Beyond Market Mood: Stock Sentiment and the Response to Corporate Earnings Announcements

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Abstract

This study establishes a relationship between stock-specific investor sentiment and stock price movements around earnings announcements. Stock-specific investor sentiment is the key determinant of price adjustment in the context of an earnings surprise. The effect of stock-specific investor sentiment dominates the effect of macro-sentiment. Finally, we provide evidence that the effect of stock-specific investor sentiment is more pronounced for stocks that are hard to value and difficult to arbitrage.

Key words: Investor sentiment, asset pricing, social media, Twitter, StockTwits, earnings surprises, uncertainty, limits to arbitrage.

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1. Introduction

The role of investor sentiment in investment decisions has been clearly established in the finance and accounting literature in recent years (e.g. Baker & Wurgler, 2006).[1] Similarly, the fact that internet stock messages and other social media may contain information or sentiment which influences price formation has also been established (Antweiler & Frank, 2004). Finally, the existence of new types of investors and new investment processes has been clearly illustrated in the recent literature on high frequency trading and a new market microstructure has been documented by O'Hara (2015) and others. Our research combines elements of these disparate strands of finance theory to indicate the role of stock-specific investor sentiment in asset pricing; more specifically the role of investor sentiment in the presence of a corporate earnings surprise. We make contributions to the existing literature in several areas. First, to the best of our knowledge, this study is the first to establish a relationship between stock-specific investor sentiment and stock price movements around earnings announcements. Second, we find that stock-specific investor sentiment is the key determinant of price adjustment in the context of a significant micro-event i.e. an earnings surprise, and that its effect is not moderated by market-wide investor sentiment in so far as this is measured by the Baker and Wurgler's (2006) sentiment index, and alternative market-wide sentiment indexes which are based on the content of the microblogging forums, Twitter and StockTwits. Our third contribution is that we

[1] See Baker and Wurgler (2006) for the merits of investment sentiment beyond the realms of classical finance theory.

provide evidence that the effect of stock-specific investor sentiment is more pronounced for stocks that are hard to value and difficult to arbitrage. This is in line with the findings of Baker and Wurgler (2006) and Mian and Sankaraguruswamy (2012) using a market-wide investor sentiment index. We also find evidence of mispricing and return reversals similar to that found by Da, Engelberg, and Gao (2015) in their study of economic sentiment and market returns.

The motivation of our research is as follows. The pace of financial and technological change in recent decades has been so significant that many of the traditional methods of investment and investment analysis have been complemented or even replaced by new methods of collection and dissemination of price sensitive information including the analysis of textual sentiment and machine based learning. The explosive growth of social media and the harnessing of advanced computing resources means that it is now possible to incorporate both qualitative and quantitative analysis into the consideration of economically significant events. Such developments have allowed us to extend research into an important corporate event, an earnings announcement surprise, from the macro or market-wide proxies for investor sentiment used in the previous literature to a stock-specific or micro proxy for investor sentiment in order to capture the effect of stock-specific investor sentiment around the period of the announcement event.[2] Research so far has focused on these macro proxies to try to capture investor sentiment in order to establish a relationship between earnings announcements and abnormal returns within a defined event-window but we believe that these proxies are too general to give significant insight into price formation

[2] We use the terms micro or stock-specific investor sentiment and macro or market-wide investor sentiment interchangeably in the text as we differentiate between the mood of the broad market and investor sentiment as captured by social media for an individual company.

behaviour in the light of a corporate earnings announcement surprise and therefore use a stock-specific (micro) measure of investor sentiment.

The seismic changes in the equity market and the nature of market participants has been noted by researchers concerned with high-frequency trading (HFT) and market microstructure (See Harris and Saad (2014), Goldstein, Kumar, and Graves (2014) and O'Hara (2015)). Indeed, these changes have been so rapid and so widespread that the Securities and Exchange Commission (SEC) (2010) sought consultation from market participants on equity market structure in order to assess "whether market structure rules have kept pace with among other things, changes in trading technology and practices" (p. 3596).

With such high volumes of financial data being generated on a minute by minute basis and the high volumes of computer generated trading based on the abilities of some traders to trade in microseconds the need for new market indicators has led some to look for electronic versions of the floor trading 'squawk box'. Harris and Saad (2014) find message traffic in electronic markets - which they label 'silent' sound - can indicate the short-term direction of equity price changes. Goldstein and Yang (2015) update the work of Grossman and Stiglitz (1980) and conclude that the information available now is so complex that informed traders tend to specialize or have a comparative advantage in different types of financial information. With many traders seeking to gain advantages in technology, including co-location of trading computers at stock exchanges, attention has switched to new sources of information on sentiment. Goldstein et al. (2014) note that the search for methods to analyse and interpret this data has extended into the areas of textual sentiment and mood based sentiment indicators. Many algorithmic traders and hedge funds not only parse news with textual sentiment but also subscribe to commercial services which supply live textual sentiment feeds. We incorporate one such system into our research using market participants generated content from Twitter and StockTwits, where traders use ‘cashtags’, ticker symbols or stock names to flag stock-specific tweets.[3] Our research is novel in that it simultaneously considers both stock-specific investor sentiment and market-wide investor sentiment. Our research forms the basis of a deeper understanding of the mechanisms by which sentiment affects stock prices and its role in the price formation process.

The importance of social media was highlighted by Antweiler and Frank (2004) who conclude that internet stock messages are not just ‘noise’. Twitter and StockTwits have become vibrant online platforms for exchanging stock-related information with a surge in usage over the period under review as noted by Chen, De, Hu, and Hwang (2014). A vast number of tweets per day, generated by a huge number of active users, are dedicated to the discussion of public companies and the trading of stocks, providing an extensive real-time stream of investment information and investment ideas. We use the output of microblogging forums, Twitter and StockTwits, to measure daily investor sentiment about individual stocks over the 5-year period, 2011-2015. We analyse 14,658 corporate earnings announcement events where earnings announced diverge from investment analysts’ forecasts. We advance research into investor sentiment by employing a measure of stock-specific tweets’ contents, which allows us to disentangle the impact of micro-sentiment from macro-sentiment during

[3] The Cashtag for Apple for example is $AAPL.

a corporate earnings surprise, and enables us to quantify the impact of stock-specific sentiment on abnormal stock returns.[4]

The remainder of the paper proceeds as follows. Section 2 considers the impact of stock-specific investor sentiment on the market's evaluation of earnings information. Section 3 describes the influence of sentiment and social media on stock price formation. Section 4 explains our sample and variables. Section 5 tests the effect of investor sentiment on announcement-period abnormal returns. Section 6 examines the cross-sectional variation in the response to investor sentiment. Section 7 checks the robustness of our main results, and Section 8 concludes.

