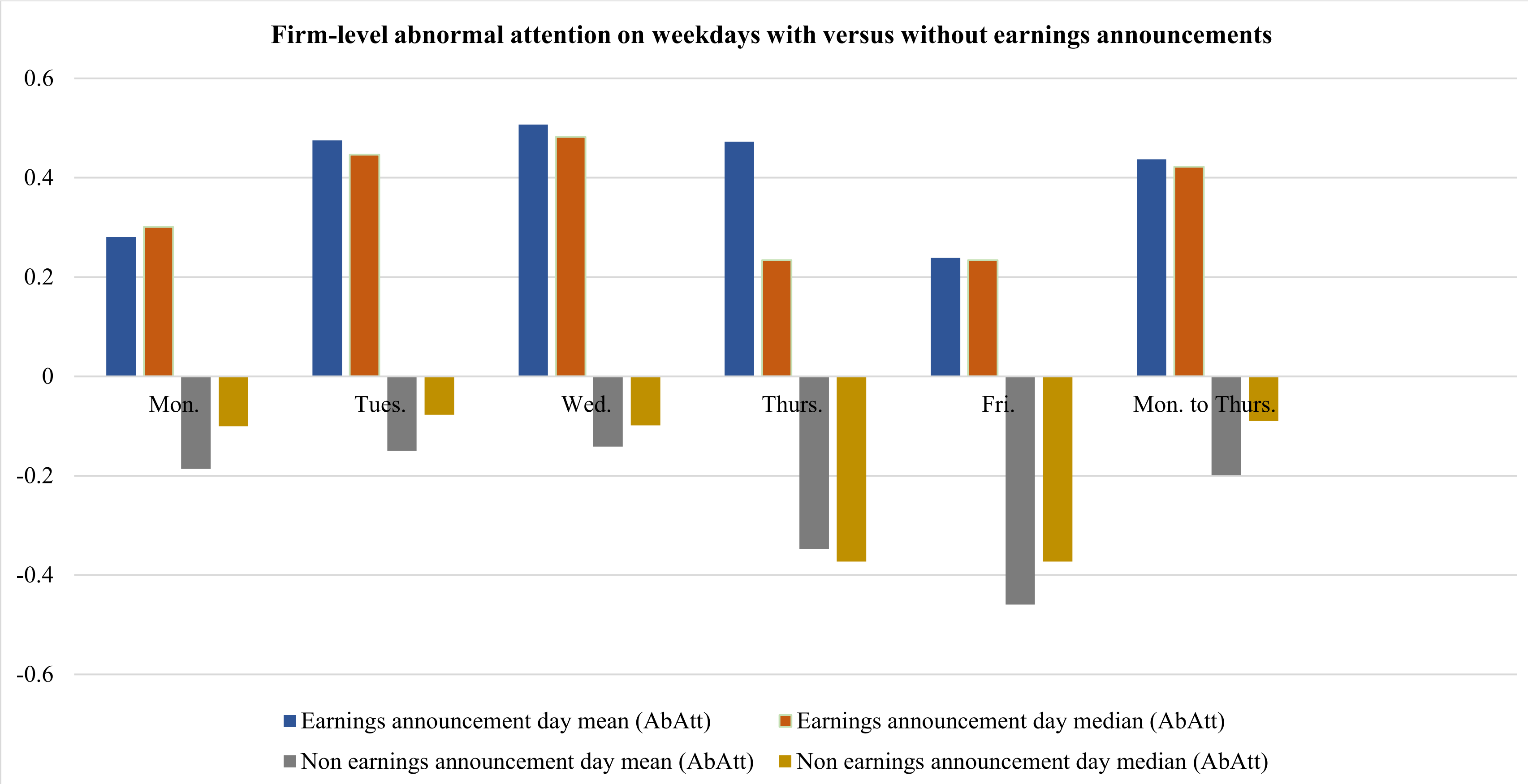

Figure 2 Firm-level abnormal attention on weekdays with vs. without earnings announcements

This figure plots the mean (median) AbAtt on weekdays with versus without earnings announcements. The detailed numbers in this figure are presented in Table 2 Panel B.

Table 3 Firm-level abnormal attention patterns: day of week

This table summarizes the day of week patterns of all firm-level abnormal attention. Panel A presents the mean and median AbAtt and total number of earnings announcements by day of week. Panel B compares the mean and median AbAtt with and without earnings announcements for the same weekday. After close announcements are matched with attention on the following trading day. In testing the differences in means, standard errors are adjusted for heteroskedasticity and clustered by date. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. t-statistics are reported in parenthesis.

Panel A: Mean and median all firm-level abnormal attention

Day of week	Sun.	Mon.	Tues.	Wed.	Thurs.	Fri.	Sat.	Mon. to Thurs.	Diff (Fri.-other weekdays)
Mean	-0.76	0.23	0.46	0.49	0.45	0.21	-0.78	0.41	-0.20***
									(-10.11)
Median	-0.76	0.28	0.44	0.46	0.44	0.22	-0.79	0.40	-0.18***
# of EA	77	11517	19741	22843	28420	5692	33		

Panel B: Mean and median firm-level attention on weekdays with versus without earnings announcements

EA day	Day of week	Mon.	Tues.	Wed.	Thurs.	Fri.	Mon. to Thurs.	Diff (Fri.-other weekdays)
Yes	Mean	0.28	0.48	0.51	0.47	0.24	0.44	-0.20***
								(-11.34)
No	Mean	-0.19	-0.15	-0.14	-0.35	-0.46	-0.20	-0.26**
								(-2.41)
Diff (Yes-No)		0.47***	0.63***	0.65***	0.82***	0.70***	0.64***	
		(-5.58)	(3.46)	(4.94)	(5.42)	(7.76)	(10.41)	
Yes	Median	0.30	0.45	0.48	0.45	0.23	0.42	-0.19***
No	Median	-0.10	-0.08	-0.10	-0.49	-0.37	-0.09	-0.28***
Diff(Yes-No)		0.40***	0.53**	0.58***	0.94***	0.60***	0.51***	

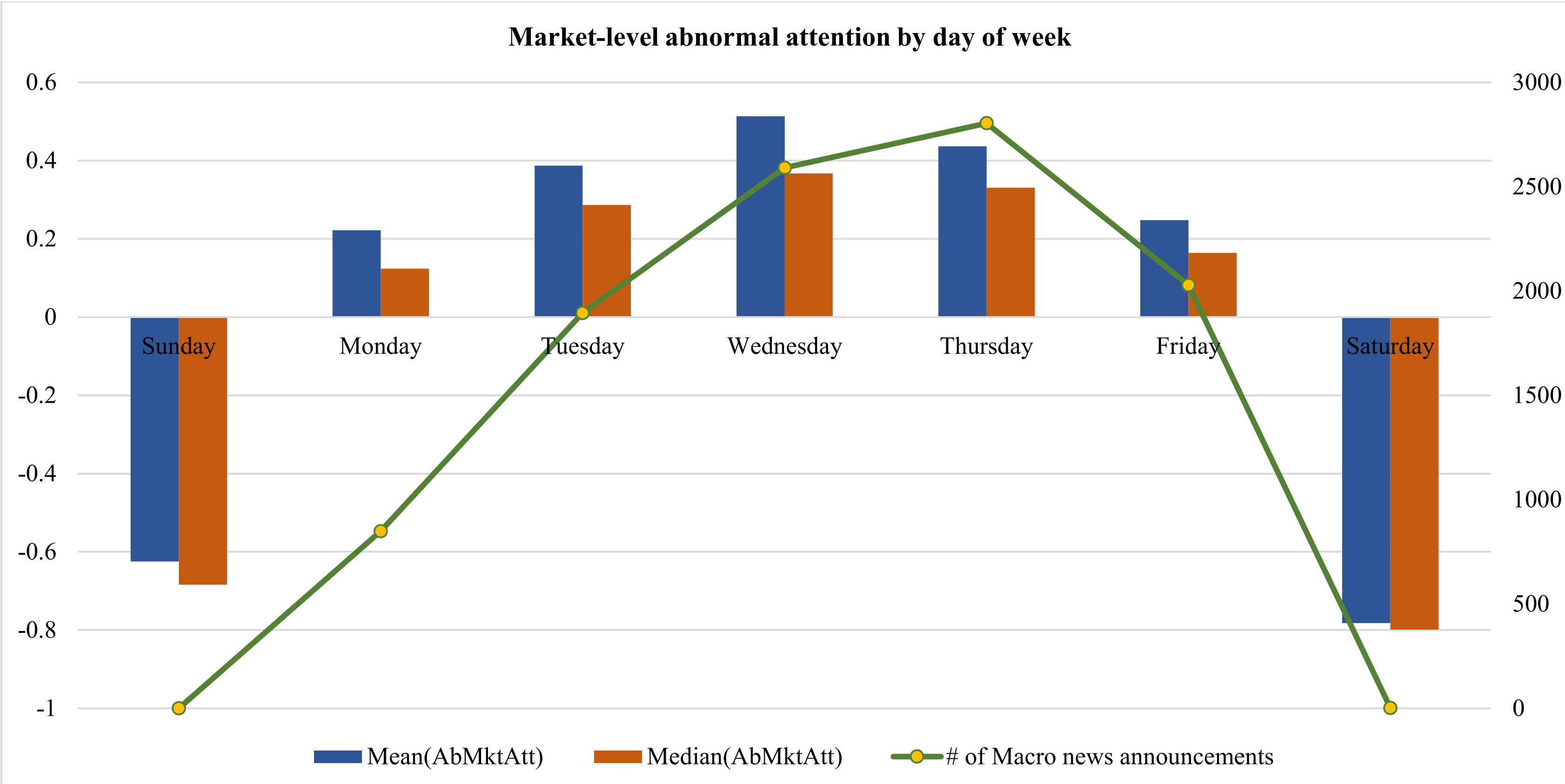

Figure 3 Market-level abnormal attention by day of week

This figure plots the mean (median) AbMktAtt by day of week. The detailed numbers in this figure are presented in Table 3 Panel A.

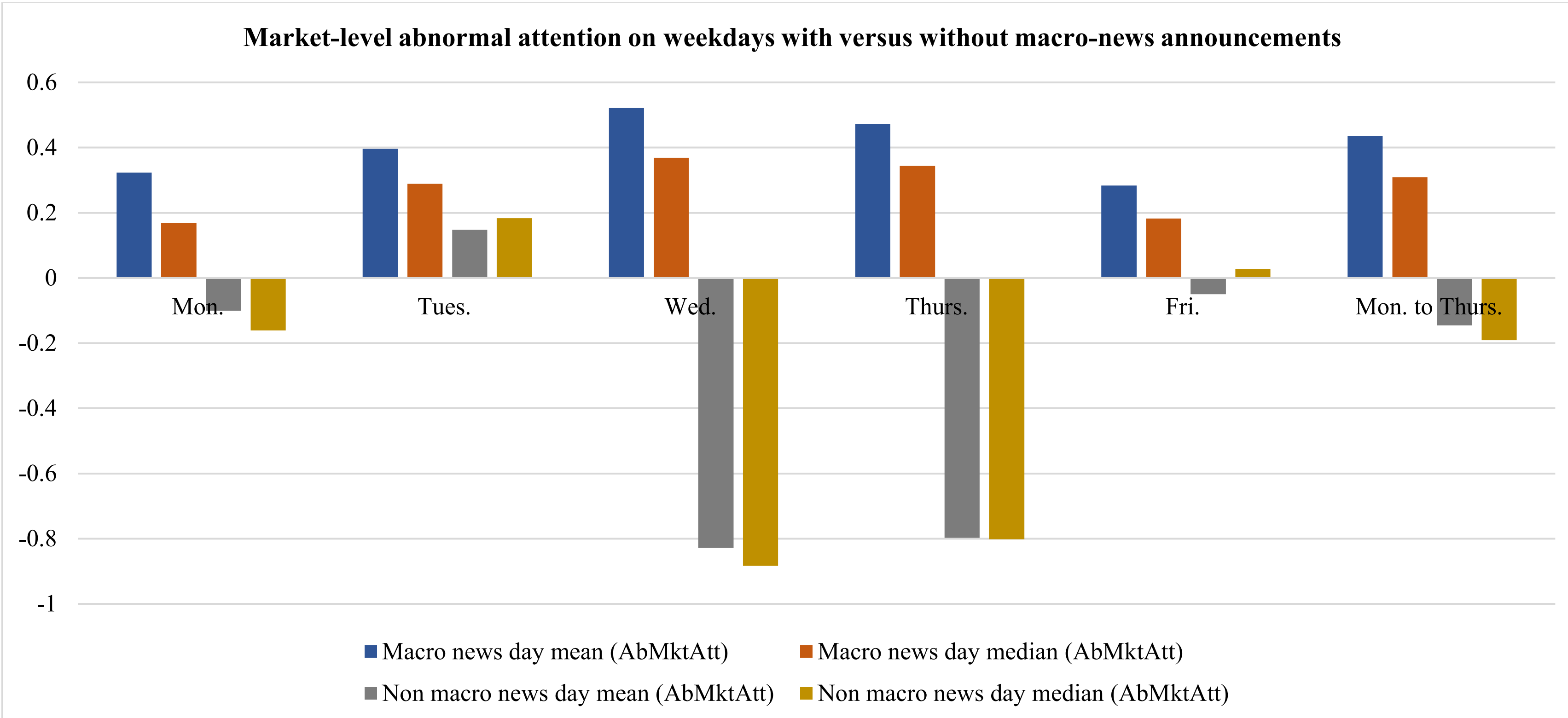

Figure 4 Market-level abnormal attention on weekdays with vs. without macro-news announcements

