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Twitter investor sentiment and corporate earnings announcements

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Abstract

We examine the impact of firm-specific investor sentiment (FSIS) on stock returns for negative and positive earnings surprises. Using a measure constructed from firm-specific tweets, we find that FSIS has a greater impact on stock returns for negative relative to positive earnings surprises. We further show that the impact of FSIS is greater for firms whose valuation is uncertain and difficult to arbitrage. Moreover, we provide evidence of return reversals over post-announcement periods. Our results highlight the importance of FSIS around earnings announcements.

KEYWORDS

earnings surprises, investor sentiment, social media, StockTwits, Twitter

JEL CLASSIFICATION

G02, G11, G12, G14

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1 | INTRODUCTION

The role of market-wide investor sentiment in investment decisions is clearly established in the finance and accounting literature in recent years (e.g., Baker & Wurgler, 2006). Similarly, the fact that Internet stock messages and other social media platforms may contain information or sentiment which influences price formation is also documented (e.g., Antweiler & Frank, 2004). However, less is known about the impact of *firm-specific investor sentiment* (FSIS) as expressed on social media platforms on individual firms' stock prices around corporate events, even though there is abundant anecdotal evidence suggesting that FSIS affects stock prices. For example, in January 2021, GameStop's share price jumped to more than 60% in after-hours trading after a positive tweet from Tesla's CEO, Mr Elon Musk, regarding the video game firm. GameStop's share price closed up 92.7% that day before plunging nearly 90% about a week later.[1]

Along these lines, Bartov et al. (2018) explore the effect of the aggregate Twitter opinion around earnings announcements. By examining the unconditioned impact of Twitter information on announcement returns, they provide evidence that the aggregate opinion from individual tweets can be used to predict firms' announcement returns. There is, however, a large body of work in social sciences that finds asymmetric responses towards negative and positive information. More specifically, there is a propensity for negative information to be given more importance than positive information during valuations, which can be attributed to a 'negativity effect'.[2] Motivated by this literature, we examine the heterogenous impact of FSIS on earnings announcement returns when the type of earnings news is jointly accounted and improve our understanding of the phenomenon.

Earnings announcements are an important source of information for the fundamental valuation of firms. There is an extensive literature documenting significant stock price movements around earnings announcements (e.g., Bartov et al., 2002; Kasznik & McNichols, 2002). Prior studies address the conceptualization of the earnings–return relationship and concur that firms with positive (negative) earnings outcomes, experience significantly positive (negative) abnormal stock price performance. These studies assume that rational investors efficiently impound accounting information into stock prices and arbitrageurs offset the actions of irrational investors. Our paper acknowledges that investors may be irrational and arbitrage may be limited and argues that a behavioural aspect is related to firms' short-term performance at the time of earnings announcements.[3] We argue investors may be prone to sentiment and rational investors may face limits to arbitrage, therefore, stock

[1] *Source*: Financial Times, 'Moment of weakness: Amateur investor left counting GameStop losses', 5 February 2021.

[2] The 'negativity effect' is a behavioural/psychological idea defined by a larger effect of negative versus positive environmental stimuli on an organism (Peeters & Czapiński, 1990). There are two main interpretations of this effect: (1) in decisions under risk, the potential downside risk is more heavily weighted than any potential benefits and (2) in the formation of overall valuations, negative signals are weighted more heavily than positive ones. Some related studies dealing with this effect include Kanouse and Hanson (1971), Peeters (1971), Kernell (1977), Kahneman and Tversky (1979), Ronis and Lipinski (1985), Aragones (1997), Singh and Teoh (2000), Baumeister et al. (2001), Akhtar et al. (2011) and Chau et al. (2016).

[3] Inspired by De Long et al. (1990), we argue that the differences of opinion can be large around earnings announcements, therefore, investors' responses to earnings surprises may be compatible with their prevailing sentiment. In addition, we argue if the change in sentiment around earnings announcements is unpredictable, trading against irrational investors' trades may become costly and risky for arbitrageurs, as a result, arbitrageurs may reduce the size of the position they take and become unable to drive stock prices back to fundamental values.

prices may not be at their fundamental values at the arrival of new information about earnings. Any abnormal price movement which cannot be explained by corporate earnings may be considered a mispricing, therefore, we investigate the relationship between mispricing and FSIS in the days preceding the earnings announcement. We examine the impact of FSIS in the context of earnings announcements as the expected direction of earnings announcements and the corresponding price reactions can be clearly developed and predicted. This allows us to formulate and examine our hypotheses in relation to the heterogeneous impact of FSIS.

In our analysis, we use data from a unique and comprehensive Twitter and StockTwits investor sentiment database; PsychSignal.[4] PsychSignal is a leading provider of real-time sentiment data to investors and traders covering more than 10,000 individual securities including all stocks in the NASDAQ100 and S&P500 indices.[5] PsychSignal investor sentiment database is based on the linguistic processing of millions of firm-related messages posted on Twitter and StockTwits analyzed by a highly specialized natural language processing (NLP) engine. We acknowledge that there may be certain limitations in using PsychSignal sentiment measures for our research purposes as the technical details of their algorithm are undisclosed due to confidentiality. However, using commercial providers' data such as PsychSignal is an improvement over self-collected and self-analyzed social media investor sentiment data.[6] PsychSignal's NLP engine process the language used in tweets the same way a professional trader would do, therefore, it is able to provide its subscribers with the most granular investor sentiment data. Furthermore, PsychSignal represents an accurate investor sentiment data set used by actual investors as it is a commercial provider that directly feeds analyzed Twitter and StockTwits data to its subscribers. PsychSignal's unique data set allows its users to account for the near-instant information flows in social media that might have a different effect on stock returns relative to information from other sources.

We construct our FSIS measure by using PsychSignal data for individual firms over the period 2011–2015 and analyze its impact on the announcement of 14,423 corporate earnings where actual earnings diverge from investment analysts' forecasts. We demonstrate that FSIS is heterogeneously related to abnormal stock returns during earnings surprises. Our results indicate that investors are more prone to behavioural biases around negative events, as the impact of FSIS on abnormal returns is larger for negative than for positive earnings surprises. This result is consistent with evidence that responses to negative and positive information are asymmetric due to a 'negativity bias' (e.g., Akhtar et al., 2011; Aragones, 1997; Baumeister et al., 2001; Chau et al., 2016; Kahneman & Tversky, 1979; Kanouse & Hanson, 1971; Kernell, 1977; Peeters, 1971; Ronis & Lipinski, 1985; Singh & Teoh, 2000). Our results also indicate that the impact of FSIS is larger for firms that face uncertainty in valuation and difficulty in arbitrage; small firms, young firms, firms with high return volatility, growth and value firms and non-dividend-paying firms. We also show that the impact of

[4]We use the daily data from PsychSignal which is based on social media feeds for the days before earnings announcements. See the Supporting Information: Internet Appendix Section A for further information about PsychSignal data.

[5]The need for new sources of information is highlighted by Goldstein and Yang (2015) who conclude that the information available to investors now is so complex that informed traders tend to specialize or have a comparative advantage in different types of financial information. Many traders seek to gain advantages in technology by subscribing to commercial services which supply live textual sentiment feeds.

[6]There has been a significant increase in the use of sentiment data of commercial providers among both market participants and academic researchers in recent years. There is prior evidence of secondary data of sentiment and other features, as provided by commercial providers, having significant effects on the financial markets. Indeed, Behrendt and Schmidt (2018) validate the relevance of Bloomberg sentiment data to stock markets and Cathcart et al. (2020) indicate that Thomson Reuters News Analytics media tone explains and predicts CDS returns.

FSIS on abnormal returns reverses, at least partially, over the days following the announcements, giving further support to the argument that the market reaction is an irrational short-term overreaction or underreaction to information (e.g., Baker & Wurgler, 2007; Da et al., 2015).

Our study makes several contributions to the literature. First, we contribute to the behavioural and corporate finance literature by highlighting the significance of FSIS in stock price formation during the announcement of new fundamental information to the market. We show that the impact of FSIS is greater for negative than positive earnings surprises suggesting that, due to a 'negativity effect', investors are affected more by sentiment at the announcement of negative than positive earnings surprises. Second, in an improvement over self-collected and self-analyzed social media sentiment data, we deploy a specialized natural language processing engine that uses an enormous lexicon evaluated by hundreds of trading professionals, thus, minimizing misclassification. Finally, prior literature has placed emphasis on the use of market-wide sentiment. We use a daily measure of investor sentiment which captures more accurately the effect of sentiment around significant corporate events.

Our study is closely related with Mian and Sankaraguruswamy (2012) and Bartov et al. (2018). Mian and Sankaraguruswamy (2012) use a monthly market-wide investor sentiment measure and study the moderating role of investor sentiment on the stock price sensitivity (*earnings response coefficient* [ERC]) to earnings surprises. We, instead, use a daily measure of FSIS and study the effect of investor sentiment on announcement period abnormal returns (*earnings announcement premium* [EAP]) by considering the moderating role of earnings news (positive vs. negative). We argue that there might be opposing moods towards various firms at the market level and, therefore, it is important to investigate the impact of FSIS on stock price movements around earnings announcements, in addition to market-wide investor sentiment. Bartov et al. (2018) find that the aggregate opinion provided by Twitter can be used to predict firms' forthcoming earnings and announcement returns. However, Bartov et al. (2018) examine the unconditioned impact of Twitter information on the EAP. In our study, we conduct a more nuanced analysis by examining the impact of Twitter information when conditioned on the type of earnings surprises (positive vs. negative). As negative news is expected to have a greater impact on investors than positive news, we argue that investors may be more prone to the prevailing sentiment at the announcement of negative earnings surprises. For example, investors may overweight information when they respond to negative earnings announcements due to a 'negativity effect' and as a result, their reactions become more irrational at the time of negative surprises. Our study is also related to the earnings announcement literature by Bartov et al. (2002), Kasznik and McNichols (2002), Kinney et al. (2002) and Lopez and Rees (2002), among others, that study earnings announcements, however, without considering the impact of FSIS. Our work contributes to the understanding of stock price formation around earnings announcements while considering the effect of FSIS.