2. Price Formation and Investor Sentiment

There is extensive literature which documents significant stock price movements around earnings announcements (Brown, Hagerman, Griffin, & Zmijewski, 1987; Bartov, Givoly, & Hayn, 2002; and Kasznik & McNichols, 2002). These studies conclude that firms with positive (negative) earnings outcomes experience significant positive (negative) abnormal stock-price performance and assume that rational investors efficiently impound accounting information into stock prices and arbitrageurs offset demands of irrational investors.

A number of studies investigate the impact of investor sentiment on stock prices with significant early theoretical contributions to the debate being made by Black

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[4] Our sentiment measure is released ahead of market opening hours (at approximately 12:01 AM EST) and is measured at t-1 days relative to our measure of cumulative abnormal returns which is measured at t. This validates the predictive ability of the measure and avoids reverse causality concerns.

(1986) and De Long, Shleifer, Summers, and Waldmann (1990) followed by Neal and Wheatley (1998) and Chau, Deesomsak, and Koutmos (2016) who provide evidence that investor sentiment contains unique information for asset pricing which influences equity returns and is a significant determinant of stock price variation. Baker and Wurgler (2006) construct an investment sentiment index and illustrate that time-varying investor sentiment affects the cross-section of stock returns.[5] Huang, Jiang, Tu, and Zhou (2015) use a variant of Baker and Wurgler's (2006) investment sentiment model and find a strong negative relationship between high levels of investment sentiment and future stock market returns.[6] This finding is supported by Da et al. (2015) who create a macro investment sentiment index based on focused Google search terms reflecting financial and economic attitudes filtered by textual analysis. Other studies find that changes in sentiment and the limits to arbitrage may impact price formation (Shleifer & Vishny, 1997). Lemmon and Portniaguina (2006), Kaplanski and Levy (2010), and Da et al. (2015) confirm stock mispricing due to investor sentiment. The general consensus in the literature is that investors become overly optimistic (pessimistic) during periods of high (low) investor sentiment, making mistakes in the valuation of future expected cash flows of stocks, leading to overvaluation (undervaluation) that reverses in time. A common feature of the prior studies of investor sentiment and stock price discovery is that proxies used are measured on an economy-wide or market-wide basis, so their examination sheds light on the effect of market-wide investor sentiment or market mood rather than addressing sentiment about individual stocks. Frequently used proxies include consumer

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[5] We use the Baker and Wurgler's (2006) index as a proxy for market-wide investor sentiment.
[6] Huang et al. (2015) use Baker and Wurgler's proxies for investor sentiment and a partial least squares methodology to consider the predictive value of macro investor sentiment.

confidence surveys such as the University of Michigan Survey Research Center (Bergman & Roychowdhury, 2008 and Seybert & Yang, 2012) or Baker and Wurgler's (2006) composite sentiment index (Mian & Sankaraguruswamy, 2012; Brown, Christensen, Elliott, & Mergenthaler, 2012; and Chau et al., 2016).[7]

It should also be noted that the effect of sentiment on price formation is not homogenous across stocks or sectors, it is more pronounced for stocks whose expected cash flows are more uncertain and more difficult to value. Baker and Wurgler (2006, 2007) indicate that stocks which are difficult to value or are difficult to arbitrage - small, young, high volatility, non-dividend-paying, distressed (i.e., low market-to-book), extreme growth (i.e., high market-to-book), and unprofitable stocks - are more likely to be influenced by sentiment while large, mature, stable, high-divided-paying, and medium-growth companies are less likely to be influenced by sentiment. Da et al. (2015) concur with Baker and Wurgler (2006) that limits to arbitrage exacerbate the effect of investor sentiment on asset prices. Huang et al. (2015) find that there are significant differences in the response of portfolios sorted by industry to the effect of investor sentiment and also confirm that stocks which are difficult to value, difficult to arbitrage or speculative are more likely to be sensitive to investor sentiment. In a similar vein, Mian and Sankaraguruswamy (2012) validate the relationship between investor sentiment and the stock market's response to unexpected earnings announcements. They indicate that investors react more to earnings news that is compatible with prevailing investor sentiment and that the effect of investor sentiment

[7] Others include the Conference Board (Lemmon & Portniaguina, 2006 and Chau et al., 2016), the American Association of Individual Investors (AAII) (Brown & Cliff, 2004 and Chau et al., 2016), Investors Intelligence Survey Index (Brown & Cliff, 2004), closed-end fund discounts and net mutual fund redemptions (Neal & Wheatley, 1998), and the Chicago Board Options Exchange Volatility Index (VIX) (Chau et al., 2016).

is especially pronounced for small stocks, young stocks, high volatility stocks, non-dividend-paying stocks, and stocks with extremely high and low market-to-book ratios. Lemmon and Portniaguina (2006) also find that investor sentiment forecasts the returns of small stocks and stocks with low institutional ownership far more efficiently than large stocks and stocks with high institutional ownership.

In our study, we contribute to the literature concerning the linkage between investor sentiment and the stock pricing process around earnings announcements by considering the following questions. Does stock specific investor sentiment play a more significant role in price formation around a stock specific event than market-mood? Is the effect of stock specific sentiment more pronounced for difficult to value or limited arbitrage stocks?

3. Investor Sentiment and Social Media

Major developments have taken place in the interpretation of investor sentiment using textual analysis or computational linguistics in recent years which seeks to move the study away from macro-based sentiment variables and the published opinions of professional investors. Many of the studies use internet based opinions but samples are often small, cover a short time period or focus solely on technology stocks. Antweiler and Frank (2004) focus on 45 Dow Jones Industrial Average companies' messages posted on Yahoo! Finance and Raging Bull message boards[8] and find that the effect of sentiment is statistically significant but economically small. Das and Chen (2007) focus on 24 out of the 35 stocks in the Morgan Stanley High-Tech Index (MSH)

[8] More than 1.5 million messages.