This figure plots the mean (median) AbMktAtt on weekdays with versus without macro-news announcements. The detailed numbers in this figure are presented in Table 3 Panel B.

Table 4 Market-level abnormal attention patterns: day of week

This table summarizes the day of week patterns of market-level abnormal attention. Panel A presents the mean and median AbMktAtt and total number of macro-news announcements by day of week. Panel B compares the mean and median AbMktAtt with and without macro-news announcements for the same weekday. In testing the differences in means, standard errors are adjusted for heteroskedasticity and clustered by date. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. t-statistics are reported in parenthesis.

Panel A: Mean and median market-level abnormal attention

Day of week	Sun.	Mon.	Tues.	Wed.	Thurs.	Fri.	Sat.	Mon. to Thurs.	Diff (Fri.-other weekdays)
Mean	-0.63	0.22	0.39	0.51	0.44	0.25	-0.78	0.39	-0.14*** (-4.09)
Median	-0.68	0.12	0.29	0.37	0.33	0.16	-0.80	0.29	-0.13***
# of MA	0	849	1895	2590	2804	2028	2		

Panel B: Mean and median on weekdays with versus without macro-news announcements

MA day	Day of week	Mon.	Tues.	Wed.	Thurs.	Fri.	Mon. to Thurs.	Diff (Fri.-other weekdays)
Yes	Mean	0.32	0.40	0.52	0.47	0.28	0.44	-0.16*** (-4.33)
No	Mean	-0.10	0.15	-0.83	-0.80	-0.05	-0.15	0.10 (-0.81)
Diff (Yes-No)		0.42*** (5.49)	0.25** (2.01)	1.35*** (25.73)	1.27*** (36.61)	0.33*** (3.09)	0.59*** (9.96)	
Yes	Median	0.17	0.29	0.37	0.34	0.18	0.31	-0.13***
No	Median	-0.16	0.18	-0.88	-0.80	0.03	-0.19	0.22
Diff(Yes-No)		0.33***	0.11	1.25*	1.14***	0.15***	0.50***	

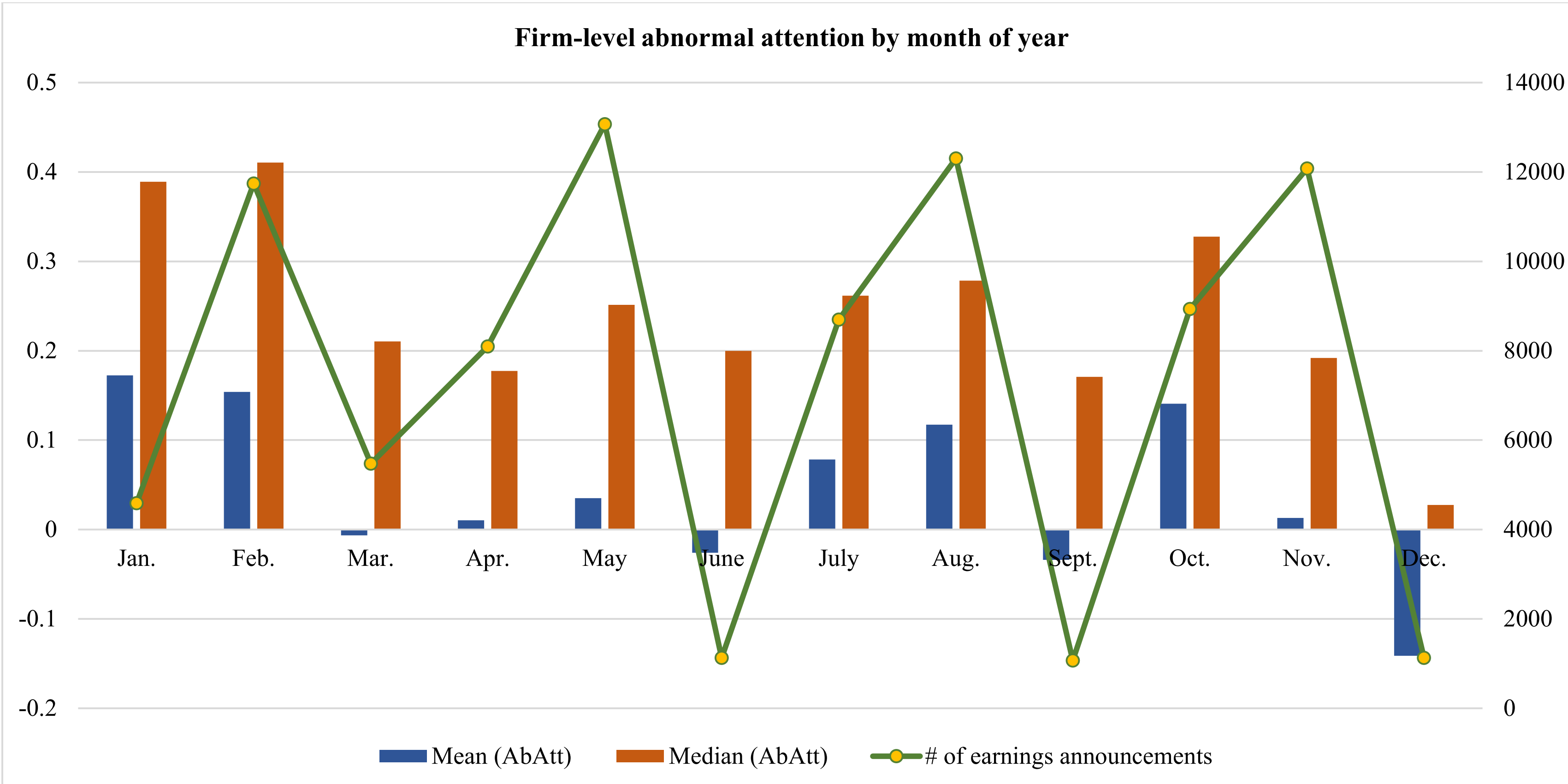

Figure 5 Firm-level abnormal attention by month of year

This figure plots the mean (median) AbAtt by month of year. The detailed numbers in this figure are presented in Table 4 Panel A.

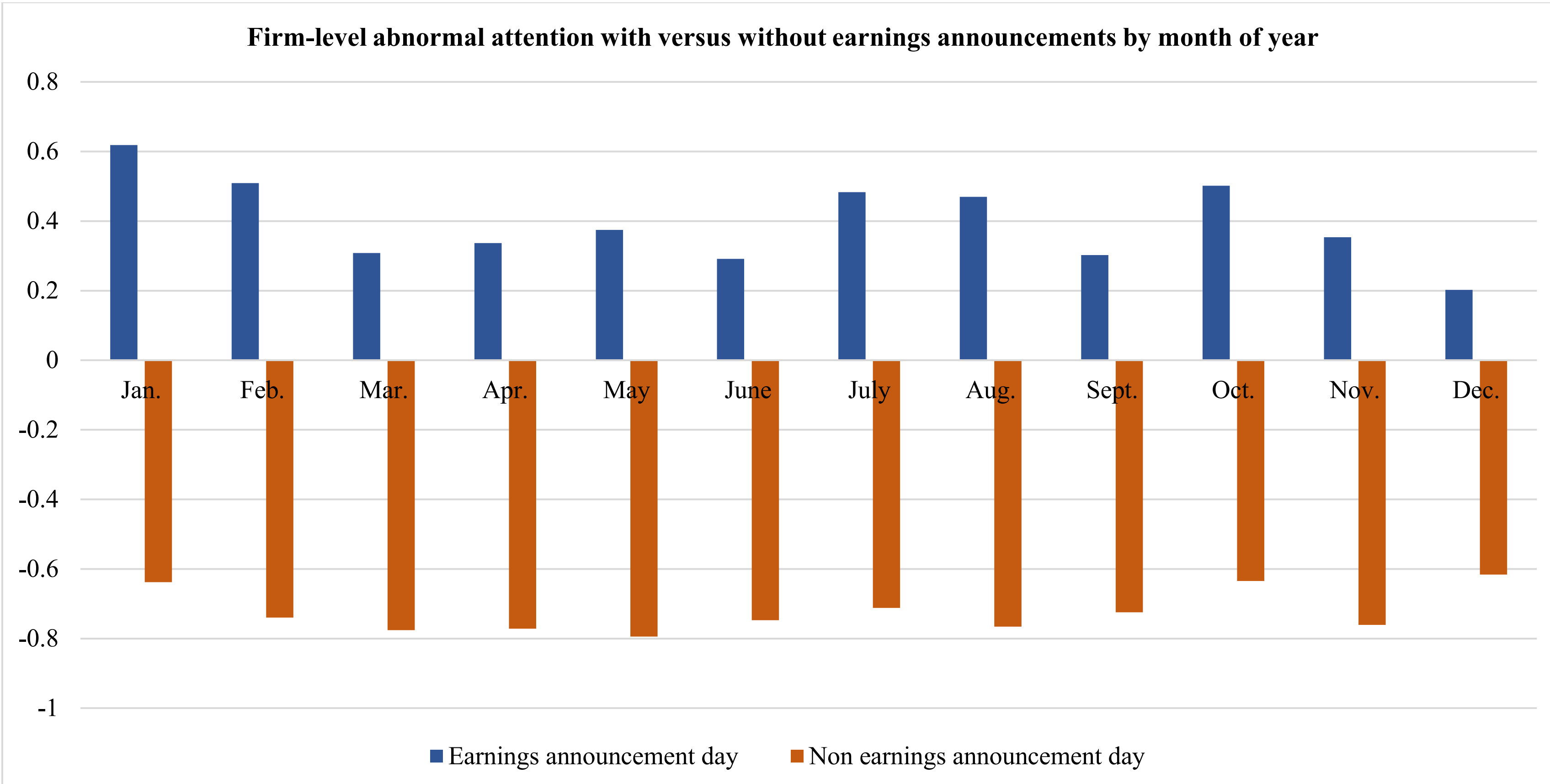

Figure 6 Firm-level abnormal attention with vs. without earnings announcements by month of year

This figure plots the mean (median) AbAtt with vs. without earnings announcements by month of year. The detailed numbers in this figure are presented in Table 4 Panel B.