The remainder of this paper proceeds as follows. Section 2 reviews the literature. Section 3 describes our sample selection and variables. Section 4 discusses the methodology and main results. Section 5 performs the robustness analysis. Section 6 concludes.

2 | LITERATURE REVIEW

The view that investor sentiment contains unique information for asset pricing and is a significant determinant of stock price variation is shared by many, including Black (1986), De Long et al. (1990), Daniel et al. (1998), Neal and Wheatley (1998) and Hirshleifer (2001). The consensus in the literature is that investors become overly optimistic (pessimistic) during periods of high (low) sentiment, making mistakes in the estimation of firms' expected cash flows, which leads to an overvaluation (undervaluation) that eventually reverses in time. Numerous studies validate the impact of investor sentiment in financial markets using a variety of sentiment measures including market-based measures, survey-based measures and nonfinancial factors (e.g., Baker & Wurgler, 2006; Chelley-Steeley et al., 2019; Hirshleifer & Shumway, 2003; Lemmon & Portniaguina, 2006; Shefrin, 2015).[7] A common thread in these studies is the acknowledgement that the effect of investor sentiment on price formation is not homogeneous across stocks or sectors and, therefore, it is important to use focused and direct investor sentiment measures. To this end, in recent years major developments have taken place in investor sentiment analysis using text-based machine learning and seeking to move the measurement issue away from market-based and survey-based variables toward real-time information sources (e.g., Aziz et al., 2022).[8] Multiple studies use Internet-based opinions to address this concern and the results suggest that Internet stock messages and social media platforms are valid sources of investor sentiment.[9] These findings illustrate that Internet-based investor sentiment measures have a significant impact on stock markets and individual stock performance.

Although the early research often covers small samples, examines short periods and focuses solely on technology stocks (e.g., Antweiler & Frank, 2004; Das & Chen, 2007; Tumarkin & Whitelaw, 2001), more recently research utilizes larger samples and longer periods to validate the impact of Internet-based investor sentiment measures in financial markets. Among the recent studies, Chen et al. (2014) analyze the reports and comments on a quasi-professional investor forum (Seeking Alpha) and find that sentiment has a statistically significant and economically meaningful impact on stock returns.[10] Da et al. (2011), Joseph et al. (2011) and Da et al. (2015) indicate that online searches on Google can predict stock prices and returns. Da et al. (2015) argue that their investment sentiment proxies based on Internet search behaviour provide information that is more timely than monthly macro surveys and more focused than market-based measures. Sprenger et al. (2014) find an association between Twitter investor sentiment and stock returns, message volume and trading volume and disagreement and volatility. They argue that Twitter users are exposed to the most recent information for all stocks. Danbolt et al. (2015) use Facebook's Gross National Happiness Index as a measure of investor sentiment and show that acquirers' abnormal returns are positively related to investor sentiment. Sun et al. (2016) illustrate that high-frequency investor sentiment based on a collection of news and social media content can predict intraday stock returns at the market level. Liew and Wang (2016) find

[7]These also include, among others, Neal and Wheatley (1998), Lee et al. (2002), Baker and Stein (2004), Brown and Cliff (2004, 2005), Edmans et al. (2007), Schmeling (2007), Bergman and Roychowdhury (2008), Kaplanski and Levy (2010), Brown et al. (2012), Hribar and McInnis (2012), Seybert and Yang (2012), Heiden et al. (2013), Huang et al. (2015), Baek (2016), Chau et al. (2016), Frijns et al. (2017), Li and Luo (2017), Aboody et al. (2018), Chen et al. (2019) and Gao et al. (2021).

[8]A parallel development has also occurred in the field of textual analysis of printed media and corporate reports with notable contributions made by Tetlock (2007) and Loughran and McDonald (2011) using dictionary-based analysis capturing the qualitative element of linguistic media and corporate filings.

[9]See Barber and Odean (2001) for an early overview of the impact of the Internet on investors and investor practices.

[10]Seeking Alpha is a popular social media platform for investors in the United States. However, there is concern that Seeking Alpha's articles do not necessarily represent traders' moods as investors' articles are generally reviewed by an editorial board and Seeking Alpha's contributors receive compensation depending on the number of page views that their articles receive. Therefore, it can be argued that accepted articles which receive attention do not necessarily reflect what investors find important. Ultimately, market participants and their perception of stock value determine market prices.

that there is a contemporaneous relationship between Initial Public Offerings' (IPO) tweet investor sentiment and stock returns on the first trading day and that prior days' IPO investor sentiment can predict first-day stock returns. Renault (2017) analyses messages published on the platform StockTwits and finds that the first half-hour change in investor sentiment derived from these messages predicts the last half-hour market returns. Similarly, Fan et al. (2020) use a large sample of tweets and find significant relations between bot tweets and stock returns, volatility and trading volume at both daily and intraday levels.

In addition, there are a few studies examining the impact of investor sentiment around earnings announcements that are closer to our work. Mian and Sankaraguruswamy (2012) study the moderating impact of market-wide investor sentiment on ERC around the announcements of unexpected earnings. Using the market-wide Baker and Wurgler's (2006) investor sentiment index, they show that investors react more to earnings news when is in line with the prevailing sentiment. They find that investor sentiment-driven momentum is embedded in the valuation of stocks; in bullish market periods the ERC is stronger for earnings above expectations and in bearish market periods the ERC is stronger for earnings below expectations. Mian and Sankaraguruswamy's (2012) study provides valuable insights into the relationship between market-wide investor sentiment and stock price sensitivity to unexpected earnings announcements, however, the use of a market-wide investor sentiment measure may not capture effectively various important aspects of investor sentiment for individual firms, particularly when there is high divergence in investor sentiment across firms. For instance, at the market level, there might be opposing moods towards different firms. Therefore, it seems more relevant to use a measure that reflects investor sentiment at the firm level. Indeed, Aboody et al. (2018) suggest that FSIS is better suited to address firm-level issues compared to market-wide investor sentiment measures. In our work, we apply an FSIS measure which can arguably represent more effectively the information flows for individual firms as it is found in social media, and study the effect of FSIS on the EAP by considering the moderating role of earnings news (positive vs. negative) instead.

In another study, Bartov et al. (2018) find that the aggregate opinion provided by Twitter can be used to predict firms' forthcoming earnings and announcement returns. However, in the analysis of the EAP, Bartov et al. (2018) examine the unconditioned impact of Twitter information. In our study, we conduct a more nuanced analysis by examining the impact of Twitter information when conditioned on the type of earnings surprises (positive vs. negative). Our motivation derives from a large body of research in social sciences that examines the asymmetric effect of positive and negative information in decision making. There is a tendency for negative information to be given more significance than positive information during valuations and it can be attributed to a 'negativity effect'. For example, in one of the earlier studies in psychology, Bolster and Springbett (1961) show that interviewers are more sensitive to negative information about the job applicant compared to positive ones. The authors find that negative information had a disproportionately larger effect on hiring decisions compared to positive information. Along similar lines, Fiske (1980) showed that subjects spend more time and effort looking at negative rather than positive stimuli. In a different study, Aragones (1997) constructs a dynamic model of political competition in which voters put more emphasis on the negative aspects of the parties' past performance than the positive ones. More specifically, voters' choices are driven by dissatisfaction rather than satisfaction with the policies chosen by the parties. Finally, in a study examining the link between investor sentiment and market reaction, Akhtar et al. (2011) find that the announcement of negative news induces a negative reaction which in absolute terms is much larger than the positive reaction induced by positive news. As a result, we argue that behavioural biases can justify a heterogeneous impact of FSIS on announcement period abnormal returns when the type of earnings news is taken into account.

Our research moves from a general consideration of market-wide investor sentiment to a particular consideration of FSIS and its impact on stock returns around earnings announcements, especially around negative events and for hard-to-value and difficult-to-arbitrage firms and, therefore, it provides new insights regarding the effect of investors' behavioural biases in the valuation of individual firms during an important corporate event such as an earnings announcement.

3 | DATA DESCRIPTION

This section describes the sample and provides the definitions of variables. It also presents the descriptive statistics of the variables.

3.1 | Data

Our sample consists of earnings surprises announced by companies listed on NYSE and NASDAQ markets between 1 January 2011 and 31 December 2015 and is obtained from the Institutional Brokers' Estimate System (I/B/E/S) database.[11] The primary requirement of our sample is that data on earnings surprises can be matched with a sample of companies covered by PsychSignal. We use daily PsychSignal's measures of bullish and bearish intensity to construct the main variable of interest; FSIS.[12] PsychSignal is a leading social media and sentiment analysis firm that uses an enormous lexicon of *n*-grams and has recently been deployed to analyze and test the effect of investor sentiment in various settings (e.g., Agrawal et al., 2018; Dong et al., 2022; Rakowski et al., 2021). PsychSignal firm-specific measures of bullish and bearish intensity represent the strength of optimism and pessimism revealed in tweets about firms. We combine these two measures to create a net measure of FSIS. Following Antweiler and Frank (2004), the *cumulative firm-specific investor sentiment* (CFSIS) is calculated as:

$$\mathrm{CFSIS}_{i,(-2,-1)} = \sum_{t=-2}^{-1} \mathrm{Ln}\left(\frac{1 + \text{Bullish inensity}_{i,t}}{1 + \text{Bearish intensity}_{i,t}}\right), \tag{1}$$

where firm *i*'s FSIS on Day *t* is defined as the natural logarithm of $(1 + \text{Bullish intensity}_{i,t})$ divided by $(1 + \text{Bearish intensity}_{i,t})$. The CFSIS is the sum of FSIS over a 2-day window, from 2 days before until 1 day before the earnings announcement date. When investor sentiment about a firm is bullish (bearish), CFSIS has a positive (negative) value, respectively.

[11]The start date of the sample is driven by the availability of sentiment data from PsychSignal.

[12]Social media platforms such as Twitter and StockTwits make available a huge amount of unstructured data (e.g., Big Data) that can be processed by text-based machine learning and be included in the decision-making process of economic agents (e.g., Aziz et al., 2022). Big Data are an important source of real-time estimation because of its high-frequency generation and acquisition at low cost.