for two months, July and August 2001, and find that sentiment affects the MSH index but has weaker links to individual stocks.[9] Chen et al. (2014) take a different approach and cover an extensive sample of stocks, more than 7,000, based on reports and comments on Seeking Alpha, a quasi-professional investors forum where reports are edited and are similar to institutional investors and investment banks reports, for the period 2005-2012. They find evidence of the impact of sentiment on both stock returns and earnings surprises in the period after a report is published (3-month period) that is statistically significant and economically meaningful. Chen et al. (2014) also make the point that social media have evolved meaningfully in the context of stock reports in recent years. Like Chen et al. (2014) we utilise a broader based sample with a longer time horizon than earlier studies and successfully extract the influence of investor sentiment on individual stocks. Sprenger, Sandner, Tumasjan, and Welpe (2014) analyse stock-related Twitter messages for a 6 month period in 2010 with the focus of the study on classification of events using textual sentiment as a method of event identification.[10] Their methodology, based on spikes in message frequency, is only partially successful in determining earnings announcements, identifying 224 out of 672 earnings announcements within their sample and study period, but they conclude that in the case of good news there is information leakage before earnings announcements with abnormal returns generated in the run up to announcements but negative news is reflected in the wake of corporate earnings announcements. Da et al.'s (2015) investment index is based on Google search terms reflecting economic and financial

[9] The stock effect may be affected by their practice of normalising individual stock returns rather than calculating abnormal returns relative to a stock market index.

[10] Only 6.9% of the messages they use are related to discussion of earnings results and event categories include Corporate Governance (3%), Financial Issues (13%), Operations (20%), Restructuring (6%), Legal Issues (4%) and the largest category Technical Trading signals (34%) with 23% not classified by their algorithm.

sentiment which have proved to influence market prices and they argue that this information is more timely than monthly macro surveys such as the University of Michigan Consumer Sentiment Index and more focused than typical market based measures such as trading volume Thus whilst the studies noted, and others, have suggested that individual stock-sentiment channelled through internet message sites and Twitter have established the relevance of social media for stock price formation our study is the first to provide a comprehensive review of the effect of stock sentiment in the case of corporate earnings announcements over a meaningful time horizon; 14,658 earnings announcements between 2011-2015.

4. Sample Selection, Variable Definitions, and Summary Statistics

4.1. Sample Selection

To investigate the interaction between stock-specific investor sentiment and abnormal returns around the time of an earnings announcement, we collect a sample from the NYSE and NASDAQ for the period 2011-2015. We filter stocks based on meeting the following criteria; stocks that release quarterly earnings surprises and whose sentiment data, based on Twitter and StockTwits, is available from PsychSignal.

Data is drawn from the following sources. Micro – stock-specific sentiment data - is obtained from PsychSignal and macro-sentiment data - Baker and Wurgler’s investment sentiment index - is downloaded from Jeffery Wurgler’s website. Earnings data; forecasts, actual earnings and analyst coverage comes from the Institutional Brokers’ Estimate System (I/B/E/S). Stock price data including price, bid-ask spreads, and volatility is collected by the Center for Research in Security Prices (CRSP). Accounting data is from Compustat. Stock style classifications are from Morningstar and institutional ownership records are from Thomson Reuters. After matching stocks across the databases, we arrive at a large sample of 14,658 firm-quarter observations which meet our selection criteria.[11]

4.2. Variable Definitions

For the construction of our main variable of interest we utilize PsychSignal social mood data to create a stock-level proxy of investor sentiment.[12] We use two measures of sentiment analysis, bullish intensity and bearish intensity which reveal how the public mood about specific stocks is trending on a daily basis. These sentiment intensity measures are provided by the PsychSignal technology that uses a sophisticated natural language processing algorithm that is programmed to analyze millions of stock specific messages mood in the native language of traders. As the words people use in daily life reflect their thought process, emotional states, intentions, and motivations (Tausczik & Pennebaker, 2010), we believe that the language people use in social media posts related to firms' securities reveals their psychological levels of optimism and pessimism and therefore it can be linked to the behavior of certain groups of stock market investors.

We combine the two measures of sentiment intensity to generate a stock specific measure of investor sentiment. Following Antweiler and Frank (2004), we define stock *i's* investor sentiment index (SI) as the natural logarithm of (1+Bullish $\text{Intensity}_{i,t}$) divided by (1+Bearish $\text{Intensity}_{i,t}$); where bullish (bearish) intensity

[11] For full descriptions of the data and sources see Appendix A: Variable Definitions and Sources.
[12] We use the daily data feed from PsychSignal which is based on social media feeds for the day prior to our measurement of stock price movement. See Appendix B for further information about PsychSignal data.

represents the strength of optimism (pessimism) that is revealed in the tweets about stock *i* on day *t*. We consider the sum of SIs in a three-day window, from 2 days before the earnings announcement until the date of the announcement as the cumulative stock-specific investor sentiment (CSI), that is:

$$\mathrm{CSI}_{i,(-2,0)} = \sum_{t=-2}^{0} \mathrm{Ln}\left(\frac{1+\text{Bullish Intensity}_{i,t}}{1+\text{Bearish Intensity}_{i,t}}\right).$$

We employ the investor sentiment index developed by Baker and Wurgler (2006) (B&W), as a proxy for market-wide investor sentiment in the month of the earnings announcements. Baker and Wurgler's investor sentiment index is based on the common variation in six underlying proxies for sentiment determined by principal components analysis: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The effect of this investor sentiment index on market movements has been documented by previous research (e.g. Baker & Wurgler, 2006 and Mian & Sankaraguruswamy, 2012).

We use the sensitivity to investor sentiment to test sentiment-driven stock price movements around earnings announcements. We control for CSI and B&W measures in our regression models to capture the effects of investors' sentiment toward firms' specific information and investors' optimism and pessimism about the market in general on stocks prices.

We measure the difference between actual earnings and the average of I/B/E/S analyst forecasts at the release of earnings as a proxy for unexpected earnings (UE) associated with each earnings announcement. We standardize UE by the standard deviation of forecast errors, which is:

$$\mathrm{SUE}_{\mathrm{i,t}} = \frac{\text{Actual EPS} - \text{Forecast EPS}}{\sigma\ (\text{Actual EPS} - \text{Forecast EPS})}.$$

A positive (negative) earnings surprise consists of an actual earnings announcement that is higher (lower) than expectations.