Table 5 Firm-level abnormal attention patterns: month of year

This table summarizes the month of year patterns of all firm-level abnormal attention. Panel A presents the mean and median AbAtt and total number of earnings announcements by each month of year. Panel B compares the mean AbAtt with and without earnings announcements by each month of year. After close announcements are matched with attention on the following trading day. In testing the differences in means, standard errors are adjusted for heteroskedasticity and clustered by date. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively. t-statistics are reported in parenthesis.

Panel A: Mean and median firm-level abnormal attention by month of year

Month of year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Diff (Summer -other months)
Mean	0.17	0.15	-0.01	0.01	0.04	-0.03	0.08	0.12	-0.03	0.14	0.01	-0.14	0.07* (1.9)
Median	0.39	0.41	0.21	0.18	0.25	0.20	0.26	0.28	0.17	0.33	0.19	0.03	0.05**
# of EA	4592	11745	5477	8096	13071	1126	8699	12303	1069	8933	12076	1132	

Panel B: Mean firm-level abnormal attention with versus without earnings announcements by month of year

EA day	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Diff (Summer -other months)
Yes	0.62	0.51	0.31	0.34	0.38	0.29	0.48	0.47	0.30	0.50	0.35	0.20	0.10** (4.58)
No	-0.64	-0.74	-0.78	-0.77	-0.80	-0.75	-0.71	-0.77	-0.72	-0.64	-0.76	-0.62	-0.02 (-1.27)
Diff(Yes-No)	1.26*** (25.54)	1.25*** (37.37)	1.09*** (46.88)	1.11*** (40.84)	1.18*** (43.29)	1.04*** (31.98)	1.19*** (29.42)	1.24*** (51.11)	1.02*** (24.41)	1.14*** (22.62)	1.11*** (27.96)	0.82*** (18.09)	

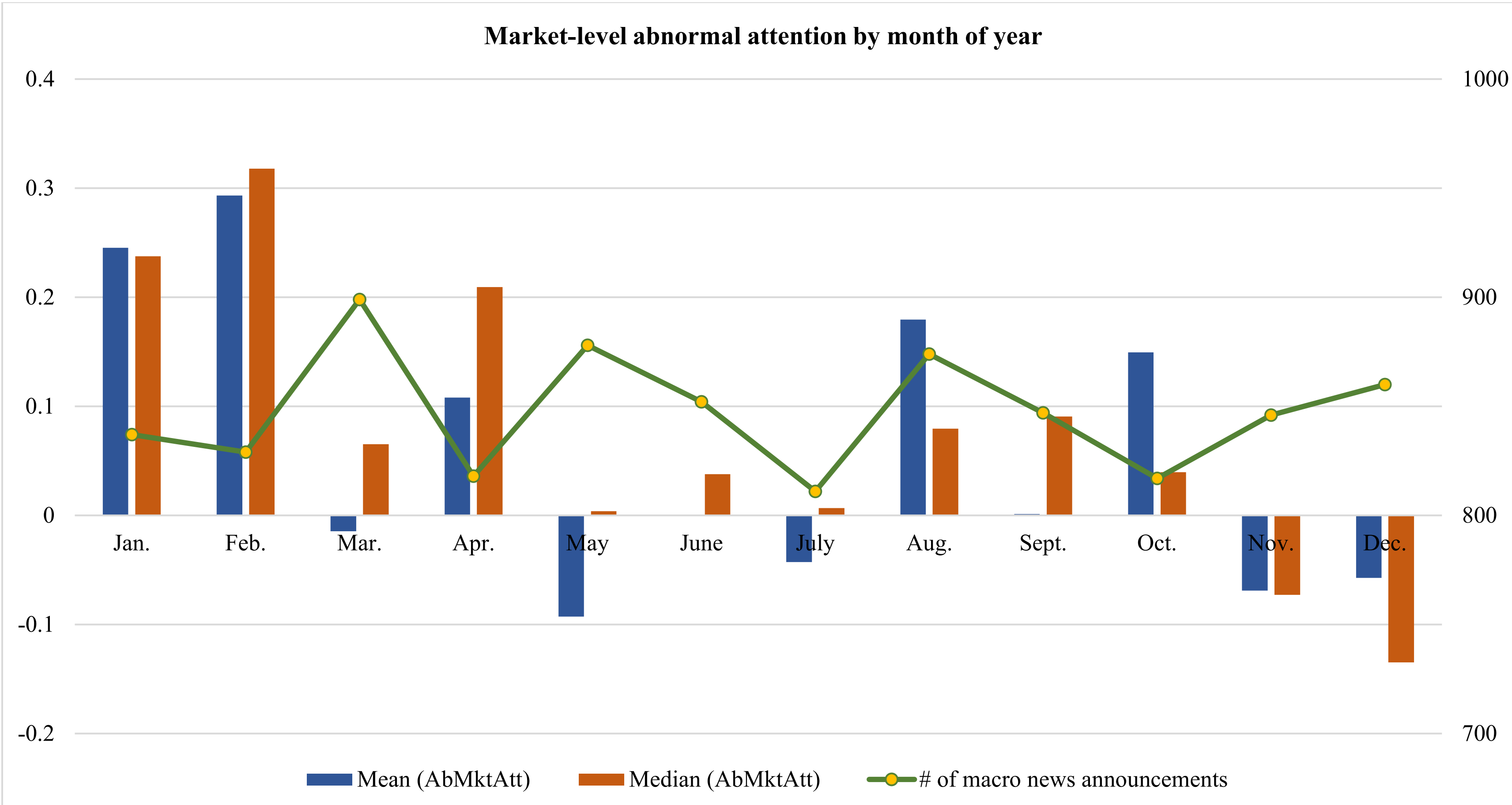

Figure 7 Market-level abnormal attention by month of year

This figure plots the mean (median) AbMktAtt by month of year. The detailed numbers in this figure are presented in Table 5 Panel A.

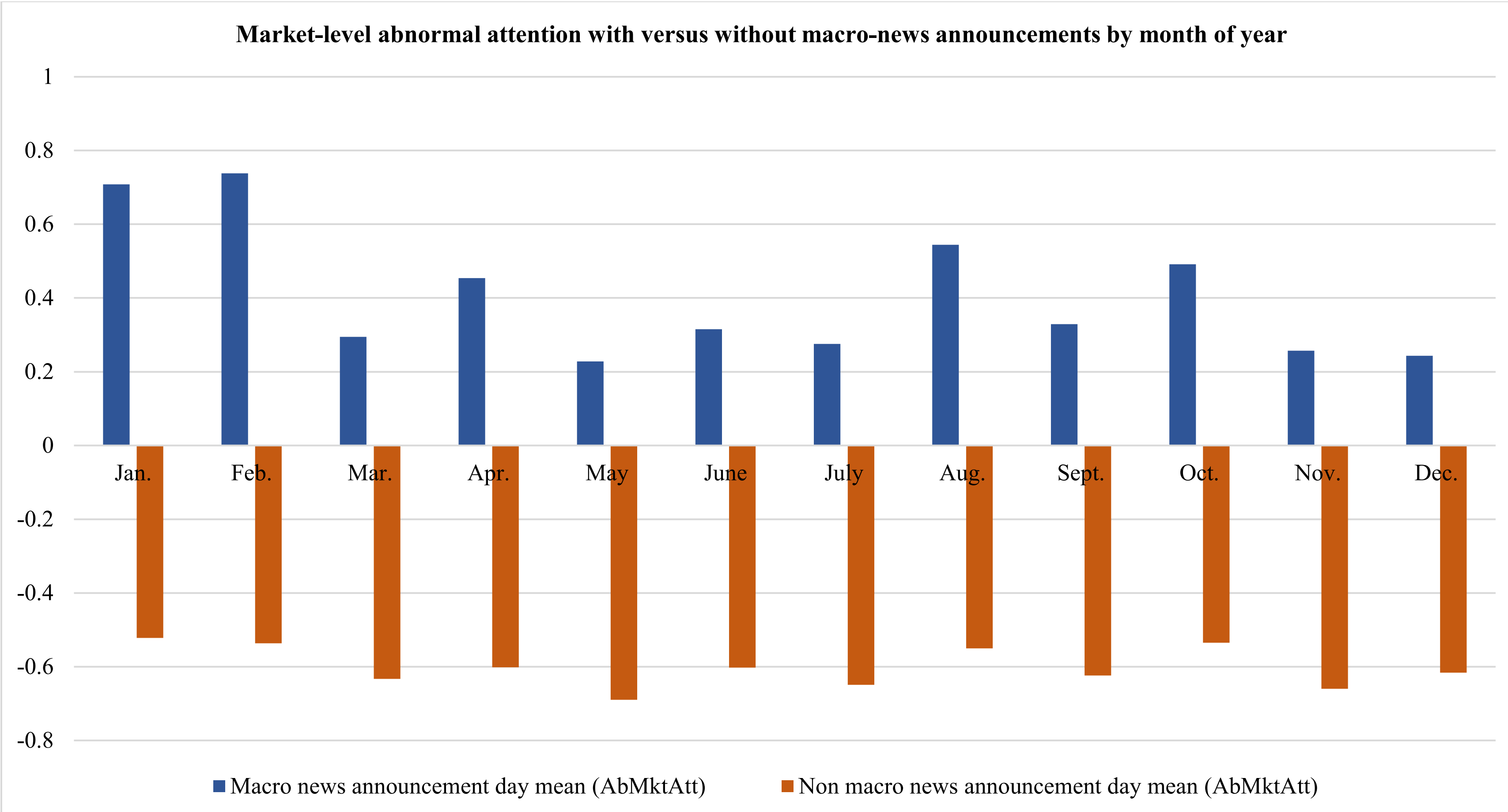

Figure 8 Market-level abnormal attention with vs. without macro-news announcements by month of year

This figure plots the mean (median) AbMktAtt with vs. without macro-news announcements by month of year. The detailed numbers in this figure are presented in Table 5 Panel B.

Table 6 Market-level abnormal attention patterns: month of year

This table summarizes the month of year patterns of market-level abnormal attention. Panel A presents the mean and median AbMktAtt and total number of macro-news announcements by each month of year. Panel B compares the mean AbMktAtt with and without macro-news announcements by each month of year. In testing the differences in means, standard errors are adjusted for heteroskedasticity and clustered by date. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively. t-statistics are reported in parenthesis.

Panel A: Mean and median market-level abnormal attention by month of year

Month of year	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Diff (Summer-other months)
Mean	0.25	0.29	-0.02	0.11	-0.09	-0.00	-0.04	0.18	0.00	0.15	-0.07	-0.06	0.01 (0.33)
Median	0.24	0.32	0.07	0.21	0.00	0.04	0.01	0.08	0.09	0.04	-0.07	-0.14	-0.02
# of MA	837	829	899	818	878	852	811	874	847	817	846	860	

Panel B: Mean market-level abnormal attention with versus without macro-news announcements by month of year

MA day	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.	Diff (Summer-other months)
Yes	0.71	0.74	0.30	0.45	0.23	0.32	0.28	0.54	0.33	0.49	0.26	0.24	0.01 (0.19)
No	-0.52	-0.54	-0.63	-0.60	-0.69	-0.60	-0.65	-0.55	-0.62	-0.54	-0.66	-0.62	0.00 (0.04)
Diff(Yes-No)	1.23*** (14.6)	1.28*** (15.39)	0.93*** (18.11)	1.05*** (16.18)	0.92*** (19.74)	0.92*** (13.72)	0.93*** (17.2)	1.09*** (12.47)	0.95*** (17.34)	1.03*** (12.22)	0.92*** (15.59)	0.86*** (13.98)	

Table 7 Investor attention allocation on earnings announcement days

The table presents the determinants of investor attention allocation on earnings announcement days. $AbMktAtt$ is the abnormal market-level attention on that day and $ImpMAday$ is a dummy variable equaling 1 if a day is an announcement day for one of the important macroeconomic announcements (i.e., FOMC, GDP, ISM PMI, nonfarm payroll, initial jobless claims and CPI). Control variables include $NumEA$, $NumMA$, $AbsSUE$, $LnSize$, $LnBM$, $NumAnalyst$, $InstOwn$, $ILLIQ$, $AbTurnover$, $SDRet$, and dummy variables for Friday and Summer. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