The other main measures of investor sentiment are Baker and Wurgler's (2006) *monthly market-wide investor sentiment index* (B&W) and PsychSignal *daily market-wide mood indices* ($CMIS_{ndx}$ and $CMIS_{spx}$) which are collected from Jeffrey Wurgler's website and PsychSignal, respectively. Baker and Wurgler's (2006) investor sentiment index is based on six underlying market components: the closed-end fund discount, the NYSE share turnover, the number of IPOs, the average 1st-day returns on IPOs, equity share in new issues and the dividend premium. This index is available up to the end of September 2015 on Jeffrey Wurgler's website. Holt-Winters nonseasonal smoothing model is used to forecast the index for the months October, November and December 2015. The index is estimated for these 3 months based on the value of the index over the period January 2011 to September 2015. We also use PsychSignal mood indices to control for market-wide investor sentiment in our study. PsychSignal market-wide mood indices are real-time aggregated investor sentiment indices which measure commentators' sentiment on the NASDAQ100 and S&P500 stock market indices.

The earnings data which provides us with our measure of earnings surprise, published earnings and analysts' forecasts, comes from I/B/E/S. The primary measure of earnings surprise is the quarterly *standardized unexpected earnings* (SUE) and is the difference between actual earnings and the average of I/B/E/S analysts' forecast at the time of the earnings announcement adjusted for the standard deviation of analysts' forecasts:

$$\text{SUE} = \frac{\text{Actual EPS} - \text{Forecasted EPS}}{\sigma\,(\text{Forecasted EPS})}. \tag{2}$$

A positive (negative) earnings surprise consists of an actual earnings announcement that is higher (lower) than expectations. We measure earnings surprises against I/B/E/S analysts' forecasts as analysts' forecasts reflect more current information about firms. We define an *indicator variable of earnings surprises* (NEG), based on the value of SUE. NEG is equal to 1 if firms report negative unexpected earnings and 0 otherwise. It should be noted that in our study we explore the heterogeneous effect of FSIS on EAP and not the moderating effect on ERC. As a result, in our analysis, we use the indicator variable NEG instead of the continuous variable SUE, which is standard in the ERC literature, as it helps with the design of the multivariate regression analysis and the interpretation of the results.

To measure the short-term impact of investor sentiment, we use a 3-day event window and estimate the *cumulative abnormal returns* (CAR) over the window (0,+2) by obtaining data from the Center for Research in Security Prices (CRSP). Following Danbolt et al. (2015) our abnormal returns window commences on the day of the earnings announcement as small investors are likely to be more prone to sentiment and unlikely to be aware of potential leaks of information before earnings announcements.[13] CAR for the day of the earnings announcement and the two subsequent days are calculated as:

$$\text{CAR}_{i,(0,+2)} = \sum_{t=0}^{+2}\Big(R_{i,t} - \big(\alpha_i + \beta_i R_{m,t}\big)\Big). \tag{3}$$

[13]We estimate CAR by subtracting the expected stock return ($E(R_{i,t})$) from the actual stock return ($R_{i,t}$). The expected return ($E(R_{i,t})$) is calculated as ($\alpha_i + \beta_i R_{m,t}$) using the market model parameters estimated over the period between 300 and 46 days before the earnings announcement. The CRSP value-weighted index return is the market return ($R_{m,t}$).

It should be noted that the FSIS variable (CFSIS) measures sentiment over the window (−2,−1) and the measure of stock returns (CAR) measures abnormal returns over the window (0,+2). This design is appropriate because it helps to examine the short-term causal relation between investor sentiment and CAR and mitigate the reverse causality issue.

While our focus is on the impact of FSIS on stock returns around earnings surprises, we incorporate several firm characteristics in our analysis. Other firm characteristics that are controlled for are *loss* (LOSS), *book-to-market ratio* (BM), *size* (SIZE), *leverage* (LEVERAGE), *return on assets* (ROA), *stock price momentum* (MOMENTUM), *cumulative abnormal stock-trading volume* (CAV) and *abnormal short interest* (ASI). Including these control variables allow us to test the independent impact of FSIS from the impact of these variables on CAR. Our firm variables are constructed from standard data sources; price and trading volume data are obtained from CRSP and accounting data are from Compustat. A detailed definition of all variables is presented in the Appendix.

3.2 | Summary statistics

Table 1 reports summary statistics for the overall sample and further partitions the sample by type of earnings surprises, announcement year, sector and stock exchange listing. Our sample contains 14,423 earnings surprises over the period 2011–2015. Only a small proportion of the sample (4.24%) is drawn from the year 2011 as Twitter and StockTwits had not gained critical mass as a vehicle for comments on firms at that point then. Overall, 63.37% of the earnings announcements represent positive news, whereas the remaining 36.63% of the earnings announcements represent negative news.

Table 2 displays descriptive statistics for the key variables. Nonbinary variables, apart from SIZE that is log-transformed, are winsorized at 1% and 99% of their respective distributions to mitigate the impact of outliers. LEVERAGE is winsorized only at 99% of its distribution. Table 2 offers initial indications that the stock price reaction is more marked for negative earnings surprises and that FSIS and B&W capture different aspects of investor sentiment in the market. We find that the stock price response to earnings surprises, the mean of CAR, is close to zero which implies that although there are significantly more positive than negative earnings surprises in the sample, the price reaction is more marked for negative earnings surprises. The mean of CFSIS is a positive 0.5935, which illustrates that the average investor sentiment has been bullish. B&W, however, has a negative mean close to zero, which shows that during the sample period overall investor mood has been neutral. The opposing signs between CFSIS and B&W can be considered as a first indication that these two variables capture different aspects and levels of investor sentiment. A comparison of the standard deviations also highlights the differences between the variables. CFSIS has a standard deviation of 0.8847 and B&W has a standard deviation of 0.0972, which indicates that FSIS is more volatile than market-wide investor sentiment. This is to be expected as the heterogeneity of sentiment for CFSIS is larger due to the firm-level focus. It is important to keep in mind that during the period of this study, market-wide investor sentiment is neither high nor low and as a result, it is not likely to play a significant role in the stock price reaction to earnings announcements. For example, looking at the Baker and Wurgler monthly index, the bottom 30% and top 30% (i.e., low and high investor sentiment) are around −0.33 and 0.31, respectively. Given that our sample's minimum and maximum market-wide investor

TABLE 1 Summary statistics

This table reports summary statistics by earnings surprises, announcement year, sector and market. The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. Standardized unexpected earnings (SUE) is measured as the difference between the Institutional Brokers' Estimate System (I/B/E/S) actual earnings and the average of estimates at the release of earnings, divided by the standard deviation of forecasts. Positive (negative) SUE consists of actual earnings that are higher (lower) than the average of I/B/E/S analyst forecasts. Announcement year is earnings announcement calendar year. Sector is classified based on Global Industry Classification Standard (GICS) and stock exchange is the market that stocks are traded on.

	N	%		*N*	%
Sample	14,423	100.00	Sector		
			Energy	1,269	8.80
			Materials	823	5.71
			Industrials	1,688	11.70
Positive and negative SUE			Consumer discretionary	2,346	16.27
SUE > 0	9,140	63.37	Consumer staples	612	4.24
SUE < 0	5,283	36.63	Health care	1,889	13.10
			Financials	2,233	15.48
			Information technology	2,974	20.62
Announcement year			Communication services	204	1.41
2011	612	4.24	Utilities	385	2.67
2012	1,907	13.22			
2013	3,060	21.22	Stock exchange		
2014	4,622	32.05	NYSE	8,605	59.66
2015	4,222	29.27	NASDAQ	5,818	40.34

sentiment values are −0.21 and 0.29, it is reasonable to assume that the period we examine is a period of moderate investor sentiment in the market.[14]

Table 3 presents the correlations of the variables. There is a positive correlation between CAR and CFSIS, suggesting that positive (negative) abnormal returns are associated with bullish (bearish) FSIS. In addition, CAR is positively correlated with SUE, suggesting that abnormal returns are higher (lower) for firms experiencing positive (negative) earnings surprises. Importantly, the positive correlation between CFSIS and SUE is only 0.1234, which indicates that the FSIS variable is not affected by multicollinearity with earnings surprises. This suggests that FSIS is not a mere reflection of the information about the firms' actual earnings; a signed news flow, but it represents users' beliefs about firms that are beyond the fundamental hard information that is included in actual earnings. From this preliminary description of the univariate statistics, it seems that FSIS captures an element of soft information which is not captured by the earnings surprise alone. This should be examined through a multivariate

[14]We thank an anonymous referee for pointing this out.

TABLE 2 Descriptive statistics: key variables

This table reports descriptive statistics of the key variables in this study; cumulative abnormal returns (CAR), cumulative firm-specific investor sentiment (CFSIS), standardized unexpected earnings (SUE), Baker and Wurgler's (2006) sentiment index (B&W), loss (LOSS), book-to-market ratio (BM), size (SIZE), leverage (LEVERAGE), return on assets (ROA), stock price momentum (MOMENTUM), cumulative abnormal stock-trading volume (CAV) and abnormal short interest (ASI). The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. See Appendix for detailed definitions of the variables. Firm-specific investor sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Jeffrey Wurgler's website. Earnings data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock price, trading volume and index return data come from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat.

	N	Mean	Median	SD	Min.	Max.
CAR	14,423	−0.0004	0.0006	0.0845	−0.2662	0.2488
CFSIS	14,423	0.5935	0.6043	0.8847	−1.4872	2.4749
SUE	14,423	0.9913	0.6667	3.6807	−10.8136	16.5344
B&W	14,423	−0.0129	−0.0263	0.0972	−0.2072	0.2909
LOSS	14,423	0.2070	0.0000	0.4052	0.0000	1.0000
BM	14,418	0.4819	0.3899	0.3988	−0.3813	1.9598
SIZE	14,418	7.5559	7.5175	1.7314	2.0819	12.8383
LEVERAGE	14,344	0.2539	0.2291	0.2197	0.0000	0.8784
ROA	14,416	−0.0084	0.0296	0.1820	−0.9204	0.2822
MOMENTUM	13,505	−0.0406	−0.0312	0.4727	−1.5488	1.5330
CAV	14,374	0.5228	−0.6983	15.3825	−120.5106	104.5484
ASI	14,385	0.0010	0.0002	0.0128	−0.0431	0.0531

regression analysis, where abnormal returns are conditioned on both CFSIS and earnings surprises. It is also important to highlight that there is no high correlation between CFSIS and MOMENTUM, CAV and ASI ahead of the earnings announcements, which indicates that FSIS does not represent potential leaks of information before the announcements.[15]

4 | METHODOLOGY AND RESULTS

This section presents the methodology we use to examine the heterogeneous effect of FSIS on the EAP. It also presents the results of the multivariate regression analysis. We follow an event study methodology to examine whether FSIS is a significant factor of CAR during earnings announcements.