To examine the effect of uncertainty, we employ four proxies for stocks that may be considered hard/easy to value. Following Baker and Wurgler (2006) and Mian and Sankaraguruswamy (2012) we use volatility, firm size and stock valuation as proxies for uncertainty and following Hong, Lim, and Stein (2000) our fourth proxy of uncertainty is analyst coverage. Volatility, as measured by the standard deviation of stock daily abnormal returns, captures the variation in the market's estimation of firm value. We use volatility as a direct measure of stock uncertainty since it is based on the decisions made by market participants. We consider firm size as the second proxy of uncertainty because larger firms tend to have lower valuation uncertainty. Our third proxy, stock style, is also likely to be a good measure of uncertainty as growth stocks are generally considered riskier and more difficult to value than value stocks. We employ the Morningstar Style Box classification to assign stocks to size and style sectors. Morningstar categorises stocks based on market capitalization. They also use a range of growth and valuation measures to establish the growth-value orientation of stocks and then assigns them to stock style categories; growth, core, and value. Finally, following Hong et al. (2000) our fourth proxy of uncertainty is analyst coverage, which is defined as the number of analysts following a stock, with higher analyst coverage indicating lower information uncertainty.

To assess the effect of limits to arbitrage, we consider two aspects, potential transaction costs and shareholders' sophistication. Following Lam and Wei (2011) we use four proxies for limits to arbitrage; Amihud illiquidity, the number of institutional shareholders, dollar trading volume, and bid-ask spread. Our first proxy, Amihud illiquidity, is defined as the absolute value of daily stock return divided by daily dollar trading volume (Amihud, 2002). We consider this illiquidity measure because arbitrage is risky and costly for stocks with low liquidity (Brunnermeier & Pedersen, 2005). Our second proxy for limits to arbitrage is the number of institutional shareholders which, as a measure of shareholders sophistication, influences the risk of arbitrage (Ali, Hwang, & Trombley, 2003). High institutional ownership has implications for stock lending and arbitrage opportunities. Dollar trading volume is our third proxy, indicating likely price pressure and the time required to trade a large block of shares. Our last proxy for limits to arbitrage is the bid-ask spread as arbitrage tends to be particularly risky and costly for stocks that are more costly to trade (Amihud & Mendelson, 1986).

For the construction of our main dependent variable we use a three-day event window around the earnings announcement to estimate the cumulative abnormal returns (CARs). We compute the abnormal return (AR) for each stock on three days by subtracting the value-weighted market return (R_{mt}) from the stock return (R_{it}) and calculate the cumulative abnormal return:

$$\mathrm{CAR}_{i,(-1,+1)} = \sum_{t=-1}^{+1}(\mathrm{R}_{i,t} - \mathrm{R}_{m,t}).$$

It should be noted that our sentiment variable CSI measures stock-specific sentiment based on the day’s messages ahead of our measure of abnormal price movement and thus avoids any element of reverse causality.

4.3. Summary Statistics

Our sample includes 14,658 earnings announcements over the period 2011-2015 for which we can compute our measure of firm specific investor sentiment $CSI_{i,(-2,0)}$ as well as the cumulative abnormal returns $CAR_{i,(-1,+1)}$ around the earnings surprise announcement.

Table 1 shows summary statistics for our sample broken down by earnings surprise, market cap, stock style, market, sector, and announcement year. It can be inferred that about two-thirds of the 14,658 earnings announcements in our sample represent positive news, whereas about one-third represent negative news. According to the Morningstar Style Box classification the number of small stocks in our sample is more than twice that of large stocks, while the number of growth and value stocks are about the same. Breaking the sample down based on Global Industry Classification Standard (GICS) indicates that 51% of the stocks in our sample are from information technology, consumer discretionary, and financials sectors, while only 4% of the stocks are from telecommunication services and utilities. Also, looking at the time horizon of the sample illustrates that only 4% of the earnings in our sample were announced in 2011 as the popularity of Twitter and StockTwits gains critical mass. The highest level of the announcements comes from 2014 which is 32% of the announcements in our sample.

Table 2 reports the descriptive statistics of our key variables for the overall sample. All variables are winsorized at 1% and 99% of their respective distributions to mitigate the impact of outliers. Even though our sample is dominated by positive earnings surprises the mean of $CAR_{(-1,+1)}$, which represents the average response to positive and negative earnings surprises, is -0.03%. The positive mean of 0.9982 for SUE indicates that the earnings news has on average been positive. The mean of $CSI_{(-2,0)}$ is +0.8678, which indicates that the tweets about the stocks in our sample have on average been bullish. Our measure of market-wide investor sentiment (B&W) has a negative mean close to zero (-0.0130). The reverse signs of $CSI_{(-2,0)}$ and B&W

can be considered as an indication that these two sentiment indexes are different. Comparison of $CSI_{(-2,0)}$ and B&W standard deviations (1.1550 for $CSI_{(-2,0)}$ and 0.0972 for B&W) also illustrates that the $CSI_{(-2,0)}$ values are spread out over a wider range while B&W values are close to the mean. It should be noted that the correlation between $CSI_{(-2,0)}$ and SUE is only 0.16 indicating that the PsychSignal measure is not highly collinear with the SUE variable. This is an indication that $CSI_{(-2,0)}$ is not just a mere proxy for information about the firms' actual earnings (*signed news flow*) and that it is capturing important elements of investor sentiment and noise trading.[13]

4.4. Modelling Investor Sentiment

We use regression analysis to determine the relationships between announcement-period abnormal returns, stock-specific investor sentiment, market-wide investor sentiment, and earnings surprises. More specifically, we use cross-sectional regressions to evaluate whether stock-specific investor sentiment is helpful in explaining abnormal returns of stocks announcing earnings surprises. We consider a variety of cross-sectional regression models which range from a parsimonious model using only stock-specific/market-wide investor sentiment to a model that incorporates a list of additional control variables that can affect firms' abnormal returns around earnings announcements. Our model with the full list of variables takes the following form:

$$\mathrm{CAR}_{\mathrm{i},(-1,+1)} = \alpha_1 + \beta_1 \mathrm{CSI}_{\mathrm{i},(-2,0)} + \beta_2 \mathrm{SUE} + \beta_3 \mathrm{B\&}W + \beta_4 \mathrm{CSI}_{\mathrm{i},(-2,0)} * \mathrm{B\&}W + \beta_5 \mathrm{Loss} + \beta_6 \mathrm{BM} + \beta_7 \mathrm{Size} + \beta_8 \mathrm{Leverage} + \beta_9 \mathrm{ROA} + \beta_{10} \mathrm{CAR}_{\mathrm{i},(-205,-6)} + \varepsilon \qquad (1)$$

[13] See Appendix C Table C.1 for correlation.