$\boldsymbol{AbAtt}$ **as a dependent variable** Variables	(1)	(2)	(3)
$ImpMAday$	1.16 ***		0.65*
	(3.09)		(1.68)
$NumEA$	-6.40***		-4.44***
	(-27.43)		(-7.42)
$NumMA$	-0.72**		-1.03***
	(-2.29)		(-2.63)
$AbMktAtt$	-0.14		-0.76**
	(-0.43)		(-2.46)
$Friday$	-3.65***		-3.95***
	(-8.66)		(-7.63)
$Summer$	1.04**		0.65
	(2.44)		(1.40)
$AbsSUE$		0.46**	0.39**
		(2.08)	(2.48)
$SDRet(\times 100)$		-3.68***	-3.33***
		(-13.84)	(-11.95)
$InstOwn$		5.77***	6.02***
		(4.04)	(4.09)
$LnSize$		0.61	0.66
		(0.82)	(0.86)
$LnBM$		1.36***	1.42***
		(3.48)	(3.59)
$ILLIQ$		1.65***	1.61***
		(3.89)	(3.69)
$NumAnalyst$		-1.65**	-2.11***
		(-2.41)	(-3.16)
$AbTurnover$		6.10***	6.04***
		(4.13)	(4.00)
$Constant$	48.96***	15.04***	38.49***
	(36.83)	(3.42)	(5.67)
Year fixed effect	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes
Weekday fixed effect	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes
Observations	47559	33123	32362
Adjusted R^2	0.026	0.34	0.36

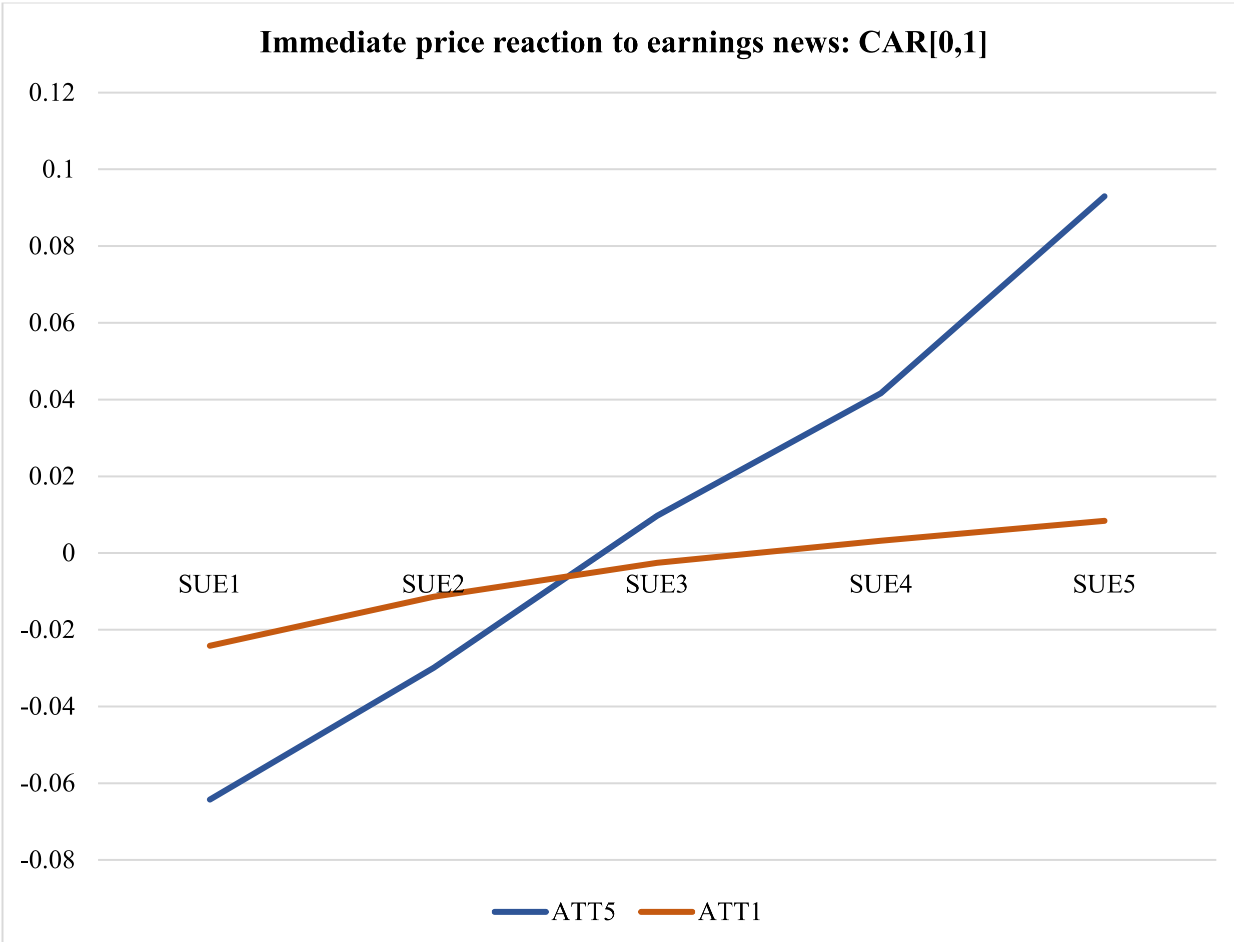

Figure 9 Immediate price reaction to earnings news: CAR[0,1]

Figure 9 shows the mean CAR[0,1] against earnings surprise quintiles (SUE5: the most positive, SUE1: the most negative) for the highest abnormal attention quintile ATT5 and the lowest abnormal attention quintile ATT1.

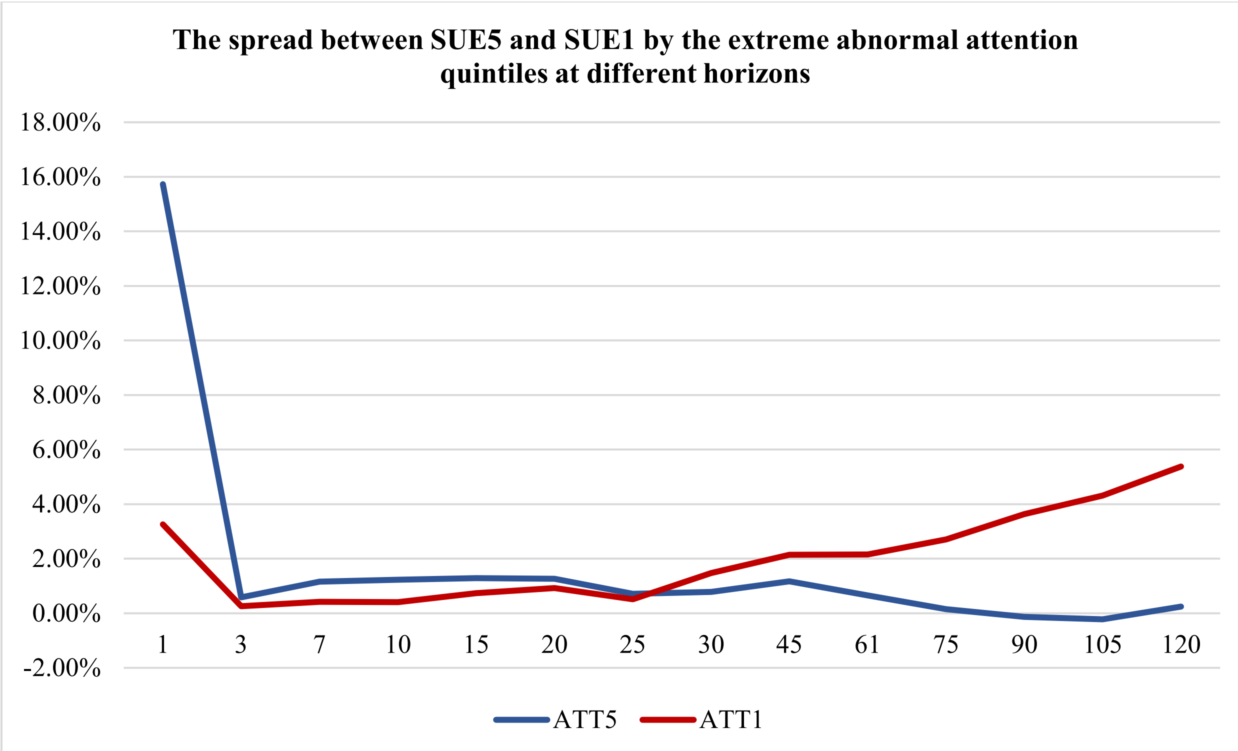

Figure 10 The spread between the extreme earnings surprise quintiles by the extreme abnormal attention quintiles at different horizons

Figure 10 shows the spread in average cumulative abnormal returns between the extreme earnings surprise quintiles (SUE5-SUE1) by the extreme abnormal firm-level attention quintiles (ATT5 and ATT1) at alternative horizons. X-axis is the event time window, and Y-axis is the spread in average cumulative abnormal returns.

Table 8 CAR of earnings surprise quintiles by extreme abnormal firm-level attention quintiles

I calculate the mean $CAR[0,1]$ and $CAR[2,75]$ across earnings surprise quintiles by the extreme attention quintiles. Standard errors are adjusted for heteroscedasticity and clustered by date. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively. t-statistics are reported in parenthesis.

$CAR[0,1]$	$ATT5$	$ATT1$	$ATT5-ATT1$
$SUE5$	9.30%	0.84%	8.46%*** (17.46)
$SUE4$	4.17%	0.32%	3.85%*** (15.13)
$SUE3$	0.97%	-0.26%	1.23%*** (5.10)
$SUE2$	-2.99%	-1.14%	-1.85%*** (-7.04)
$SUE1$	-6.43%	-2.42%	-4.01%*** (-10.99)
$SUE5-SUE1$	15.73%*** (27.80)	3.26%*** (14.67)	
$CAR[2,75]$	$ATT5$	$ATT1$	$ATT5-ATT1$
$SUE5$	3.04%	1.54%	1.50% (1.39)
$SUE4$	0.26%	-2.74%	3.00%*** (3.49)
$SUE3$	-0.80%	-4.21%	3.41%*** (5.47)
$SUE2$	0.42%	-2.88%	3.30%*** (4.47)
$SUE1$	2.89%	-1.17%	4.06%*** (3.77)
$SUE5-SUE1$	0.15% (0.18)	2.71%** (2.47)	

Table 9 Market reactions to earnings news: firm-level and market-level investor attention

This table reports the multivariate tests of the effect of firm-level and market-level investor attention on the relation between $CAR[0,1]$, $CAR[2,75]$ and earnings surprises. The dependent variable is indicated under each column heading. Control variables include $LnSize$, $LnBM$, $NumAnalyst$, $SDRe$, and $CAR[-202,-3]$. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	$CAR[0,1]$		$CAR[2,75]$	
Variables	(1)	(2)	(3)	(4)
SUE	-0.0014	-0.0012	0.0072**	0.006*
	(-1.34)	(-1.19)	(2.17)	(1.77)
$AbAtt$	-0.0178***	-0.018***	0.0105***	0.0103***
	(-23.47)	(-23.96)	(4.73)	(4.84)
$SUE \times AbAtt$	0.0073***	0.0073***	-0.0015**	-0.0013**
	(28.74)	(28.3)	(-2.25)	(-2.03)
$AbMktAtt$	0.0022***	0.0023***	0.0016	0.0032
	(3.14)	(3.32)	(0.75)	(1.56)
$SUE \times AbMktAtt$	-0.0007***	-0.0007***	0.0005	0.0001
	(-2.98)	(-3.05)	(0.74)	(0.19)
$ImpMAday$	-0.0046**	-0.0042**	0.0094	0.01*
	(-2.35)	(-2.10)	(1.50)	(1.66)
$SUE \times ImpMAday$	0.002***	0.002***	-0.0034*	-0.0039**
	(3.18)	(2.97)	(-1.76)	(-2.09)
Constant	-0.009***	-0.0067*	-0.052***	-0.022
	(-2.95)	(-1.65)	(-4.77)	(-1.62)
Controls	N	Y	N	Y
Year fixed effect	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
Weekday fixed effect	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes
Observations	48640	45296	48626	45282
Adjusted R^2	0.12	0.12	0.002	0.04