[15]Multicollinearity tests are conducted to ensure that the variables are not highly correlated with each other. The results of the variance inflation factor (VIF) tests show that there is no multicollinearity problem as VIF values are substantially lower than 10.

TABLE 3 Correlation matrix

This table reports the correlation matrix of the variables used in this study as Table 2. The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. See Appendix for detailed definitions of the variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) CAR	1.0000											
(2) CFSIS	0.1244	1.0000										
(3) SUE	0.2797	0.1234	1.0000									
(4) B&W	0.0066	−0.0215	0.0045	1.0000								
(5) LOSS	−0.0981	−0.0470	−0.2244	0.0008	1.0000							
(6) BM	0.0162	0.0173	−0.0563	0.0243	−0.0259	1.0000						
(7) SIZE	0.0241	−0.0444	0.0706	−0.0154	−0.4137	−0.1553	1.0000					
(8) LEVERAGE	0.0159	0.0244	−0.0946	−0.0069	−0.1067	−0.0252	0.1301	1.0000				
(9) ROA	0.0313	0.0000	0.0759	−0.0032	−0.6057	0.0513	0.4401	0.0799	1.0000			
(10) MOMENTUM	−0.0194	0.0700	0.0351	−0.0495	−0.0091	0.0494	−0.0392	−0.0026	−0.0767	1.0000		
(11) CAV	−0.0264	0.0053	−0.0235	−0.0230	0.0581	−0.0324	−0.0712	−0.0150	−0.1246	0.1420	1.0000	
(12) ASI	−0.0233	−0.0248	−0.0042	−0.0305	0.0381	−0.0417	−0.0323	−0.0366	−0.0388	−0.0293	0.2368	1.0000

TABLE 4 Firm-specific investor sentiment (FSIS) and earnings surprises: univariate results

This table reports cumulative abnormal returns (CAR) for four firm subsamples. The sample is split into subsamples that reflect prevailing sentiment (CFSIS) ahead of positive and negative earnings surprises (standardized unexpected earnings [SUE]). The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. Cumulative abnormal returns are calculated over the 3-day event window (0,+2), where Day 0 is the earnings announcement date. Abnormal returns are estimated by subtracting the expected stock return from the actual stock return. The expected returns are calculated using the market model parameters estimated over the period between 300 and 46 days before the earnings announcement. The CRSP value-weighted index return is the market return. CFSIS is a cumulative FSIS index over a 2-day window from 2 days before the earnings announcement date until 1 day before the date of the announcement, where FSIS is measured as the natural logarithm of (1 + bullish intensity)/(1 + bearish intensity). SUE is measured as the difference between the Institutional Brokers' Estimate System (I/B/E/S) actual earnings and the average of estimates at the release of earnings, divided by the standard deviation of forecasts. Panel A presents the results for positive earnings surprises (SUE) and Panel B presents the results for negative earnings surprises (SUE). The p values reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Positive SUE	***N***	**CAR**
Positive CFSIS $[a]$	6,732	0.0203***
		(0.0000)
Negative CFSIS $[b]$	1,945	0.0056**
		(0.0104)
Difference $[a - b] = 0$		0.0148***
		(0.0000)
Panel B: Negative SUE	***N***	**CAR**
Negative CFSIS $[a]$	1,563	−0.0443***
		(0.0000)
Positive CFSIS $[b]$	3,077	−0.0241***
		(0.0000)
Difference $[a - b] = 0$		−0.0202***
		(0.0000)

4.1 | FSIS and earnings surprises: univariate results

To examine the heterogeneous effect of FSIS on EAP, we first undertake a univariate analysis of the relationship between FSIS and negative/positive earnings surprises' CAR. The sample is split into subsamples that represent the prevailing investor sentiment ahead of the earnings announcements. Table 4 presents the stock price responses to negative/positive earnings surprises across both positive and negative CFSIS portfolios.[16] We observe that the relationship between earnings surprises and FSIS is not always linear. Some firms with positive earnings

[16]Firms with zero sentiment are not included in this analysis.

surprises have negative sentiment and *vice versa*. This observation is consistent with the low correlation between SUE and CFSIS reported in Table 3 (0.1234). We find that CFSIS is significantly related to stock price responses to earnings surprises. Furthermore, when we compare the responses to positive earnings surprises (Panel A), we observe that the market reaction is stronger for the positive CFSIS portfolio (CAR of 2.03%) than for the negative CFSIS portfolio (CAR of 0.56%). The difference in returns between the two portfolios is statistically and economically significant.

Similarly, when we compare the stock price responses to negative earnings surprises (Panel B), we observe that the market reaction is stronger for the negative CFSIS portfolio (−4.43%) than for the positive CFSIS portfolio (−2.41%). The difference in returns between the two portfolios is statistically and economically significant. These results support our hypothesis that FSIS is heterogeneously related to announcement returns. When the direction of earnings surprises and FSIS is the same, the stock price reaction to surprises is stronger. However, when the direction of earnings surprises and FSIS is opposite, the stock price reaction is weaker. It seems that the effect of FSIS on abnormal returns needs to be conditioned on the information from the earnings surprises (positive vs. negative) to understand its implications.

4.2 | FSIS and earnings surprises: multivariate results

In this section, we use a multivariate regression analysis to examine the heterogeneous impact of FSIS on CAR. More specifically, we test whether the relationship between FSIS and CAR is different in the announcement of negative relative to positive earnings surprises.

As previously highlighted, the literature suggests that negative information has a greater impact on decision making than positive information due to a 'negativity bias' (e.g., Akhtar et al., 2011; Aragones, 1997; Baumeister et al., 2001; Chau et al., 2016; Kahneman & Tversky, 1979; Kanouse & Hanson, 1971; Kernell, 1977; Peeters, 1971; Ronis & Lipinski, 1985; Singh & Teoh, 2000). In this respect, we argue that as negative news is expected to have a greater impact on investors than positive news, investors may be more prone to the prevailing sentiment at the announcement of negative earnings surprises. For example, investors may overweight information when they respond to negative earnings announcements and as a result, their reactions become more irrational at the time of negative surprises. We believe that FSIS should have a larger impact on the announcement of earnings below expectations (negative surprises) compared to the announcement of earnings above expectations (positive surprises). We expect that when FSIS is bearish (bullish), it reinforces (moderates) the negative impact of an earnings disappointment and leads to lower (higher) abnormal returns.

We consider a variety of regression models which range from parsimonious ones (using only FSIS and earnings surprises) to models that incorporate additional control variables known to affect abnormal returns around earnings announcements. The dependent variable in all regression models is the 3-day CAR, which is used to analyze the market response at the arrival of new earnings information and the impact of accumulated short-term investor sentiment just before the release of new information. The regression model takes the following form:

$$\begin{aligned} \mathrm{CAR}_{i,(0,+2)} = \alpha + \beta_1 \mathrm{CFSIS}_{i,(-2,-1)} + \beta_2 \mathrm{NEG} + \beta_3 \mathrm{CFSIS}_{i,(-2,-1)} \times \mathrm{NEG} + \sum \mathrm{CONTROLS} \\ + \mathrm{YEAR\ F.\ E.} + \mathrm{SECTOR\ F.\ E.} + \epsilon, \end{aligned} \tag{4}$$

where CAR is cumulative abnormal returns, CFSIS is cumulative firm-specific investor sentiment and NEG is an indicator variable for negative SUE. Control variables (CONTROLS) include Baker and Wurgler's investor sentiment index (B&W), firm loss (LOSS), book-to-market ratio (BM), firm size (SIZE), leverage ratio (LEVERAGE), return on assets (ROA), stock price momentum (MOMENTUM), cumulative abnormal trading volume (CAV) and abnormal short interest (ASI).

We control for the impact of Baker and Wurgler's (2006) investor sentiment index in our regression models. The inclusion of a macro measure of investor sentiment allows a separate examination of the roles of firm-specific and market-wide investor sentiment in the price formation process. As Baker and Wurgler's (2006) investor sentiment index represents the broad market mood, it might overlap with firm-specific mood.[17] The effect of FSIS on investors' responses to earnings announcements might, therefore, be attributed to the prevailing sentiment at the aggregate level. Furthermore, we add other control variables to measure the effect of FSIS over and above these variables. In this respect, the following control variables are used: LOSS, BM, SIZE, LEVERAGE, ROA, MOMENTUM, CAV and ASI. We consider three different proxies for stock price momentum and information leakage before earnings announcements (MOMENTUM, CAV and ASI) to make sure that the effect of CFSIS on abnormal returns is not conflated by such considerations (Henry et al., 2015; Sanders & Zdanowicz, 1992; Schwert, 1996). All models include year and sector fixed effects to control for these broad characteristics that may influence the relationship between the dependent and independent variables. Additionally, in all models, we adjust the standard errors for heteroskedasticity and clustering at the firm level.

Finally, to examine the heterogeneous impact of FSIS, we use an interaction analysis between CFSIS and NEG. In Equation (4) the coefficient β_1 represents the impact (slope) of CFSIS in predicting CAR for firms with positive earnings surprises (NEG = 0). The coefficient β_3 represents the incremental impact (change in slope) and the sum of the coefficients ($\beta_1 + \beta_3$) represents the impact (slope) of CFSIS in predicting CAR for firms with negative earnings surprises (NEG = 1).