The dependent variable is the three-day cumulative abnormal returns ($CAR_{i,(-1,+1)}$) which measures the sensitivity of stock prices to stock-specific investor sentiment ($CSI_{i,(-2,0)}$), quarterly earnings surprises (SUE), and market-wide investor sentiment (B&W). As we measure CAR in the short event window around earnings announcement surprises, we analyse the main price reactions that occur with the arrival of the new earnings information and the impact of sentiment in the run up to the release of this new information.

Our regression model has several benefits. Inclusion of both micro and macro measures of investor sentiment and an interaction variable between them ($CSI_{i,(-2,0)}$ * B&W) allows us to carefully examine the individual and joint effect that micro and macro investor sentiment has in the price formation process. By using both measures of investor sentiment in the regression design, we examine whether or not the effect of stock-specific investor sentiment is affected by market-wide investor sentiment. The interaction variable helps us investigate whether the impact of stock-specific investor sentiment is moderated, reinforced, or unaffected by market-wide investor sentiment. As Baker and Wurgler's (2006) investor sentiment index (B&W) represents the broad market mood, it might overlap with the stock-specific investor mood and affect it. The effect of stock-specific investor sentiment ($CSI_{i,(-2,0)}$) on investors' reactions to earnings announcements might therefore be related to the prevailing investor sentiment at the aggregate market level (B&W). Furthermore, the model includes a set of control variables; loss, book-to-market ratio, size, leverage, return on assets, and stock price momentum (historical cumulative abnormal returns) prior to earnings announcements. Adding these control variables into our regression model enables us to test the independence of our results from the effects of these well-known variables that exert an impact on the market reaction to earnings information.[14]

5. The Effect of Investor Sentiment on Abnormal Stock Returns

In this section we analyse whether stock-specific investor sentiment plays a significant role in stock price movements around earnings surprises. To this end, we provide a graphical representation of CARs around earnings announcements in Figure 1. We plot the CAR series for four groups of firms: a) The portfolio of firms with positive SUE and positive $CSI_{(-2,0)}$ which includes 7,296 firm-quarter observations (50% of the sample); b) The portfolio of firms with positive SUE and negative $CSI_{(-2,0)}$ which includes 1,739 firm-quarter observations (12% of the sample); c) The portfolio of firms with negative SUE and positive $CSI_{(-2,0)}$ which includes 3,375 firm-quarter observations (23% of the sample); and d) The portfolio of firms with negative SUE and negative $CSI_{(-2,0)}$ which includes 1,638 firm-quarter observations (11% of the sample).[15] The reported abnormal returns are cumulative from day -10 through day +10, where day 0 is the day of the earnings' announcements.

Figure 1 shows that the relation between the earnings surprises and the stock-specific investor sentiment is not highly linear. There exist some firms with positive earnings surprises where the prevailing investor sentiment is negative and *vice versa*.

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[14] We conduct multicollinearity tests in order to ensure that our variables are not highly correlated with each other. The results of the VIF tests show that there is no multicollinearity problem as VIF values are substantially lower than 10. We present the correlation matrix in Appendix C Table C.1.

[15] The four portfolios of firms in Figure 1 cover the 96% of the total sample, since in our sample there exist two additional portfolios of firms: a) The portfolio of firms with positive SUE and zero $CSI_{(-2,0)}$ which includes 263 firm-quarter observations (2% of the sample); and b) The portfolio of firms with negative SUE and zero $CSI_{(-2,0)}$ which includes 347 firm-quarter observations (2% of the sample). However, the last two portfolios of firms are not reported in Figure1 for the ease of exposition and interpretation of the main results.

This is an indication that for a certain number of corporate earnings announcements (35% of the sample) the stock-specific investor sentiment (noise), and the actual earnings news (fundamental information) work in different directions, and it highlights the distinct impact of these two variables.[16] Therefore, both variables, the earnings surprises and the stock-specific sentiment, need to be considered when examining the stock market reaction around earnings announcements.

The comparison between the CAR series in Figure 1 is interesting. One should expect that the CARs for the portfolio of firms with positive (negative) SUE should increase (decrease) accordingly, but this is not always what we observe. While there is a sharp increase in the CARs for the portfolio of firms with positive SUE and positive $CSI_{(-2,0)}$ around the announcement date (there is a positive relation between fundamental information and investor sentiment), there is no increase in the CARs for the portfolio of firms with positive SUE and negative $CSI_{(-2,0)}$ (there is a negative relation between fundamental information and investor sentiment). The portfolio of firms with positive SUE and positive $CSI_{(-2,0)}$ experiences a CARs increase of almost 2.00% positive on day +1. On the other hand the portfolio of firms with positive SUE and negative $CSI_{(-2,0)}$ experiences a CARs decrease of almost -1.50% negative on day +1. The CARs of both firms' portfolios with negative SUE have a sharp decline around the announcement date, but the portfolio of firms with negative $CSI_{(-2,0)}$ experience a more than two times larger decline (-6.00%) than the portfolio of firms with positive $CSI_{(-2,0)}$ (-2.50%).

[16] This is consistent with the low correlation coefficient of 0.16 between SUE and $CSI_{(-2,0)}$ (see also Section 4.3 and Table C.1 in Appendix C).

Overall, the comparison of the CARs' for these four portfolios of firms illustrates clearly the stunning effects of positive and negative investor sentiment on firms' abnormal returns. These results suggest that for a significant number of firms the effect of investor sentiment is not in line with the effect of actual earnings information (35% of the sample), and that in some cases the effect of investor sentiment dominates the effect of actual earnings information (12% of the sample). Additionally, these results indicate that the impact of bearish investor sentiment leads to more dramatic stock price reactions than the impact of bullish investor sentiment during the earnings announcements period. Collectively, the results from Figure 1 are the first evidence that stock-specific investor sentiment plays a critical role in the market reaction around earnings announcements.

The main results of our multivariate analysis are presented in Tables 3 and 4. Panel A in Table 3 presents the OLS estimates of regressing the value-weighted $CAR_{(-1,+1)}$ on the two investor sentiment indexes (CSI and B&W). Panel B in Table 3 presents the OLS estimates of regressing the equally-weighted $CAR_{(-1,+1)}$ on the two investor sentiment indexes (CSI and B&W). In both Panels A and B of Table 3, the coefficients on $CSI_{(-2,0)}$ are positive and significant at the 1% level after controlling for year and sector fixed effects. This indicates a strong influence of stock-specific investor sentiment on announcement-period abnormal returns even after controlling for the earnings surprise variable (SUE). These results confirm our expectations regarding the impact of CSI on stocks' abnormal returns. The coefficients on SUE are also in line with the expectations; a positive earnings surprise should coincide with an increase in announcement abnormal returns and vice versa.