Table 10 Volume reaction: firm-level and market-level investor attention

This table reports the concurrent correlation between investor attention and the stock trading volume. The dependent variable is the abnormal trading volume $AbVol$. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

$\boldsymbol{AbVol}$ **as a dependent variable** Variables	(1)	(2)
$AbAtt$	0.077 ***	0.054***
	(4.26)	(5.05)
$AbMktAtt$	-0.028	0.073**
	(-0.55)	(2.02)
$ImpMAday$	0.085	0.011
	(0.75)	(0.26)
$AbsSUE$	0.087	-0.088***
	(0.69)	(-2.84)
$SDRet(\times 100)$		0.32***
		(7.62)
$InstOwn$		0.17
		(1.22)
$LnSize$		-0.31***
		(-3.69)
$LnBM$		-0.24***
		(-7.67)
$ILLIQ$		-0.26***
		(-5.04)
$Constant$	1.58***	1.46***
	(5.03)	(3.16)
Year fixed effect	Yes	Yes
Month fixed effect	Yes	Yes
Weekday fixed effect	Yes	Yes
Sector fixed effect	Yes	Yes
Observations	46384	33123
Adjusted R^2	0.11	0.34

Table 11 Post-Announcement drift over alternative windows

This table reports the multivariate tests of the effect of firm-level and market-level investor attention on the relation between CAR[2,90], CAR[2,105] and earnings surprises. The dependent variable is indicated under each column heading. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	$CAR[2,90]$		$CAR[2,105]$	
Variables	(1)	(2)	(3)	(4)
SUE	0.0084**	0.0073**	0.0103**	0.009**
	(2.22)	(2.00)	(2.46)	(2.35)
$AbAtt$	0.0122***	0.0124***	0.0133***	0.0135***
	(4.84)	(5.24)	(4.78)	(5.24)
$SUE \times AbAtt$	-0.0020***	-0.0019**	-0.0023***	-0.0022***
	(-2.62)	(-2.57)	(-2.75)	(-2.69)
$AbMktAtt$	-0.0002	0.0016	-0.0013	0.0014
	(-0.07)	(0.71)	(-0.49)	(0.54)
$SUE \times AbMktAtt$	0.0008	0.0003	0.0006	-0.0001
	(1.02)	(0.44)	(0.70)	(-0.09)
$ImpMAday$	0.0109	0.0119*	0.0129*	0.0138*
	(1.54)	(1.78)	(1.65)	(1.90)
$SUE \times ImpMAday$	-0.0039*	-0.0044**	-0.0044*	-0.005**
	(-1.80)	(-2.14)	(-1.84)	(-2.19)
Constant	-0.051***	-0.014	-0.0535***	-0.01
	(-4.08)	(-0.91)	(-3.85)	(-0.64)
Controls	N	Y	N	Y
Year fixed effect	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
Weekday fixed effect	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes
Observations	48626	45282	48626	45282
Adjusted R^2	0.0016	0.048	0.0013	0.053

Table 12 Market reactions to earnings news: alternative measures of earnings surprise quintiles

This table reports the multivariate tests of the effect of firm-level and market-level investor attention on the relation between $CAR[0,1]$, $CAR[2,75]$ and earnings surprises by using alternative measures of earnings surprise quintiles. The dependent variable is indicated under each column heading. Control variables include $LnSize$, $LnBM$, $NumAnalyst$, $SDRe$, and $CAR[-202,-3]$. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	$CAR[0,1]$		$CAR[2,75]$	
Variables	(1)	(2)	(3)	(4)
SUE	-0.001	-0.0005	0.005	0.004
	(-1.11)	(-0.50)	(1.54)	(1.34)
$AbAtt$	-0.019***	-0.019***	0.01***	0.01***
	(-23.75)	(-23.49)	(4.20)	(4.27)
$SUE \times AbAtt$	0.007***	0.007***	-0.001*	-0.001*
	(29.20)	(29.12)	(-1.94)	(-1.72)
$AbMktAtt$	0.002***	0.002***	0.003	0.005**
	(2.65)	(3.13)	(1.32)	(2.08)
$SUE \times AbMktAtt$	-0.0005***	-0.0006***	-0.0000	-0.0004
	(-2.65)	(-2.91)	(-0.04)	(-0.58)
$ImpMAday$	-0.004**	-0.004*	0.007	0.008
	(-2.00)	(-1.66)	(0.95)	(1.13)
$SUE \times ImpMAday$	0.002***	0.002***	-0.002	-0.003
	(2.84)	(2.61)	(-1.15)	(-1.50)
Constant	-0.009***	-0.004	-0.047***	-0.02
	(-2.85)	(-0.82)	(-3.94)	(-1.40)
Controls	N	Y	N	Y
Year fixed effect	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes
Weekday fixed effect	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes
Observations	48640	45296	48626	45282
Adjusted R^2	0.11	0.12	0.0016	0.041

Table 13 Firm-level investor sentiment on earnings announcement days

The table presents the determinants of investor sentiment on earnings announcement days. CSI is the University of Michigan Consumer Sentiment Index. $MktDSS$ is the daily market sentiment score extracted from StockTwits. SUE is the earnings surprise and ATT is investor attention. Control variables include $LnSize$, $LnBM$, $CAR[-202,-3]$, and the dummy variable $Friday$. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

***DSS* as a dependent variable** Variables	(1)	(2)
SUE	0.21 ***	0.21***
	(46.80)	(45.07)
ATT	-0.02***	-0.03***
	(-4.44)	(-6.38)
$MktDSS$	0.015***	0.016***
	(3.32)	(3.31)
CSI	0.006***	0.005***
	(7.03)	(5.93)
$Friday$	-0.07***	-0.06***
	(-4.44)	(-3.80)
$LnSize$		0.08***
		(22.84)
$LnBM$		-0.07***
		(-9.02)
$CAR[-202,-3]$		0.08***
		(3.02)
Constant	1.87***	1.32***
	(22.31)	(14.97)
Year fixed effect	Yes	Yes
Sector fixed effect	Yes	Yes
Weekday fixed effect	Yes	Yes
Month fixed effect	Yes	Yes
Observations	48640	45296
Adjusted R^2	0.045	0.06

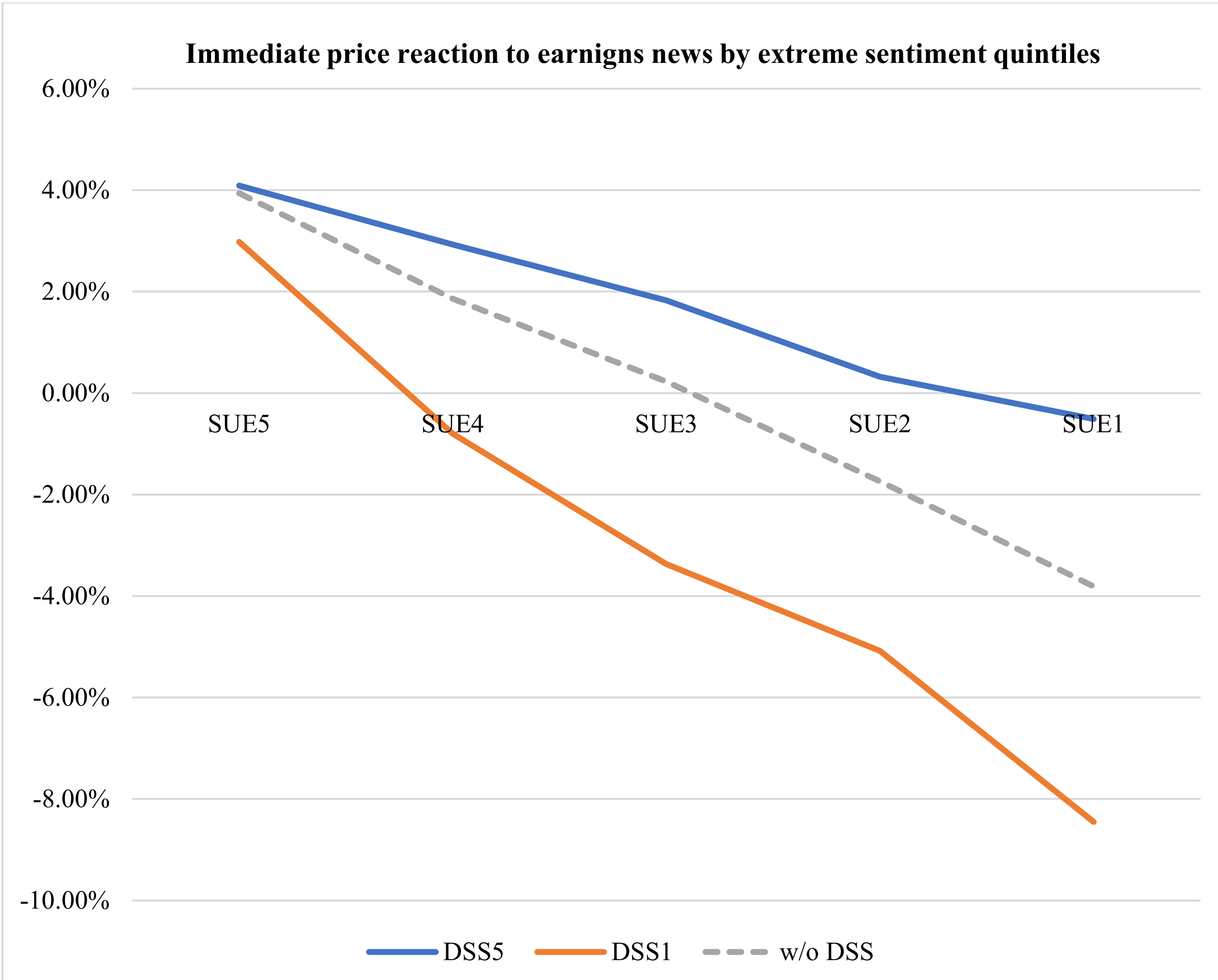

Figure 11 Immediate price reaction to earnings news by the extreme sentiment quintiles

Figure 11 shows the mean CAR[0,1] against earnings surprise quintiles (SUE5: the most positive, SUE1: the most negative) for the most bullish sentiment quintile DSS5 and the most bearish sentiment quintile DSS1. The dash line plots the mean CAR[0,1] that is without the impact of sentiment.

Table 14 CAR of earnings surprise quintiles by extreme firm-level sentiment quintiles

I calculate the mean $CAR[0,1]$ and $CAR[2,90]$ across earnings surprise quintiles by the extreme sentiment quintiles. Standard errors are adjusted for heteroscedasticity and clustered by date. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively. t-statistics are reported in parenthesis.