The hypothesis that the impact of FSIS on CAR is significant, but different between earnings surprises, implies that $\beta_1, \beta_3 > 0$. As β_1 and β_3 contain information that reciprocally affects their estimation, it is suggested to use a joint hypothesis (*Wald Test*) that assumes dependent parameters, *H0*: $(\beta_1 + \beta_3) = 0$ versus *H1*: $(\beta_1 + \beta_3) > 0$ and not separate hypotheses (t test) that assume independent parameters, to reduce statistical errors in our inferences.

Table 5 presents the results of the multivariate regression analysis. All models include CFSIS, NEG and their interaction term. Our primary focus is on the coefficients β_1 and β_3 and their joint effect ($\beta_1 + \beta_3$). In column (1), we find that the coefficient of CFSIS for positive earnings surprises is positive (0.0061) and significant at 1% level and that the incremental coefficient of CFSIS for negative earnings surprises is positive (0.0053) and significant at 1% level. Additionally, the coefficient of CFSIS for negative earnings surprises is positive (0.0061 + 0.0053 = 0.0114) and significant at a 1% level based on the one-tailed p value of the Wald test which is reported at the bottom of the table. The results indicate a statistically and economically significant difference between the impact of CFSIS for negative and positive

[17]However, given the low correlation between our firm-specific and market-wide investor sentiment (see Table 3) this is less likely to be the case. In addition, as already mentioned in Section 3.2, our period falls into a medium market-wide sentiment period and as a result, the effect of market-wide sentiment is not expected to be as strong.

TABLE 5 Firm-specific investor sentiment (FSIS) and earnings surprises: multivariate results

This table reports the results of the ordinary least squares regressions of cumulative abnormal returns (CAR) on cumulative firm-specific investor sentiment (CFSIS) and negative earnings surprises (NEG). The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. Cumulative abnormal returns are calculated over the 3-day event window (0,+2), where Day 0 is the earnings announcement date. Abnormal returns are estimated by subtracting the expected stock return from the actual stock return. The expected returns are calculated using the market model parameters estimated over the period between 300 and 46 days before the earnings announcement. The CRSP value-weighted index return is the market return. CFSIS is a cumulative FSIS index over a 2-day window from 2 days before the earnings announcement date until 1 day before the date of the announcement, where FSIS is measured as the natural logarithm of (1 + bullish intensity)/(1 + bearish intensity). See Appendix for detailed definitions of the variables. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t statistics reported in parentheses are adjusted for heteroskedasticity and stock clustering. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Wald tests of linear hypotheses and one-tailed p values are reported at the bottom.

	(1)	(2)	(3)	(4)	(5)
CFSIS [β_1]	0.0061***	0.0059***	0.0058***	0.0058***	0.0058***
	(5.93)	(5.62)	(5.64)	(5.63)	(5.59)
NEG	−0.0474***	−0.0473***	−0.0464***	−0.0463***	−0.0472***
	(−26.08)	(−24.58)	(−24.94)	(−24.98)	(−24.49)
CFSIS × NEG [β_3]	0.0053***	0.0050***	0.0058***	0.0057***	0.0050***
	(3.29)	(3.03)	(3.57)	(3.57)	(3.04)
B&W		0.0145	0.0169*	0.0174*	0.0139
		(1.56)	(1.86)	(1.92)	(1.49)
LOSS		−0.0120***	−0.0122***	−0.0120***	−0.0121***
		(−4.17)	(−4.41)	(−4.34)	(−4.18)
BM		0.0075***	0.0068***	0.0069***	0.0073***
		(3.46)	(3.26)	(3.30)	(3.37)
SIZE		−0.0002	−0.0005	−0.0005	−0.0003
		(−0.53)	(−1.14)	(−1.10)	(−0.61)
LEVERAGE		0.0121***	0.0122***	0.0123***	0.0120***
		(3.49)	(3.68)	(3.71)	(3.44)
ROA		−0.0140**	−0.0138**	−0.0125**	−0.0143**
		(−2.07)	(−2.16)	(−1.97)	(−2.09)
MOMENTUM		−0.0066***			−0.0067***
		(−3.25)			(−3.25)
CAV			−0.0017**		−0.0002
			(−2.01)		(−0.25)
ASI				−0.1059	−0.1252*
				(−1.52)	(−1.69)

TABLE 5 (Continued)

	(1)	(2)	(3)	(4)	(5)
CONSTANT	0.0090**	0.0012	0.0041	0.0034	0.0020
	(2.39)	(0.19)	(0.67)	(0.56)	(0.32)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
N	14,423	13,427	14,283	14,294	13,407
Adjusted R^2	0.0799	0.0884	0.0837	0.0834	0.0886
Wald test: $[\beta_1 + \beta_3] = 0$	58.85	50.24	56.77	56.59	50.03
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

surprises, as the coefficient of CFSIS is 87% larger for negative relative to positive earnings surprises.

In columns (2)–(5), we include additional control variables to re-examine these relationships and observe the same patterns. In particular, in column (5)—which includes all the control variables—the coefficient of CFSIS is positive (0.0058) and significant at 1% level and the incremental coefficient of CFSIS is positive (0.0050) and significant at 1% level. Also, the joint coefficient of CFSIS is positive ($0.0058 + 0.0050 = 0.0108$) and significant at 1% level. These results indicate a statistically and economically significant difference between the impact of CFSIS on negative and positive surprises, as the coefficient of CFSIS is 86% larger for negative relative to positive earnings surprises. Notably, in columns (3) and (4), this difference is even more striking, as the coefficient of CFSIS is 100% larger for negative relative to positive earnings surprises.

The impact of the control variables is in line with prior studies (e.g., Baker & Wurgler, 2006; DeHaan et al., 2015; Hayn, 1995; Savor & Wilson, 2016). Consistent with prior studies, our results show that negative earnings surprises are negatively related to CAR as the coefficient of NEG is negative and significant at a 1% level in all models. We find that CAR is negatively related to firms reporting a loss and having a high level of ROA, MOMENTUM, CAV and ASI ahead of earnings announcements. CAR is also influenced by B&W, BM and LEVERAGE as it tends to be higher for firms with a high level in these measures.

In summary, this section shows that, in general, FSIS affects abnormal returns for both positive and negative earnings surprises and that, in particular, its effect is stronger for negative earnings surprises, thus providing support to our research question.

4.3 | FSIS and hard-to-value/difficult-to-arbitrage firms

To better gauge the heterogeneous impact of FSIS on market participants' valuations of earnings across firms, we continue our analysis by considering special cases where investor sentiment may have a greater influence on stock returns, namely, firms which face uncertainty in valuation and firms with limits to arbitrage. We conjecture that the effect of FSIS should be more pronounced for firms that are subject to greater uncertainty and are difficult to arbitrage.

As prior studies suggest that the effect of investor sentiment may differ systematically across firms (e.g., Baker & Wurgler, 2006, 2007; Joseph et al., 2011), we examine also whether the effect of FSIS is more pronounced for hard-to-value and difficult-to-arbitrage firms. Following Baker and Wurgler (2006) and Mian and Sankaraguruswamy (2012), we use five individual firm characteristics for which investor sentiment may differ, namely, size, age, volatility, book-to-market ratio and dividend payout, to classify our observations into subsamples. Baker and Wurgler (2006) and Mian and Sankaraguruswamy (2012) suggest that small, young, volatile (high volatility), distressed (firms with a high book-to-market ratio), extreme growth (firms with a low book-to-market ratio) and non-dividend-paying firms are more likely to be affected by investor sentiment, while large, mature, stable (low volatility), medium growth and high-dividend-paying firms are less likely to be affected by investor sentiment. They argue that in the first group, firms are hard to value and difficult to arbitrage and this makes them especially prone to changes in investor sentiment.

To test for cross-sectional differences in the impact of FSIS, we use each individual firm characteristic to form groups that are more or less exposed to investor sentiment. The first characteristic, *size*, is the market capitalization of the firm in the month before the earnings announcement. We classify firms that fall in the bottom (top) quintile using NYSE breakpoints as small (large) firms. The second characteristic, *age*, is the number of months since the firm first appeared on CRSP in the month before the earnings announcement. We classify firms that fall in the bottom (top) quintile using NYSE breakpoints as young (mature) firms. The third characteristic, *volatility*, is the standard deviation of daily returns over the (−202,−3) day interval before the earnings announcement. We classify firms that fall in the top (bottom) quintile sorted on volatility as firms with a high (low) level of volatility. The fourth characteristic, *book-to-market ratio*, is the book value of equity divided by the market value of equity in the year before the earnings announcement. We classify firms that fall in the top and bottom (other) quintiles sorted on book-to-market ratio as growth and value (staid) firms. The fifth characteristic, *dividend payout*, is the annual dividend divided by the annual earnings in the year before the earnings announcement. We classify firms that do not pay dividends as nonpayers and firms that fall in the top quintile of the remaining dividend-paying firms sorted on dividend payout as high payers.

The results of this analysis are presented in Table 6. The first group for each characteristic is expected to be more exposed to FSIS and the second group is expected to be less exposed to FSIS. In this analysis, our focus is on the joint coefficient of CFSIS ($\beta_1 + \beta_3$) (slope) and the incremental impact (change in slope) between exposed and nonexposed groups. To this end, at the bottom of Table 6, we use two sets of Wald tests. First, a test for the impact of CFSIS ($\beta_1 + \beta_3$) in each group separately similar to the analysis in Table 5 and second, a test for the difference (change in slope) of CFSIS ($\beta_1 + \beta_3$) between groups, *H0*: Exposed ($\beta_1 + \beta_3$) = Nonexposed ($\beta_1 + \beta_3$) versus *H1*: Exposed ($\beta_1 + \beta_3$) > Nonexposed ($\beta_1 + \beta_3$).

In Table 6, columns in odd numbers represent *exposed* while columns in even numbers represent *nonexposed* groups. We observe that for all five groups the coefficient of CFSIS ($\beta_1 + \beta_3$) is positive and significant at 1% level, with the only exception of the coefficient for mature firms in column (4), which is insignificant at conventional levels. We also observe that for all five groups the difference of CFSIS ($\beta_1 + \beta_3$) between exposed and nonexposed firms has the expected positive sign and is statistically significant at conventional levels. For example, in columns (1) and (2), the coefficient of CFSIS for small firms is (0.0047 + 0.0082 = 0.0129), while the coefficient of CFSIS for large firms is (0.0051 + 0.0021 = 0.0072) and their difference (0.0057) is statistically significant at 5% level. We observe similar differences and statistical significance between the exposed and nonexposed firms in all four remaining characteristics (age, volatility, book-to-market ratio and dividend payout).