Results from Table 3 also suggest that there is only weak evidence of a market-wide investor sentiment effect (B&W) on announcement-period abnormal returns as the B&W measure is statistically insignificant in 3 out of 4 specifications. This is in contrast to prior studies (e.g. Mian & Sankaraguruswamy, 2012). We find however, that announcement-period abnormal returns are strongly related to stock-specific investor sentiment. These findings provide support for the notion that stock-level investor sentiment plays a significant role in the stock pricing process around an earnings announcement.

In Table 4 we examine the effect of investor sentiment when we control for additional firm specific variables. The coefficient on $CSI_{(-2,0)}$[17] is positive and statistically significant in all models at the 1% level. The highly significant coefficients of $CSI_{(-2,0)}$ demonstrate that after controlling for B&W, SUE, Loss, BM, Size, Leverage, ROA, and $CAR_{(-205,-6)}$ the stock-specific sentiment variable (CSI) contributes significantly to the market's short term assessment of the stocks' value. Additionally, the results show that the variable B&W has a moderate effect on announcement abnormal returns. Although the coefficient on B&W is positive and significant at the 5% level in Model 1, its effect is insignificant after we include the additional control variables.

We also examine the joint effect of the two investor sentiment indexes by including an interaction variable between $CSI_{(-2,0)}$ and B&W in Models 2 and 3. The

[17] In order to establish causality our investor sentiment proxy CSI is released ahead of market opening hours (at approximately 12:01 AM EST) and is measured in the (-2,0) days around the earnings announcements date while our dependent variable CAR is measured in the (-1,+1) days around the earnings announcements date, so any potential reverse causality concerns, where the level of abnormal returns drives first the level of investors' sentiment and not the opposite are mitigated considerably. Additionally, in Model 3 we include the $CAR_{(-205,-6)}$ which controls for the firm's past stock performance and naturally reflects the CARs during the two previous quarter earnings' announcements, and our CSI measure is unaffected by this inclusion. If the abnormal returns were driving the level of investor sentiment and not *vice versa*, then including a lagged measure of abnormal returns in the models should render the effect of contemporaneous CSI insignificant. However, we find that this inclusion does not affect the statistical significance of our sentiment variable and that the $CSI_{(-2,0)}$ variable *Granger-causes* the dependent variable $CAR_{(-1,+1)}$ (Granger, 1980).

coefficient on the interaction variable in Model 2 is significant at the 10% level, which indicates a weak joint effect between micro and macro investor sentiment. However, when we control for the additional variables, in Model 3, the statistically insignificant coefficient of the interaction variable implies that the role of micro investor sentiment in the valuation of earnings is independent from macro investor sentiment.

Most of our control variables are significant and carry the expected signs. In line with Hayn (1995), we find that reporting a loss has a negative impact on announcement-period abnormal returns. The coefficient on BM is significantly positive which shows that value firms earn higher abnormal returns which is consistent with the findings in de Haan, Shevlin, and Thornock (2015), and Savor and Wilson (2016). Additionally, and similar to Savor and Wilson (2016), Leverage is positive and significant which shows that the market reaction to earnings' news is larger for firms with high leverage. Momentum, as measured by $CAR_{(-205,-6)}$ is negative and significant which indicates that abnormal returns are lower when there is a strong run-up in the firms' stock returns in the period prior to the earnings announcements. This negative relationship corroborates the results in Rees and Thomas (2010). We find no evidence however, that firm size and profitability, as measured by ROA, have any significant effects on announcement-period abnormal returns.

So far, our regression results show a strong relationship between the variable CSI and the abnormal stock returns during the announcements of earnings' surprises. We also find that the effect of CSI is not altered by the inclusion of the B&W in our models, and that the impact of the B&W is less relevant for the investors' valuations of the firm's earnings.

6. Cross-Sectional Variation in the Response to Stock-Specific Investor Sentiment

We continue our analysis by focusing on the mechanisms by which investor sentiment affects stock prices: uncertainty in valuation and limits to arbitrage. We examine how uncertainty in valuation and the limits to arbitrage enhance or mitigate the effect of investor sentiment on the market's reaction to earnings surprises. To this end, we run our multivariate regression models for sub-samples based on firm characteristics to better gauge the effect of CSI on market participants' valuations of earnings across firms.

To examine the effect of uncertainty, we partition our sample into difficult/easy to value stocks based on four proxies of uncertainty - volatility, firm size, stock valuation, and analyst coverage - and investigate the effect of CSI on abnormal returns for each sub-group. We form stock groups on the basis of top and bottom quartiles (1 & 4) for each of these variables. We employ Morningstar Style Box classification to classify stocks according to size and style. We examine whether the effect of investor sentiment is more pronounced for stocks that are subject to uncertainty - stocks with high volatility, growth stocks, small stocks, and stocks with low analyst coverage - which compounds the difficulties of pricing or valuing these stocks.

Similarly, to assess the effect of limits to arbitrage, we partition our sample into high/low limits to arbitrage stocks based on four proxies of limits to arbitrage - Amihud illiquidity, the number of institutional shareholders, dollar trading volume, and bid-ask spread - and investigate the effect of stock-specific investor sentiment on abnormal returns in each sub-group. We form stock groups on the basis of top and bottom quartiles (1 & 4) of Amihud illiquidity, number of institutional shareholders, dollar trading volume, and bid-ask spread distributions. We investigate whether investor sentiment has a stronger effect on stocks that are difficult to arbitrage - stocks with high Amihud illiquidity, a small number of institutional shareholders, low dollar trading volume, and high bid-ask spread- due to arbitrageurs' failure to drive stock prices back to their fundamental values. In accordance with the uncertainty and limits to arbitrage hypotheses we expect the impact of stock-specific investor sentiment to be greater for the portfolios of stocks that are difficult to value and difficult to arbitrage.

Table 5 presents the estimates of our multivariate regression models for sub-groups of stocks classified according to our proxies of uncertainty. The effect of our main variable $CSI_{(-2,0)}$ is greater for the first group of each proxy, a finding which confirms that the effect of micro investor sentiment on the price formation process around earnings announcements is more pronounced for stocks with a higher level of uncertainty. Stocks with high volatility, small stocks, growth stocks, and stocks with low analyst coverage, which are subject to greater valuation uncertainties, are more sensitive to investor sentiment compared to stocks with low volatility, large stocks, value stocks, and stocks with high analyst coverage. At the bottom of the table we report the p-values of the Chow tests for the differences between the $CSI_{(-2,0)}$ coefficients across the groups, which confirm that the impact of $CSI_{(-2,0)}$ between the groups is significantly different at a level equal or higher than 5%.