Panel A CAR[0,1]

$CAR[0,1]$	$Without\ sentiment\ effect$	$DSS5$	$DSS1$	$DSS5 - DSS1$
$SUE5$	3.94%	4.09%	2.98%	1.11%*** (2.70)
$SUE4$	1.86%	2.93%	-0.80%	3.73%*** (11.15)
$SUE3$	0.23%	1.83%	-3.37%	5.20%*** (22.66)
$SUE2$	-1.74%	0.32%	-5.08%	5.40%*** (23.65)
$SUE1$	-3.81%	-0.51%	-8.45%	7.94%*** (26.47)
$SUE5 - SUE1$	7.75%*** (44.23)	4.60%*** (17.02)	11.43%*** (24.99)	

Panel B CAR[2,90]

$CAR[2,90]$	$Without\ sentiment\ effect$	$DSS5$	$DSS1$	$DSS5 - DSS1$
$SUE5$	2.50%	2.58%	4.10%	-1.52% (-1.35)
$SUE4$	-1.14%	-2.09%	-0.20%	-1.89%** (-2.53)
$SUE3$	-2.05%	-2.59%	-2.10%	-0.49% (0.77)
$SUE2$	-1.32%	-1.52%	-0.66%	-0.86% (-1.07)
$SUE1$	1.10%	-0.98%	1.97%	-2.96%** (-2.14)
$SUE5 - SUE1$	1.40%*** (2.69)	3.56%** (2.55)	2.13%* (1.81)	

Table 15 The different effects of bullish and bearish sentiment on the immediate price reaction to earnings news

The table tests whether the impact of sentiment on the immediate price reaction to earnings news is different between bullish and bearish quintiles. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	$CAR[0,1]$
$SUE5$	0.036***
	(21.43)
$SUE1$	-0.027***
	(-21.42)
$DSS5$	0.014***
	(16.59)
$DSS1$	-0.04***
	(-30.14)
$SUE5 \times DSS5$	-0.015***
	(-6.01)
$SUE1 \times DSS5$	0.002
	(0.83)
$SUE5 \times DSS1$	0.029***
	(6.98)
$SUE1 \times DSS1$	-0.023***
	(-8.45)
Constant	0.005***
	(10.91)
Controls	N
Year fixed effect	Yes
Sector fixed effect	Yes
Weekday fixed effect	Yes
Month fixed effect	Yes
Observations	48640
Adjusted R^2	0.12

Table 16 The immediate price reactions to earnings news: firm-level and market-level investor sentiment

This table reports the multivariate tests of the effect of firm-level and market-level investor sentiment on the relation between CAR[0,1] and earnings surprises. Control variables include $LnSize$, $LnBM$, $CAR[-202,-3]$, $NumAnalyst$, $InstOwn$, $ILLIQ$, and $SDRet$. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

$\boldsymbol{CAR[0,1]}$ **as a dependent variable** Variables	(1)	(2)	(3)
$SUETOP$	0.06*** (31.60)		
$DSS5$	0.016*** (6.75)		
$DSS1$	-0.06*** (-26.77)		
$SUETOP \times DSS5$	-0.017*** (-5.04)		
$SUETOP \times DSS1$	0.052*** (11.34)		
SUE		0.027*** (29.40)	0.029*** (26.59)
DSS		0.021*** (30.66)	0.021*** (25.69)
$SUE \times DSS$		-0.003*** (-14.68)	-0.003*** (-12.84)
$MktDSS$		0.002*** (3.09)	0.002*** (3.06)
$SUE \times MktDSS$		-0.0005** (-2.31)	-0.0006** (-2.28)
Constant	-0.02*** (-18.66)	-0.11*** (-41.91)	-0.11*** (-21.54)
Controls	N	N	Y
Year fixed effect	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes
Weekday fixed effect	Yes	Yes	Yes
Observations	19449	48640	33123
Adjusted R^2	0.15	0.12	0.16

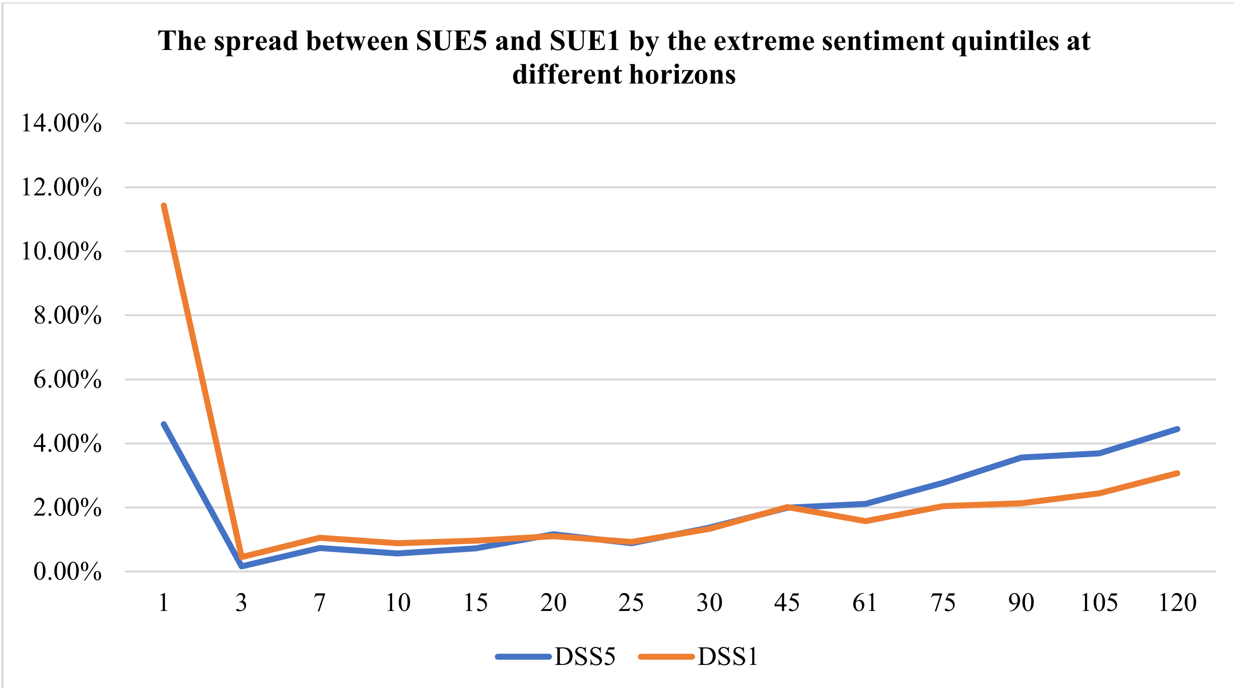

Figure 111 The spread between the extreme earnings surprise quintiles by the extreme sentiment quintiles at different horizons

Figure 12 shows the spread in average cumulative abnormal returns between the extreme earnings surprise quintiles (SUE5-SUE1) by the extreme investor sentiment quintiles (DSS5 and DSS1) over alternative windows. X-axis is the event time window, and Y-axis is the spread in average cumulative abnormal returns.

Table 17 The different effects of bullish and bearish sentiment on PEAD

The table tests whether the impact of sentiment on PEAD is different between bullish and bearish quintiles. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

$\boldsymbol{CAR[2,90]}$ **as a dependent variable** Variables	$CAR[2,90]$
$SUETOP$	0.010
	(1.41)
$DSS5$	-0.021*
	(-1.68)
$DSS1$	0.009
	(1.07)
$SUETOP \times DSS5$	0.026*
	(1.77)
$SUETOP \times DSS1$	0.012
	(0.90)
Constant	0.011**
	(2.22)
Controls	N
Year fixed effect	Yes
Sector fixed effect	Yes
Weekday fixed effect	Yes
Month fixed effect	Yes
Observations	19444
Adjusted R^2	0.0007

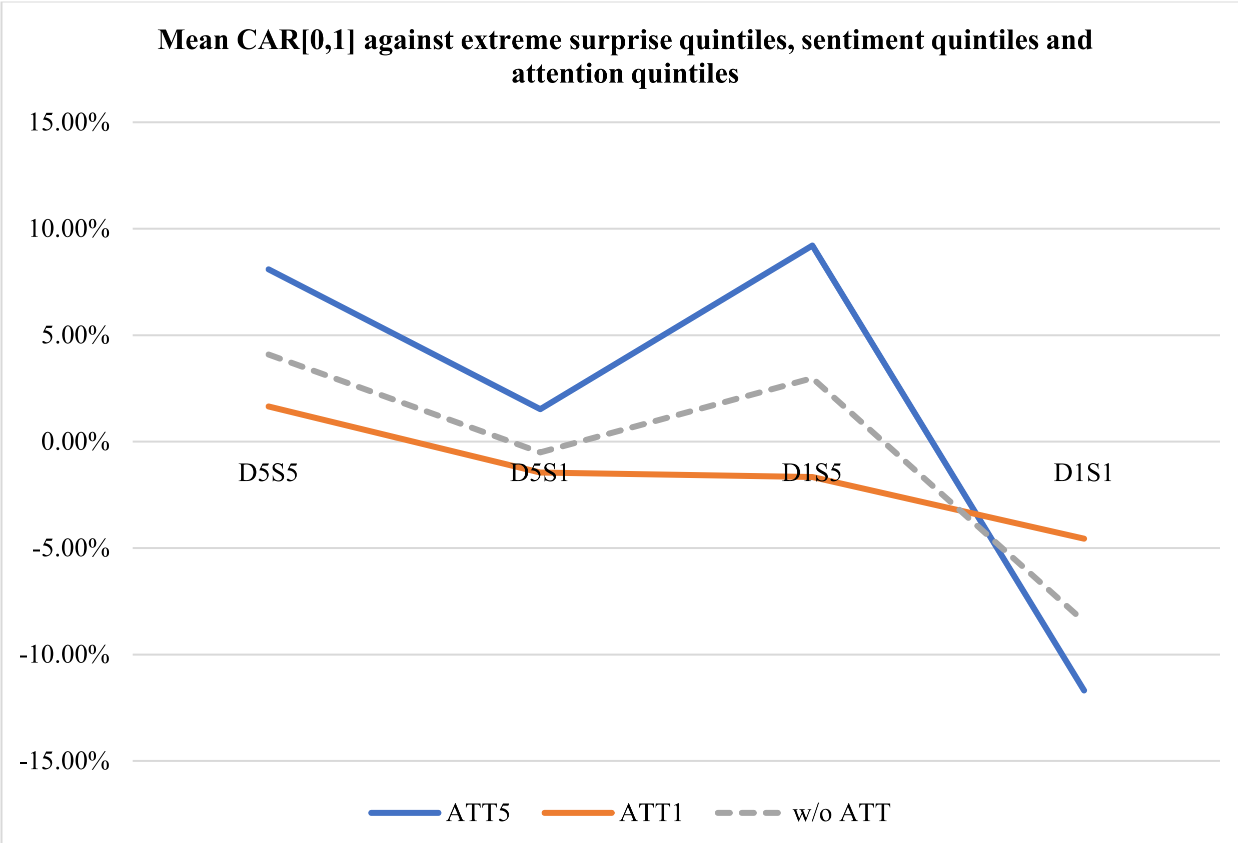

Figure 112 Immediate price reaction to earnings news by extreme earnings surprise quintiles, sentiment quintiles and attention quintiles: CAR[0,1]

Figure 13 shows the mean CAR[0,1] against the extreme earnings surprise quintiles (SUE5 and SUE1) by the extreme investor sentiment quintiles (DSS5 and DSS1) under the impact of the extreme investor attention quintiles. D5S5 indicates the most bullish sentiment and the most positive SUE group and D5S1 indicates the most bullish sentiment and the most negative SUE group. D1S5 indicates the most bearish sentiment and the most positive SUE group and D1S1 indicates the most bearish sentiment and the most negative SUE group. The dash line plots the mean CAR[0,1] that is without the impact of attention.