TABLE 6 Firm-specific investor sentiment (FSIS) and hard-to-value/difficult-to-arbitrage firms

This table reports the results of the ordinary least squares regressions of cumulative abnormal returns (CAR) on cumulative firm-specific investor sentiment (CFSIS) for difficult-/easy-to-value firms and high/low limits to arbitrage firms. The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. Cumulative abnormal returns are calculated over the 3-day event window (0,+2), where Day 0 is the earnings announcement date. Abnormal returns are estimated by subtracting the expected stock return from the actual stock return. The expected returns are calculated using the market model parameters estimated over the period between 300 and 46 days before the earnings announcement. The CRSP value-weighted index return is the market return. CFSIS is a cumulative FSIS index over a 2-day window from 2 days before the earnings announcement date until 1 day before the date of the announcement, where FSIS is measured as the natural logarithm of (1 + bullish intensity)/(1 + bearish intensity). Size is the market capitalization of the firm in the month before the earnings announcement. We classify firms that fall in the bottom (top) quintile using NYSE breakpoints as small (large) firms. Age is the number of months since the firm first appeared on CRSP in the month before the earnings announcement. We classify firms that fall in the bottom (top) quintile using NYSE breakpoints as young (mature) firms. Volatility is the standard deviation of daily returns over the (−202,−3) day interval before the earnings announcement. We classify firms that fall in the top (bottom) quintile sorted on volatility as firms with a high (low) level of volatility. Book-to-market ratio is the book value of equity divided by the market value of equity in the year before the earnings announcement. We classify firms that fall in the top and bottom (other) quintiles sorted on book-to-market ratio as growth and value (staid) firms. Dividend payout is the annual dividend divided by the annual earnings in the year before the earnings announcement. We classify firms that do not pay dividends as nonpayers and firms that fall in the top quintile of the remaining dividend-paying firms sorted on dividend payout as high payers. See Appendix for detailed definitions of the variables. All regressions control for year and sector fixed effects whose coefficients are suppressed. The *t* statistics reported in parentheses are adjusted for heteroskedasticity and stock clustering. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Wald tests of linear hypotheses and one-tailed *p* values are reported at the bottom.

	Size		**Age**		**Volatility**		**Book-to-market ratio**		**Dividend payout**	
	Small	**Large**	**Young**	**Mature**	**High**	**Low**	**Growth and value**	**Staid**	**Nonpayers**	**High payers**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
CFSIS [β_1]	0.0047	0.0051***	0.0071***	0.0035	0.0080**	0.0050***	0.0057***	0.0060***	0.0086***	0.0053**
	(1.60)	(3.92)	(5.05)	(1.30)	(2.21)	(4.57)	(2.91)	(4.88)	(4.80)	(2.50)
NEG	−0.0624***	−0.0260***	−0.0501***	−0.0416***	−0.0578***			−0.0446***	−0.0593***	
	(−13.24)	(−9.03)	(−20.03)	(−4.50)	(−10.92)			(−19.08)	(−18.70)	
CFSIS × NEG [β_3]	0.0082**	0.0021	0.0051**	0.0004	0.0029	0.0001	0.0077***	0.0030	0.0027	0.0018
	(2.00)	(0.89)	(2.36)	(0.06)	(0.55)	(0.06)	(2.73)	(1.49)	(0.92)	(0.60)

(Continues)

TABLE 6 (Continued)

	Size		Age		Volatility		Book-to-market ratio		Dividend payout	
	Small	Large	Young	Mature	High	Low	Growth and value	Staid	Nonpayers	High payers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
B&W	0.0177	−0.0061	0.0246**	−0.0321	0.0558*	−0.0026	0.0309**	0.0037	0.0180	0.0146
	(0.74)	(−0.45)	(2.00)	(−0.90)	(1.76)	(−0.26)	(2.02)	(0.32)	(1.12)	(0.68)
LOSS	−0.0241***	0.0034	−0.0132***	−0.0211	−0.0210***	−0.0012	−0.0095**	−0.0154***	−0.0099**	−0.0132**
	(−4.81)	(0.57)	(−3.88)	(−0.91)	(−3.28)	(−0.29)	(−2.25)	(−3.88)	(−2.51)	(−2.05)
BM	0.0098**	−0.0030	0.0086***	0.0100	0.0052	−0.0002	0.0057**	0.0107*	0.0067*	−0.0014
	(2.10)	(−0.84)	(3.32)	(0.61)	(0.98)	(−0.07)	(2.10)	(1.94)	(1.84)	(−0.29)
SIZE	0.0034	0.0013	0.0005	−0.0019	0.0003	−0.0008	−0.0004	0.0001	0.0002	−0.0013
	(1.32)	(1.01)	(0.82)	(−0.87)	(0.14)	(−1.38)	(−0.62)	(0.21)	(0.26)	(−1.13)
LEVERAGE	0.0116	0.0045	0.0132***	0.0172	0.0214*	0.0045	0.0166***	0.0053	0.0148**	−0.0165**
	(1.28)	(0.77)	(3.17)	(0.57)	(1.75)	(1.05)	(3.33)	(1.08)	(2.52)	(−2.11)
ROA	−0.0260**	−0.0008	−0.0241***	−0.1717***	−0.0171	−0.0337	−0.0037	−0.0284***	−0.0141	−0.0422
	(−2.49)	(−0.03)	(−3.00)	(−3.22)	(−1.49)	(−1.36)	(−0.40)	(−2.79)	(−1.60)	(−1.13)
MOMENTUM	−0.0071**	−0.0025	−0.0052**	−0.0309**	−0.0066**	−0.0094**	−0.0076**	−0.0059**	−0.0050*	−0.0018
	(−2.21)	(−0.44)	(−2.27)	(−2.13)	(−2.06)	(−2.04)	(−2.39)	(−2.30)	(−1.94)	(−0.29)
CONSTANT	−0.0065	−0.0038	−0.0052	0.0134	−0.0233	0.0161**	0.0009	0.0005	−0.0073	0.0295**
	(−0.31)	(−0.27)	(−0.65)	(0.41)	(−1.08)	(1.99)	(0.09)	(0.06)	(−0.63)	(1.97)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 6 (Continued)

	Size		Age		Volatility		Book-to-market ratio		Dividend payout	
	Small	Large	Young	Mature	High	Low	Growth and value	Staid	Nonpayers	High payers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
N	3,322	2,440	8,887	386	2,433	2,827	5,279	8,148	6,533	1,333
Adjusted R^2	0.1107	0.0567	0.0889	0.1380	0.0846	0.1010	0.0903	0.0869	0.0936	0.0798
Wald Test: $[\beta 1 + \beta_3] = 0$	11.00	16.33	39.52	0.87	6.30	17.47	25.10	26.97	22.85	7.97
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.2118)	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Wald test: E $[\beta_1 + \beta_3] = \text{NE}[\beta_1 + \beta_3]$	2.75		1.68		2.00		2.89		1.70	
(p value)	(0.0487)		(0.0974)		(0.0787)		(0.0446)		(0.0959)	

As a robustness test, presented in the Supporting Information: Internet Appendix Section B, Table B.1, we use principal component analysis (PCA) and create a composite measure between the five characteristics for exposed and nonexposed firms. In Table B.1 the coefficient of CFSIS for exposed firms is ($0.0084 + 0.0039 = 0.0123$), while the coefficient of CFSIS for nonexposed firms is ($0.0051 + 0.0013 = 0.0064$) and their difference (0.0059) is statistically significant at 10% level. This difference appears economically important as well, as the coefficient of CFSIS is 92% larger for exposed relative to nonexposed firms.

In summary, this section shows a stronger impact of FSIS on abnormal returns for firms that are hard to value and difficult to arbitrage and provides additional support to our research question.

4.4 | FSIS and return reversals

In this section, we look at temporary stock mispricing and errors in valuation caused by FSIS around earnings announcements. The main argument is that if FSIS leads to temporary mispricing, then we should observe a stock price reversal in the period following the earnings announcement date. For example, if sentiment is high, prices could temporarily increase, but later will revert to lower values.[18]

We look for evidence of return reversals by examining the relationship of CFSIS to post-announcement CAR over different short-term periods following the earnings announcement. In this analysis, we examine the predictive ability of FSIS variables by using one-tailed statistics as behavioural finance theory proposes an opposite relationship between sentiment, as evidenced by mispricing and future stock returns.[19]

The results of this analysis are provided in Table 7. CFSIS is negative and significant in columns (2) and (3) at the 10% level. The Wald test statistics on joint significance of the sentiment variables are also significant in columns (2) and (3), confirming that future abnormal returns are negatively related to past investor sentiment. Our results indicate that the initial impact of FSIS starts to reverse over the post-announcement period, although the magnitude and significance of the correction is smaller than the initial impact. This partial reversal over the post-announcement period is consistent with the evidence provided by Danbolt et al. (2015). A full reversal in stock prices is not necessarily expected as professional investors may somewhat be prone to behavioural biases (Kaplanski & Levy, 2017; Kling & Gao, 2008; Lemmon & Portniaguina, 2006).

On the other hand, our results on return reversals are different than Mian and Sankaraguruswamy (2012), since, in their work, the impact of investor sentiment does not reverse so quickly and instead contributes to the post-earnings announcement drift for a period until the next quarter's earnings announcements. One reason for this different result is that we use an FSIS measure with daily frequency, while Mian and Sankaraguruswamy (2012) use a market-wide investor sentiment measure (B&W) with monthly frequency, therefore, these two measures can reflect different levels of information and risk for investors. Professional investors might find it easier to diversify and arbitrage away the unsystematic risk component related to firm-level sentiment, relative to the systematic risk component related to market-wide sentiment and this can lead to different results during the post-announcement period.