Additionally, market-wide investor sentiment appears to be unrelated to announcement-period abnormal returns as the coefficients on B&W and $CSI_{(-2,0)}$* B&W are insignificant in the majority of our models. This picture changes however once we consider the coefficients on B&W for small, large, and growth stocks and $CSI_{(-2,0)}$ * B&W for volatile stocks. We note that market-wide investor sentiment has a positive impact on stock prices of small stocks (significant at 10% level) and growth stocks (significant at 1% level), and a negative impact on stock prices of large stocks (significant at 5% level). These results suggest that the general mood about financial markets is important for small, large, and growth stocks. In addition, the general mood about the financial market enhances the effect of stock-specific investor sentiment on announcement-period abnormal returns of volatile stocks (the coefficient on $CSI_{(-2,0)}$ * B&W is significant at 5% level), while it does not appear either to reinforce or moderate the impact of stock-specific investor sentiment in the other sub-groups.

Similarly in Table 6 we address the cross-sectional variation of the effect of stock-specific investor sentiment on announcement-period abnormal returns for sub-groups of stocks classified according to our proxies for limits to arbitrage. The results show that stock-specific investor sentiment has a positive effect on announcement-period abnormal returns of stocks that are difficult to arbitrage. The magnitude of the coefficients on $CSI_{(-2,0)}$ is much greater for stocks with high illiquidity, low number of institutional shareholders, low dollar trading volume, and high bid-ask spread compared to stocks with low illiquidity, high number of institutional shareholders, high dollar trading volume, and low bid-ask spread. The differences in the effect of stock-specific investor sentiment across related sub-groups are also confirmed with the results of the Chow tests at the bottom of the table.

In addition, the coefficients on B&W and $CSI_{(-2,0)}$ * B&W are insignificant in almost all sub-groups. The insignificant coefficients on B&W suggest that market-wide investor sentiment does not play a significant role in the stock price formation process around earnings announcements while the insignificant coefficients on $CSI_{(-2,0)}$ * B&W imply that in general there is not a significant joint effect between stock-specific and market-wide investor sentiment on abnormal returns. The only exception is the high bid-ask spread stocks sub-group where the coefficient on B&W is significant (at 1% level).

In summary, the results of our multivariate regression analysis in Tables 5 and 6 show that the effect of stock-specific investor sentiment is more pronounced for stocks that are hard to value or difficult to arbitrage.

7. Robustness Checks

We conduct a robustness check to investigate the predictive ability of our measure of stock-specific investor sentiment for post-announcement abnormal returns. In addition, we investigate whether our findings remain statistically significant when we employ different measures of market-wide investor sentiment and earnings surprises.[18]

7.1. Predicting Post-Announcement Abnormal Returns

In our main analysis, we illustrate a strong positive relationship between stock-specific investor sentiment and contemporaneous abnormal returns. In this section, we investigate whether this relationship is the result of a short-term market overreaction. If excessive optimism about a stock causes temporary mispricing and errors in valuation during the days of the earnings announcement, then we should expect that in the period following the earnings announcement stock returns will show signs of a mean reversion process, as the prices return to fundamental values (Brown & Cliff, 2005; Baker & Wurgler, 2007; and Da et al., 2015).[19] In other words, we should be

[18] We also employ a different measure of stock CARs. We use as a dependent variable the equally-weighted stock CARs in all the tables of our study, and our results are qualitatively similar with the main analysis so far (see Tables C.2, C.3 and C.4 in Appendix C).

[19] These studies examine future returns in relation to investor sentiment by using different market-level sentiment proxies. They provide evidence which confirms future returns are negatively related to investor sentiment.

able to use stock-specific investor sentiment to predict future abnormal returns in the form of return reversals. To this end we employ a regression analysis in order to relate stock-specific sentiment $CSI_{(-2,0)}$ to post-announcement abnormal returns. We estimate Model 3 of Table 4 by using as dependent variables the daily Abnormal Returns (ARs) over the following +2 to +6 days after the earnings announcements, and the Cumulative Abnormal Returns (CARs) over the windows (+3,+4), (+3,+6), and (+3,+10), where day 0 is the day of the earnings announcements. Moreover, we include the variable $CAR_{(-1,+1)}$ into the regression model to control for the effect of announcement-period abnormal returns on post-announcement abnormal returns. Since, finance theory proposes a negative relation between investor sentiment and future stock returns our hypotheses about the sign of the coefficient β on $CSI_{(-2,0)}$ are H0: $\beta(CSI_{(-2,0)}) = 0$ against H1: $\beta(CSI_{(-2,0)}) < 0$, which is closer to theory than the common alternative of H2: $\beta(CSI_{(-2,0)}) \neq 0$. Hence, the predictive ability of the $CSI_{(-2,0)}$ variable is examined by computing the statistical significance of the $CSI_{(-2,0)}$ coefficients with one-tailed tests, which have the attractive property of increasing the statistical power of our tests and accepting correctly the alternative hypothesis H1 when it is true[20] (Inoue & Kilian, 2005 and Huang et al., 2015).

Table 7 presents the results for this analysis. The results indicate that the initial impact of $CSI_{(-2,0)}$ on earnings' induced abnormal returns starts to reverse from day +3 and decrease slowly until day +10, although the magnitude and significance of the corrections are smaller than the initial overreaction. However, this smaller reaction should be expected since the magnitude of abnormal returns in the post-earnings announcement period (after day +1) is very close to 0, and a regression of the post-

[20] Technically this reduces the probability of Type II errors.

earnings abnormal returns against our independent variables will give smaller coefficient estimates relative to the main event window (-1,+1) which includes the investors' main reaction to the announcement of earnings' surprises (see also Figure 1). Overall, the results are consistent with what we would expect if the investors' reaction to earnings surprises was associated with sentiment; when investor sentiment is high, announcement-period abnormal returns are high and subsequent abnormal returns are low.