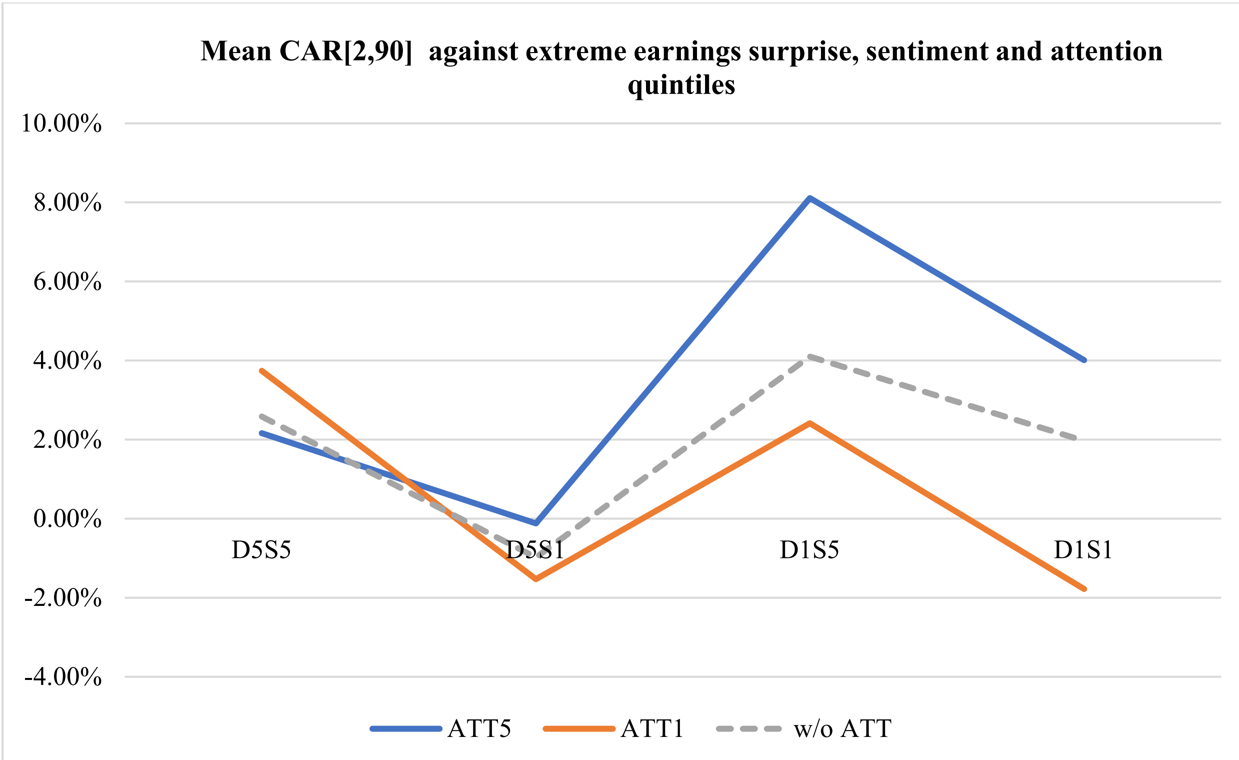

Figure 113 Post-announcement drift by extreme earnings surprise quintiles, sentiment quintiles and attention quintiles: CAR[2,90]

Figure 14 shows the mean CAR[2,90] against the extreme earnings surprise quintiles (SUE5 and SUE1) by the extreme investor sentiment quintiles (DSS5 and DSS1) under the impact of the extreme investor attention quintiles. D5S5 indicates the most bullish sentiment and the most positive SUE group and D5S1 indicates the most bullish sentiment and the most negative SUE group. D1S5 indicates the most bearish sentiment and the most positive SUE group and D1S1 indicates the most bearish sentiment and the most negative SUE group. The dash line plots the mean CAR[2,90] that is without the impact of attention.

Table 18 The impact of attention on the spread (SUE5-SUE1) in average cumulative abnormal returns by the extreme investor sentiment quintiles (DSS5 and DSS1)

D5S5 indicates the most bullish sentiment and the most positive SUE group and D5S1 indicates the most bullish sentiment and the most negative SUE group. D1S5 indicates the most bearish sentiment and the most positive SUE group and D1S1 indicates the most bearish sentiment and the most negative SUE group. ATT5 (ATT1) is the highest (lowest) attention quintile and the second column presents the results without the impact of attention. Standard errors are adjusted for heteroscedasticity and clustered by date. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. t-statistics are reported in parenthesis.

$CAR[0,1]$	$without\ ATT$	$ATT5$	$ATT1$	$ATT5-ATT1$
$D5S5$	4.09%	8.09%	1.65%	6.44%*** (12.90)
$D5S1$	-0.51%	1.53%	-1.45%	2.98%*** (3.20)
$D5S5-D5S1$	4.60%*** (17.02)	6.56%*** (6.65)	3.10%*** (7.50)	
$D1S5$	2.98%	9.21%	-1.66%	10.87%*** (10.56)
$D1S1$	-8.45%	-11.69%	-4.56%	-7.13%*** (-12.40)
$D1S5-D1S1$	11.43%*** (24.99)	20.90%*** (20.10)	2.90%*** (4.28)	
$CAR[2,90]$	$without\ ATT$	$ATT5$	$ATT1$	$ATT5-ATT1$
$D5S5$	2.58%	2.16%	3.74%	-1.58% (-0.73)
$D5S1$	-0.98%	-0.12%	-1.53%	1.41% (0.35)
$D5S5-D5S1$	3.56%** (2.55)	2.28% (0.65)	5.27%* (1.75)	
$D1S5$	4.10%	8.11%	2.41%	5.70%** (2.06)
$D1S1$	1.97%	4.01%	-1.78%	5.79%** (2.58)
$D1S5-D1S1$	2.13%* (1.81)	4.10%** (2.28)	4.19% (1.34)	

Table 19 The different effects of high and low attention across both top and bottom sentiment and earnings surprise quintiles: CAR[0,1]

The table tests the different effects of high and low attention across both top and bottom sentiment and earnings surprise quintiles. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	$CAR[0,1]$
$SUE5$	0.036***
	(21.90)
$SUE1$	-0.025***
	(-19.65)
$DSS5$	0.015***
	(17.79)
$DSS1$	-0.04***
	(-30.82)
$ATT5$	0.017***
	(12.13)
$ATT1$	-0.007***
	(-9.10)
$SUE5 \times DSS5$	-0.014***
	(-5.24)
$SUE1 \times DSS5$	0.005
	(1.63)
$SUE5 \times DSS1$	0.018***
	(3.98)
$SUE1 \times DSS1$	-0.017***
	(-5.48)
$SUE5 \times DSS5 \times ATT5$	0.024***
	(4.78)
$SUE5 \times DSS1 \times ATT5$	0.059***
	(5.93)
$SUE1 \times DSS5 \times ATT5$	-0.0004
	(-0.04)
$SUE1 \times DSS1 \times ATT5$	-0.054***
	(-9.67)
$SUE5 \times DSS5 \times ATT1$	-0.016***
	(-4.37)
$SUE5 \times DSS1 \times ATT1$	-0.025***
	(-3.64)
$SUE1 \times DSS5 \times ATT1$	-0.005
	(-1.23)
$SUE1 \times DSS1 \times ATT1$	0.042***
	(9.85)
Constant	0.003***
	(5.53)
Controls	N
Fixed effects	Yes
Observations	48640
Adjusted R^2	0.14

Table 20 The impact of attention on the in-quintile spread (SUE5-SUE1) for both bullish and bearish sentiment quintiles

The table tests the impact of attention on the in-quintile spread (SUE5-SUE1) for both bullish and bearish sentiment quintiles. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	$CAR[0,1]$
$SUETOP$	0.07***
	(21.07)
$DSS5$	0.016***
	(4.58)
$DSS1$	-0.07***
	(-18.28)
$ATTTOP$	0.021***
	(6.36)
$SUETOP \times DSS5$	-0.04***
	(-7.73)
$SUETOP \times DSS1$	0.015**
	(2.16)
$SUETOP \times DSS5 \times ATTTOP$	0.043***
	(7.06)
$SUETOP \times DSS1 \times ATTTOP$	0.087***
	(8.02)
Constant	-0.03***
	(-15.56)
Controls	N
Year fixed effect	Yes
Sector fixed effect	Yes
Weekday fixed effect	Yes
Month fixed effect	Yes
Observations	8855
Adjusted R^2	0.16

Table 21 The joint effect of investor sentiment and attention on the immediate price reaction to earnings news

The table tests the joint effect of investor sentiment and attention on the immediate price reaction to earnings news. Control variables include $LnSize$, $LnBM$, $CAR[-202, -3]$, $NumAnalyst$, $InstOwn$, $ILLIQ$, and $SDRet$. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

$\boldsymbol{CAR[0,1]}$ **as a dependent variable** Variables	(1)	(2)
SUE	0.013***	0.015***
	(11.82)	(11.45)
DSS	0.02***	0.02***
	(29.67)	(25.22)
ATT	-0.015***	-0.015***
	(-19.52)	(-18.44)
$SUE \times DSS$	-0.005***	-0.005***
	(-18.61)	(-17.25)
$SUE \times ATT$	0.005***	0.004***
	(12.31)	(11.20)
$SUE \times DSS \times ATT$	0.0006***	0.0006***
	(8.08)	(7.61)
$MktDSS$	0.003***	0.003***
	(3.70)	(3.67)
$SUE \times MktDSS$	-0.0007***	-0.0008***
	(-3.41)	(-3.29)
Constant	-0.07***	-0.07***
	(-23.10)	(-13.21)
Controls	N	Y
Year fixed effect	Yes	Yes
Sector fixed effect	Yes	Yes
Weekday fixed effect	Yes	Yes
Month fixed effect	Yes	Yes
Observations	48460	33123
Adjusted R^2	0.15	0.19

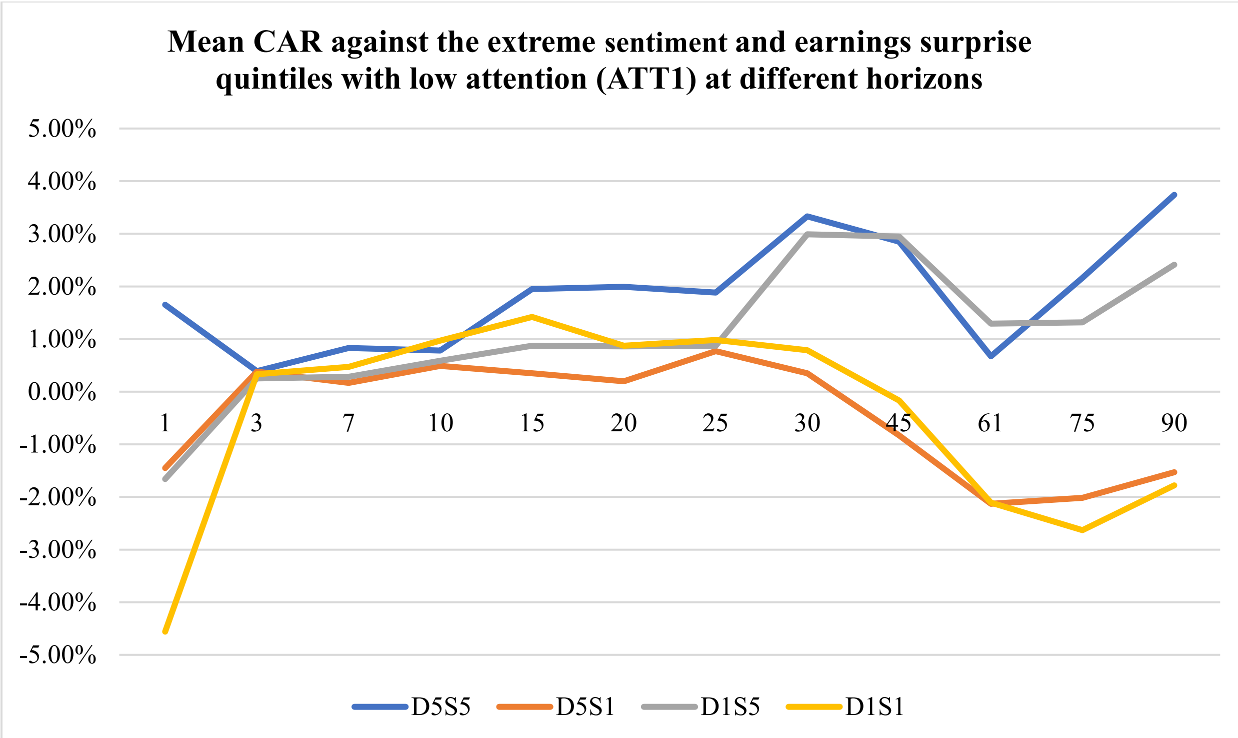

Figure 114 The mean CAR against the extreme sentiment and earnings surprise quintiles with low attention (ATT1) at different horizons

Figure 15 plots the mean CAR against the extreme sentiment and earnings surprise quintiles with low attention (ATT1) at different horizons. D5S5 indicates the most bullish sentiment and the most positive SUE group and D5S1 indicates the most bullish sentiment and the most negative SUE group. D1S5 indicates the most bearish sentiment and the most positive SUE group and D1S1 indicates the most bearish sentiment and the most negative SUE group. X-axis is the event time window, and Y-axis is the average cumulative abnormal returns.