[18]Studies by Brown and Cliff (2005), Baker and Wurgler (2007), Da et al. (2015), Danbolt et al. (2015) and Aboody et al. (2018) indeed validate the short-term and long-term reversal effects and show that future returns are negatively related to past sentiment.

[19]For further details about the use of one-tailed statistics, see Inoue and Kilian (2005) and Huang et al. (2015).

TABLE 7 Post-earnings cumulative abnormal returns and firm-specific invetor sentiment (FSIS)

This table reports the results of the ordinary least squares regressions of post-announcement cumulative abnormal returns ($CAR_{(+3,+4)}$, $CAR_{(+3,+6)}$ and $CAR_{(+3,+10)}$) on cumulative firm-specific investor sentiment (CFSIS). The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. Cumulative abnormal returns are calculated over various windows after the earnings announcement date as denoted in the subscripts. Abnormal returns are estimated by subtracting the expected stock return from the actual stock return. The expected returns are calculated using the market model parameters estimated over the period between 300 and 46 days before the earnings announcement. The CRSP value-weighted index return is the market return. CFSIS is a cumulative FSIS index over a 2-day window from 2 days before the earnings announcement date until 1 day before the date of the announcement, where FSIS is measured as the natural logarithm of (1 + bullish intensity)/(1 + bearish intensity). See Appendix for detailed definitions of the variables. All regressions control for year and sector fixed effects whose coefficients are suppressed. The *p* values are reported in parentheses. For the variables CFSIS and CFSIS × NEG one-tailed *p* values are presented. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Wald tests of linear hypotheses and one-tailed *p* values are reported at the bottom.

	$CAR_{(+3,+4)}$ (1)	$CAR_{(+3,+6)}$ (2)	$CAR_{(+3,+10)}$ (3)
CFSIS [β_1]	−0.0003	−0.0006*	−0.0009*
	(0.1943)	(0.0964)	(0.0886)
NEG	0.0001	−0.0011	−0.0011
	(0.8678)	(0.2484)	(0.3744)
CFSIS × NEG [β_3]	−0.0004	−0.0005	−0.0003
	(0.2552)	(0.2660)	(0.3986)
B&W	0.0134***	0.0197***	0.0185***
	(0.0000)	(0.0000)	(0.0034)
LOSS	−0.0028***	−0.0020	−0.0031
	(0.0087)	(0.1801)	(0.1150)
BM	0.0028***	0.0048***	0.0093***
	(0.0012)	(0.0001)	(0.0000)
SIZE	0.0002	0.0001	0.0000
	(0.3690)	(0.7171)	(0.9778)
LEVERAGE	0.0008	0.0022	0.0043*
	(0.5351)	(0.2265)	(0.0834)
ROA	−0.0057**	−0.0091**	−0.0167***
	(0.0425)	(0.0227)	(0.0020)
MOMENTUM	−0.0036***	−0.0060***	−0.0090***
	(0.0000)	(0.0000)	(0.0000)
CONSTANT	−0.0087***	−0.0072**	−0.0123**
	(0.0008)	(0.0461)	(0.0110)

(Continues)

TABLE 7 (Continued)

	$CAR_{(+3,+4)}$ (1)	$CAR_{(+3,+6)}$ (2)	$CAR_{(+3,+10)}$ (3)
Year F.E.	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes
N	13,426	13,424	13,418
Adjusted R^2	0.0066	0.0127	0.0165
Wald test: $[\beta_1 + \beta_3] = 0$	1.37	2.38	1.64
(p value)	(0.1272)	(0.0466)	(0.0971)

Overall, the results of this analysis are consistent with our research question, as FSIS may be used to predict future abnormal returns.

5 | ROBUSTNESS ANALYSIS

5.1 | Alternative measurement of CAR

So far in the analysis, we measure the impact of FSIS using CAR based on the market model parameters as the benchmark. Other studies in this literature have also used alternative methods to calculate expected returns. For example, Mian and Sankaraguruswamy (2012) and Bartov et al. (2018) use a four-factor model to account for the market, size, value and momentum factors. We re-estimate our baseline analysis to examine whether our main finding holds if we use the four-factor model as the benchmark for abnormal returns. As our CAR considers the size, value and momentum factors, these are excluded as regressors from the analysis. We obtain the factor loadings from Wharton Research Data Services. The results of this analysis are presented in Table 8. For example, in column (5), which includes all the control variables, the coefficient of CFSIS is positive (0.0060) and significant at 1% level and the incremental coefficient of CFSIS is positive (0.0062) and significant at 1% level. Additionally, the joint coefficient of CFSIS is positive (0.0060 + 0.0062 = 0.0122) and significant at 1% level. These results reflect a statistically and economically significant difference between the impact of CFSIS for negative and positive surprises, as the coefficient of CFSIS is 103% larger for negative relative to positive earnings surprises and corroborates the baseline analysis.

5.2 | Profitable firms

In our baseline analysis, we examine both profitable and loss firms. However, as Hayn (1995) shows, price reactions to earnings appear to come exclusively from the subsample of firm-years with recorded profits. Similarly, Mian and Sankaraguruswamy (2012) examine the relation between market-wide sentiment and stock price sensitivity to earnings surprises only for profitable firms. Even though we control for firm loss in our regressions, we re-estimate our baseline analysis for profitable firms only. Table 9 presents the results of this analysis. The models do not include the LOSS control

TABLE 8 Firm-specific investor sentiment (FSIS) and earnings surprises: alternative measurement of cumulative abnormal returns

This table reports the results of the ordinary least squares regressions of cumulative abnormal returns (CAR) on cumulative firm-specific investor sentiment (CFSIS) and negative earnings surprises (NEG). The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. Cumulative abnormal returns are calculated over the 3-day event window (0,+2), where Day 0 is the earnings announcement date. Abnormal returns are estimated by subtracting the expected stock return from the actual stock return. In this table, the abnormal returns are measured using the four-factor model as the benchmark. CFSIS is cumulative FSIS index over a 2-day window from 2 days before the earnings announcement date until 1 day before the date of the announcement, where FSIS is measured as the natural logarithm of (1 + bullish intensity)/(1 + bearish intensity). See Appendix for detailed definitions of the variables. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t statistics reported in parentheses are adjusted for heteroskedasticity and stock clustering. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Wald tests of linear hypotheses and one-tailed p values are reported at the bottom.

	(1)	(2)	(3)	(4)	(5)
CFSIS [β_1]	0.0062***	0.0060***	0.0060***	0.0060***	0.0060***
	(5.99)	(5.91)	(5.88)	(5.86)	(5.86)
NEG	−0.0476***	−0.0462***	−0.0462***	−0.0460***	−0.0461***
	(−26.14)	(−25.12)	(−25.02)	(−25.03)	(−24.94)
CFSIS × NEG [β_3]	0.0060***	0.0061***	0.0062***	0.0062***	0.0062***
	(3.77)	(3.87)	(3.88)	(3.90)	(3.88)
B&W		−0.0012	−0.0010	−0.0009	−0.0010
		(−0.14)	(−0.11)	(−0.10)	(−0.11)
LOSS		−0.0107***	−0.0107***	−0.0105***	−0.0107***
		(−3.90)	(−3.90)	(−3.85)	(−3.88)
LEVERAGE		0.0098***	0.0094***	0.0095***	0.0093***
		(2.98)	(2.85)	(2.90)	(2.82)
ROA		−0.0138**	−0.0154**	−0.0140**	−0.0153**
		(−2.23)	(−2.46)	(−2.27)	(−2.45)
CAV			−0.0014*		−0.0012
			(−1.71)		(−1.40)
ASI				−0.1090	−0.0824
				(−1.56)	(−1.15)
CONSTANT	0.0090**	0.0080*	0.0086*	0.0083*	0.0087**
	(2.33)	(1.82)	(1.96)	(1.89)	(1.98)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
N	14,409	14,323	14,274	14,285	14,254
Adjusted R^2	0.0806	0.0825	0.0827	0.0824	0.0827

(Continues)

TABLE 8 (Continued)

	(1)	(2)	(3)	(4)	(5)
Wald test: $[\beta_1 + \beta_3] = 0$	66.04	64.65	64.31	64.22	64.11
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

variable which is included in the baseline analysis. The results are similar to the baseline analysis suggesting that including nonprofitable firms in our analysis does not affect the robustness of the relationship between FSIS and CAR during earnings surprises.

5.3 | Alternative measure of earnings surprises

Our earnings surprise variable is constructed using I/B/E/S analysts' forecasts to account for more timely information available about firms. We construct our variable against analysts' forecasts as prior studies suggest that the relative importance of earnings benchmarks has changed over time in favour of meeting analysts' expectations (e.g., Brown & Caylor, 2005; Dechow et al., 2003). However, we also examine the robustness of our results using an alternative definition of an earnings surprise. Namely, we define a seasonal random walk standardized unexpected earnings (RWSUE) as $(EPS_{i,q} - EPS_{i,q\text{-}4})/P_{i,q}$, where EPS is the basic earnings per share excluding extraordinary items of firm i for quarter q and $P_{i,q}$ is price per share at the end of quarter q. The results are qualitatively and quantitatively similar to the baseline analysis (see Supporting Information: Internet Appendix Section B, Table B.2).

5.4 | Fixed effects and clustering

We also assess the robustness of our results using alternative fixed effects and clustering methods. For example, to reduce concerns about unobserved firm-level heterogeneity we re-estimate our baseline regressions by replacing sector fixed effects with firm fixed effects and find that our results continue to hold strongly (see Supporting Information: Internet Appendix Section B, Table B.3). In addition, we also cluster standard errors by two-way clustering, both firm and year, but also sector and year (unreported). The results are qualitatively and quantitatively similar to the baseline analysis.

5.5 | Alternative FSIS transformations

We perform some alternative transformations to the FSIS variable. For example, we use it without the natural logarithms [i.e., (1 + Bullish intensity)/(1 + Bearish intensity)] to allow for a linear relationship. We re-estimate our baseline regressions using this transformation and we find (unreported) that the results remain qualitatively and quantitatively similar to the baseline analysis. We also use the natural logarithm of the ratio bullish intensity-to-bearish intensity plus one (with and without the log transformation) and find that these variations do not affect our baseline analysis either.