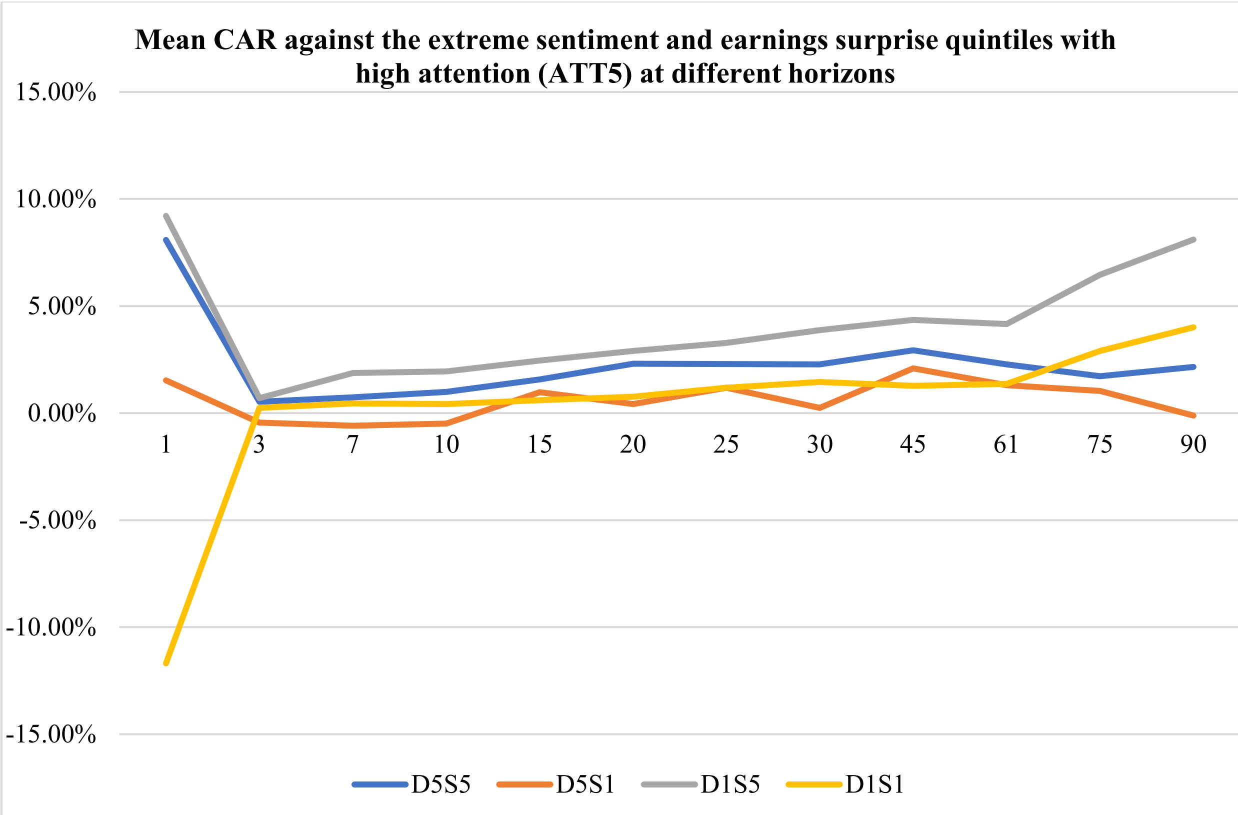

Figure 115 The mean CAR against the extreme sentiment and earnings surprise quintiles with high attention (ATT5) at different horizons

Figure 16 plots the mean CAR against the extreme sentiment and earnings surprise quintiles with high attention (ATT5) at different horizons. D5S5 indicates the most bullish sentiment and the most positive SUE group and D5S1 indicates the most bullish sentiment and the most negative SUE group. D1S5 indicates the most bearish sentiment and the most positive SUE group and D1S1 indicates the most bearish sentiment and the most negative SUE group. X-axis is the event time window, and Y-axis is the average cumulative abnormal returns.

Table 22 The different effects of high and low attention across both top and bottom sentiment and earnings surprise quintiles: CAR[2,90]

The table tests the different effects of high and low attention across both top and bottom sentiment and earnings surprise quintiles. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	$CAR[2,90]$
$SUE5$	0.035***
	(7.46)
$SUE1$	0.028***
	(5.36)
$DSS5$	-0.006**
	(-1.99)
$DSS1$	0.004
	(1.20)
$ATT5$	0.017***
	(5.92)
$ATT1$	-0.011***
	(-2.66)
$SUE5 \times DSS5$	0.009
	(0.96)
$SUE1 \times DSS5$	-0.013
	(-0.87)
$SUE5 \times DSS1$	0.004
	(0.27)
$SUE1 \times DSS1$	0.005
	(0.54)
$SUE5 \times DSS5 \times ATT5$	-0.02
	(-1.15)
$SUE5 \times DSS1 \times ATT5$	0.037**
	(1.86)
$SUE1 \times DSS5 \times ATT5$	-0.01
	(-0.31)
$SUE1 \times DSS1 \times ATT5$	0.002
	(0.14)
$SUE5 \times DSS5 \times ATT1$	0.026
	(1.26)
$SUE5 \times DSS1 \times ATT1$	0.008
	(0.28)
$SUE1 \times DSS5 \times ATT1$	0.003
	(0.12)
$SUE1 \times DSS1 \times ATT1$	-0.028
	(-1.27)
Constant	-0.016***
	(-9.01)
Controls	N
Fixed effects	Yes
Observations	48626
Adjusted R^2	0.005

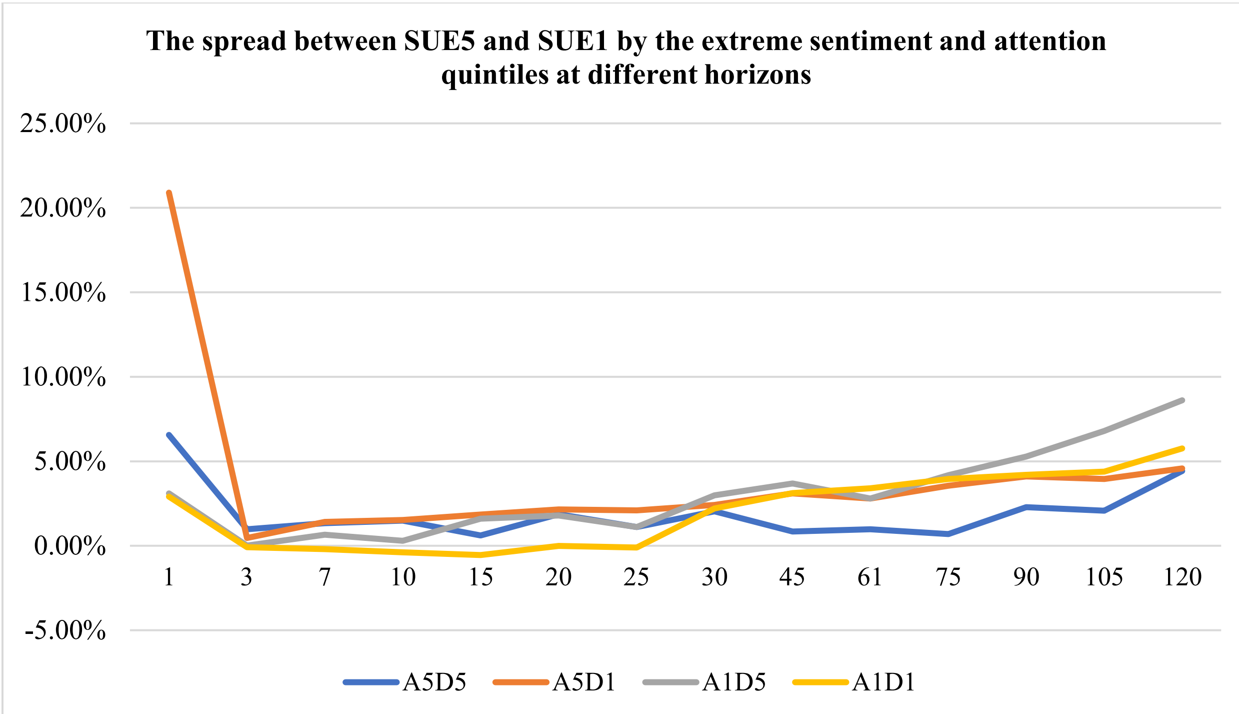

Figure 116 The spread (SUE5-SUE1) by the extreme sentiment (DSS5 and DSS1) and attention (ATT5 and ATT1) quintiles at different horizons.

Figure 7 plots the spread in average cumulative abnormal returns between the extreme earnings surprise quintiles (SUE5-SUE1) by the extreme sentiment (DSS5 and DSS1) and attention (ATT5 and ATT1) quintiles at different horizons. A5D5 indicates the highest attention and the most bullish sentiment group and A5D1 indicates the highest attention and the most bearish sentiment group. A1D5 indicates the lowest attention and the most bullish sentiment group and A1D1 indicates the lowest attention and the most bearish sentiment group. X-axis is the event time window, and Y-axis is the spread in average cumulative abnormal returns.

Table 23 The spread (SUE5-SUE1) for both bullish and bearish sentiment quintiles with different effects of high and low attention

The table tests the spread (SUE5-SUE1) for both bullish and bearish sentiment quintiles with different effects of high and low attention. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Variables	$CAR[2,90]$
$SUETOP$	0.01
	(1.04)
$DSS5$	-0.023
	(-1.12)
$DSS1$	-0.003
	(-0.27)
$ATTTOP$	0.025***
	(2.83)
$SUETOP \times DSS5$	0.04
	(1.52)
$SUETOP \times DSS1$	0.01
	(0.36)
$SUETOP \times DSS5 \times ATTTOP$	-0.041*
	(-1.67)
$SUETOP \times DSS1 \times ATTTOP$	0.032
	(1.04)
Constant	0.006
	(0.62)
Controls	N
Year fixed effect	Yes
Sector fixed effect	Yes
Weekday fixed effect	Yes
Month fixed effect	Yes
Observations	8851
Adjusted R^2	0.002

Table 24 The joint effect of investor sentiment and attention on the post-announcement drift

The table tests the joint effect of investor sentiment and attention on the post-announcement drift. Control variables include $LnSize$, $LnBM$, $CAR[-202,-3]$, $NumAnalyst$, $InstOwn$, $ILLIQ$, and $SDRet$. All regressions control for year, month, weekday and 2-digit SIC sector fixed effects. Standard errors are adjusted for heteroscedasticity and clustered by firm and day. t -statistics are reported below the coefficient estimates in parenthesis. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

$\boldsymbol{CAR[2,90]}$ **as a dependent variable** Variables	(1)	(2)
SUE	0.004	-0.006
	(0.92)	(-1.25)
DSS	-0.006**	-0.003
	(-2.41)	(-1.13)
ATT	0.01***	0.004*
	(4.30)	(1.74)
$SUE \times DSS$	0.001	0.0004
	(1.18)	(0.41)
$SUE \times ATT$	-0.0006	0.002
	(-0.56)	(1.58)
$SUE \times DSS \times ATT$	-0.0003	-0.0003*
	(-1.51)	(-1.67)
$MktDSS$	-0.003	-0.004
	(-1.05)	(-1.54)
$SUE \times MktDSS$	0.0003	0.0006
	(0.41)	(0.76)
Constant	-0.02*	0.41
	(-1.78)	(0.68)
Controls	N	Y
Year fixed effect	Yes	Yes
Sector fixed effect	Yes	Yes
Weekday fixed effect	Yes	Yes
Month fixed effect	Yes	Yes
Observations	48626	33110
Adjusted R^2	0.002	0.034

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