TABLE 9 Firm-specific investor sentiment (FSIS) and profitable firms

This table reports the results of the ordinary least squares regressions of cumulative abnormal returns (CAR) on cumulative firm-specific investor sentiment (CFSIS) and negative earnings surprises (NEG). The sample includes stocks that are traded on the NYSE and NASDAQ over the period 2011–2015. Cumulative abnormal returns are calculated over the 3-day event window (0,+2), where Day 0 is the earnings announcement date. Abnormal returns are estimated by subtracting the expected stock return from the actual stock return. The expected returns are calculated using the market model parameters estimated over the period between 300 and 46 days before the earnings announcement. The CRSP value-weighted index return is the market return. CFSIS is cumulative firm-specific investor sentiment index over a 2-day window from 2 days before the earnings announcement date until 1 day before the date of the announcement, where FSIS is measured as the natural logarithm of (1 + bullish intensity)/(1 + bearish intensity). In this table, we consider only profitable firms, that is, firms reporting positive earnings in the fiscal quarter. See Appendix for detailed definitions of the variables. All regressions control for year and sector fixed effects whose coefficients are suppressed. The *t* statistics reported in parentheses are adjusted for heteroskedasticity and stock clustering. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Wald tests of linear hypotheses and one-tailed *p* values are reported at the bottom.

	(1)	(2)	(3)	(4)	(5)
CFSIS [β_1]	0.0061***	0.0055***	0.0056***	0.0056***	0.0055***
	(5.74)	(5.14)	(5.26)	(5.27)	(5.11)
NEG	−0.0461***	−0.0476***	−0.0468***	−0.0466***	−0.0476***
	(−23.95)	(−23.72)	(−24.06)	(−23.98)	(−23.68)
CFSIS × NEG [β_3]	0.0050***	0.0053***	0.0056***	0.0055***	0.0053***
	(2.91)	(3.07)	(3.24)	(3.18)	(3.06)
B&W		0.0068	0.0082	0.0083	0.0057
		(0.69)	(0.84)	(0.84)	(0.58)
BM		0.0058**	0.0049**	0.0049**	0.0056**
		(2.31)	(2.02)	(2.04)	(2.23)
SIZE		−0.0013***	−0.0016***	−0.0016***	−0.0013***
		(−2.71)	(−3.53)	(−3.42)	(−2.87)
LEVERAGE		0.0056	0.0066*	0.0066*	0.0056
		(1.57)	(1.92)	(1.93)	(1.57)
ROA		−0.0391***	−0.0343***	−0.0337***	−0.0390***
		(−2.96)	(−2.74)	(−2.70)	(−2.96)
MOMENTUM		−0.0105***			−0.0106***
		(−4.23)			(−4.25)
CAV			−0.0018*		−0.0005
			(−1.73)		(−0.53)
ASI				−0.0777	−0.1117
				(−0.94)	(−1.28)

(Continues)

TABLE 9 (Continued)

	(1)	(2)	(3)	(4)	(5)
CONSTANT	0.0091**	0.0168**	0.0191***	0.0184***	0.0181***
	(2.35)	(2.52)	(2.99)	(2.86)	(2.74)
Year F.E.	Yes	Yes	Yes	Yes	Yes
Sector F.E.	Yes	Yes	Yes	Yes	Yes
N	11,437	10,849	11,332	11,336	10,832
Adjusted R^2	0.0808	0.0892	0.0847	0.0845	0.0895
Wald test: $[\beta_1 + \beta_3] = 0$	47.33	41.94	43.91	43.66	41.61
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

5.6 | Different proxy for market-wide investor sentiment

In this section, we examine whether our results are robust when different measures of market-wide sentiment are employed. In the main analysis, we use Baker and Wurgler's (2006) monthly sentiment index as a proxy for market-wide investor sentiment. In this section, we analyze the impact of FSIS on abnormal returns while we control for the effect of daily market-wide investor sentiment by using PsychSignal's daily mood indices for two major stock market exchange indices; NASDAQ100 and S&P500. This also addresses the timeliness concerns of Da et al. (2015). PsychSignal's market-wide mood indices represent aggregate investor sentiment for NASDAQ100 and S&P500. We control for PsychSignal's mood indices over a 2-day window, from 2 days before until 1 day before the earnings announcement date in the same manner as FSIS. The results presented in Supporting Information: Internet Appendix Section B, Table B.4, using daily proxies of market-wide investor sentiment, are similar to the baseline analysis, a finding which suggests that the relationships are not affected by selection issues of market-wide investor sentiment proxies or timeliness issues.

5.7 | Excluding financial firms

A final robustness analysis is conducted to investigate whether the main results remain unchanged if we exclude financial firms from our sample. The results of this analysis are presented in Supporting Information: Internet Appendix Section B, Table B.5. The regression models in Table 5 are re-estimated excluding financial firms and the results remain similar with the baseline analysis. This analysis implies that the characteristics of financial firms do not affect the robustness of the relationship between FSIS and abnormal returns during earnings surprises.

6 | CONCLUSION

In this study, we provide important insights into the heterogeneous relationship between FSIS and abnormal returns in the context of a significant corporate event, the earnings announcement. We move from a consideration of market-wide investor sentiment to a consideration of firm-specific investor sentiment extracted from social media and its heterogeneous impact on abnormal returns.

The results of the empirical analysis suggest that bullish (bearish) FSIS leads to higher (lower) abnormal returns on the announcement of positive and negative earnings surprises. In addition, the results suggest that the impact of FSIS at the time of earnings announcements is greater for negative earnings surprises. We also show that the impact of FSIS on abnormal returns is greater for hard-to-value and difficult-to-arbitrage firms. Finally, consistent with behavioural finance theory, we provide evidence of sentiment-driven short-term mispricing and subsequent return reversals around earnings announcements.

Our study has two important implications for academics and practitioners. First, for researchers with interests in behavioural finance, investor sentiment and corporate finance, we highlight the importance of firm-level investor sentiment in addition to market-level investor sentiment, offering further insight when the firm is the unit of analysis. We show that the FSIS has a heterogeneous impact on abnormal stock returns during corporate earnings surprises. Second, our results showcase the importance of social media in investing community and in particular in the world of high-frequency algorithmic trading where investors are looking for new inputs into their investment analysis and trading models.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX: VARIABLE DEFINITIONS AND SOURCES

Variable	Definition	Source
$CAR_{(0,+2)}$	Cumulative abnormal returns over the 3-day event window (0,+2), where Day 0 is the earnings announcement date. Abnormal returns are estimated by subtracting the expected stock return from the actual stock return. The expected returns are calculated using the market model parameters	CRSP

Variable	Definition	Source
	estimated over the period between 300 and 46 days before the earnings announcement. The CRSP value-weighted index return is the market return.	
CFSIS $_{(-2,-1)}$	Cumulative firm-specific investor sentiment index over a 2-day window from 2 days before the earnings announcement date until 1 day before the date of the announcement, where FSIS is measured as the natural logarithm of (1 + bullish intensity)/(1 + bearish intensity).	PsychSignal
SUE	Standardized unexpected earnings is measured as the difference between I/B/E/S actual earnings and the average of estimates at the release of earnings, divided by the standard deviation of forecasts.	I/B/E/S
NEG	An indicator variable equal to 1 for firms having negative unexpected earnings in the fiscal quarter and 0 otherwise.	I/B/E/S
B&W	Baker and Wurgler's (2006) index of sentiment (market-wide) for the month of the earnings announcement. Baker and Wurgler's (2006) index is available up to the end of September 2015 from Jeffrey Wurgler's website. Holt-Winters nonseasonal smoothing method is used to forecast the index for October, November and December 2015 (based on the value of the index over the period from January 2011 to September 2015).	http://people.stern.nyu.edu/jwurgler/
LOSS	An indicator variable equal to 1 for firms reporting negative earnings in the fiscal quarter.	I/B/E/S
BM	The book value of equity divided by the market value of equity in the year before the earnings announcement.	Compustat
SIZE	The natural logarithm of share price times shares outstanding in the year before the earnings announcement.	Compustat
LEVERAGE	The sum of long-term debt and debt in current liabilities divided by total assets in the year before the earnings announcement.	Compustat
ROA	The ratio of net income to total assets in the year before the earnings announcement.	Compustat
MOMENTUM	Cumulative abnormal returns relative to value-weighted market returns over the (−202,−3) day interval before the earnings announcement.	CRSP
CAV$_{(-32,-3)}$	Cumulative abnormal volume relative to value-weighted market volume over the (−32,−3) day interval before the earnings announcement.	CRSP

(Continues)

Variable	Definition	Source
ASI	Abnormal short interest is measured as the difference between short interest before the earnings announcement and the average of short interest over the past 3 months. Short interest is calculated as total short interest divided by shares outstanding.	Compustat
Small/large firms	Market capitalization classification based on size. Size is the market capitalization of the firm in the month before the earnings announcement. Firms that fall in the bottom (top) quintile using NYSE breakpoints are classified as small (large) firms.	CRSP
Young/mature firms	Age classification based on the number of months since the firm first appeared on CRSP in the month before the earnings announcement. Firms that fall in the bottom (top) quintile using NYSE breakpoints are classified as young (mature) firms.	CRSP
High-/low-volatility firms	Volatility classification based on the standard deviation of daily returns over the (−202,−3) day interval before the earnings announcement. Firms that fall in the top (bottom) quintile sorted on volatility are classified as firms with a high (low) level of volatility.	CRSP
Growth and value/staid firms	Firm style classification based on the book-to-market ratio. Book-to-market ratio is the book value of equity divided by the market value of equity in the year before the earnings announcement. Firms that fall in the top and bottom (other) quintiles sorted on book-to-market ratio are classified as growth and value (staid) firms.	Compustat
Nonpayer/high-payer firms	Dividend payout classification based on the dividend payout measure. Dividend payout is the annual dividend divided by the annual earnings in the year before the earnings announcement. Firms that do not pay dividends are classified as nonpayers and firms that fall in the top quintile of the remaining dividend-paying firms sorted on dividend payout are classified as high payers.	Compustat