7.2. Daily Market-Wide Investor Sentiment

In our main analysis, we use Baker and Wurgler's (2006) sentiment index as the proxy for market-wide investor sentiment. This sentiment index is measured on a monthly basis while our proxy for stock-specific investor sentiment is measured on a daily basis. In order to compare better the impact of micro and macro investor sentiment we adopt two alternative proxies for market-wide investor sentiment which are estimated on a daily basis. We use PsychSignal Mood Indexes for NASDAQ100 and S&P500 as the proxies for market mood. We re-examine the impact of stock-specific (micro) investor sentiment on announcement-period abnormal returns while controlling for daily market-wide investor sentiment effect (see Table 8).

The impact of stock-specific investor sentiment is similar to the results in our main analysis while the impact of market-wide investor sentiment is asymmetric. We observe that public mood about NASDAQ100 influences firms' abnormal returns while public mood about S&P500 is unrelated to stocks' abnormal returns. In addition, the impact of stock-specific (micro) investor sentiment on abnormal returns is unaffected by both macro-mood indexes.

7.3. Earnings Surprises Based on the Seasonal Random Walk Model

In the main analysis, the earnings surprises are measured against the analysts' forecasts while in this section, we examine how stock CARs are affected by investor sentiment when the earnings surprises are measured by the seasonal random walk model[21], rather than against the analysts' forecasts (see Table 9). When we replicate the regression analyses in Table 3 and Table 4 with the seasonal-earnings surprises, the results are qualitatively similar to the findings of our main analysis. The results demonstrate that the significant relationship between stock-specific investor sentiment and firm CARs in the presence of earnings' surprises continues to hold when we estimate the earnings surprises with the seasonal random walk model.

8. Conclusion

Our research acknowledges the seismic changes which have taken place in market practice and market structure in recent years and harnesses the new technology utilised by market participants in the price formation process. We provide important insights into the relationship between investor sentiment and price formation. We extend the existing work of Baker and Wurgler (2006) and Mian and Sankaraguruswamy (2012) but go beyond the market mood and move from a general consideration of market-wide investor sentiment to a consideration of stock-specific investor sentiment and its role in price formation. Our research is novel in that it simultaneously considers both stock-specific investor sentiment and market-wide

[21] Seasonal random walk model standardized unexpected earnings (RW SUE) is the difference between actual earnings and actual earnings lagged four quarters, scaled by stock price at the end of the quarter.

investor sentiment in the context of earnings announcements. We make contributions to the existing literature in several areas. This study establishes a relationship between stock-specific investor sentiment and stock price movements around earnings announcements. Stock-specific investor sentiment is the key determinant of price adjustment in the context of an earnings surprise. The effect of stock-specific investor sentiment dominates the effect of macro-sentiment. We provide evidence that the effect of stock-specific investor sentiment is more pronounced for stocks that are hard to value and difficult to arbitrage. Finally, we also find evidence of sentiment driven mispricing and subsequent return reversals which have implications for price formation. These findings have important economic implications 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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Tables

Table 1

Summary Statistics: By Earnings Surprise, Market Cap, Stock Style, Market, Sector, and Announcement Year

This table presents summary statistics by earnings surprise, market cap, stock style, market, sector, and announcement year. Positive (negative) standardized unexpected earnings (SUE) consists of actual earnings that are higher (lower) than the average of I/B/E/S analyst forecasts. Market cap and stock style are based on Morningstar Style Box classifications. Stock exchange is the market that stocks are traded on. Sector is classified based on Global Industry Classification Standard (GICS) and announcement year is earnings announcement calendar year. See Appendix A for detailed definitions of the variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015.

Total Number of Observations	14,658	Sector	
		Energy	9%
		Materials	6%
Positive & Negative SUE		Industrials	12%
SUE>0	63%	Consumer Discretionary	16%
SUE<0	37%	Consumer Staples	5%
		Health Care	13%
Market Cap		Financials	15%
Large	20%	Information Technology	20%
Small	45%	Telecommunication Services	1%
		Utilities	3%
Stock Style			
Value	25%	Announcement Year	
Growth	30%	2011	4%
		2012	13%
Stock Exchange		2013	21%
NYSE	60%	2014	32%
NASDAQ	40%	2015	30%

Table 2

Descriptive Statistics: Key Variables

This table presents summary statistics; reports the numbers of observations, means, medians, standard deviations, minimums, and maximums of cumulative abnormal returns (CAR), cumulative stock-specific investor sentiment (CSI), standardized unexpected earnings (SUE), Baker & Wurgler's (2006) sentiment index (B&W), loss (Loss), book-to-market ratio (BM), firms size (Size), leverage (Leverage), return on assets (ROA), as well as the proxies of uncertainty including volatility (Volatility) and analyst coverage (Analyst), and the proxies of limits to arbitrage including Amihud (2002) illiquidity (Illiquidity), number of institutional shareholders (InstOwner), dollar trading volume ($Volume), and bid-ask spread (Bid-Ask). See Appendix A for detailed definitions of the variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific investor sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Institutional ownership records come from Thomson Reuters. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers.

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
$CAR_{(-1,+1)}$	14,658	-0.0003	0.0005	0.0801	-0.2581	0.2336
$CSI_{(-2,0)}$	14,658	0.8678	0.8890	1.1550	-1.8335	3.5353
SUE	14,658	0.9982	0.6685	3.6760	-10.7698	16.5128
B&W	14,658	-0.0130	-0.0263	0.0972	-0.2072	0.2909
Loss	14,658	0.2053	0.0000	0.4039	0.0000	1.0000
BM	14,653	0.4830	0.3899	0.4011	-0.3786	1.9921
Size	14,653	7.5694	7.5302	1.7173	3.7731	11.7664
Leverage	14,579	0.2544	0.2301	0.2192	0.0000	0.8784
ROA	14,651	-0.0078	0.0298	0.1814	-0.9204	0.2822
$CAR_{(-205,-6)}$	14,017	-0.0332	-0.0228	0.4787	-1.5889	1.5500
Volatility	14,607	0.0216	0.0183	0.0123	0.0071	0.0685
Analyst	14,633	10.4794	8.0000	7.6101	1.0000	35.0000
Illiquidity (x 10^{-7})	14,608	0.1590	0.0107	0.5530	0.0001	4.1800
InstOwner	12,979	212.26	139.00	220.64	9.00	1261.00
$Volume (M)	14,608	57.5000	15.8000	109.000	0.1108	683.0000
Bid-Ask	14,608	0.0265	0.0140	0.0360	0.0099	0.2449

Figure 1

Cumulative Abnormal Returns Plots for Samples by Earnings Surprises and Stock-Specific Investor Sentiment

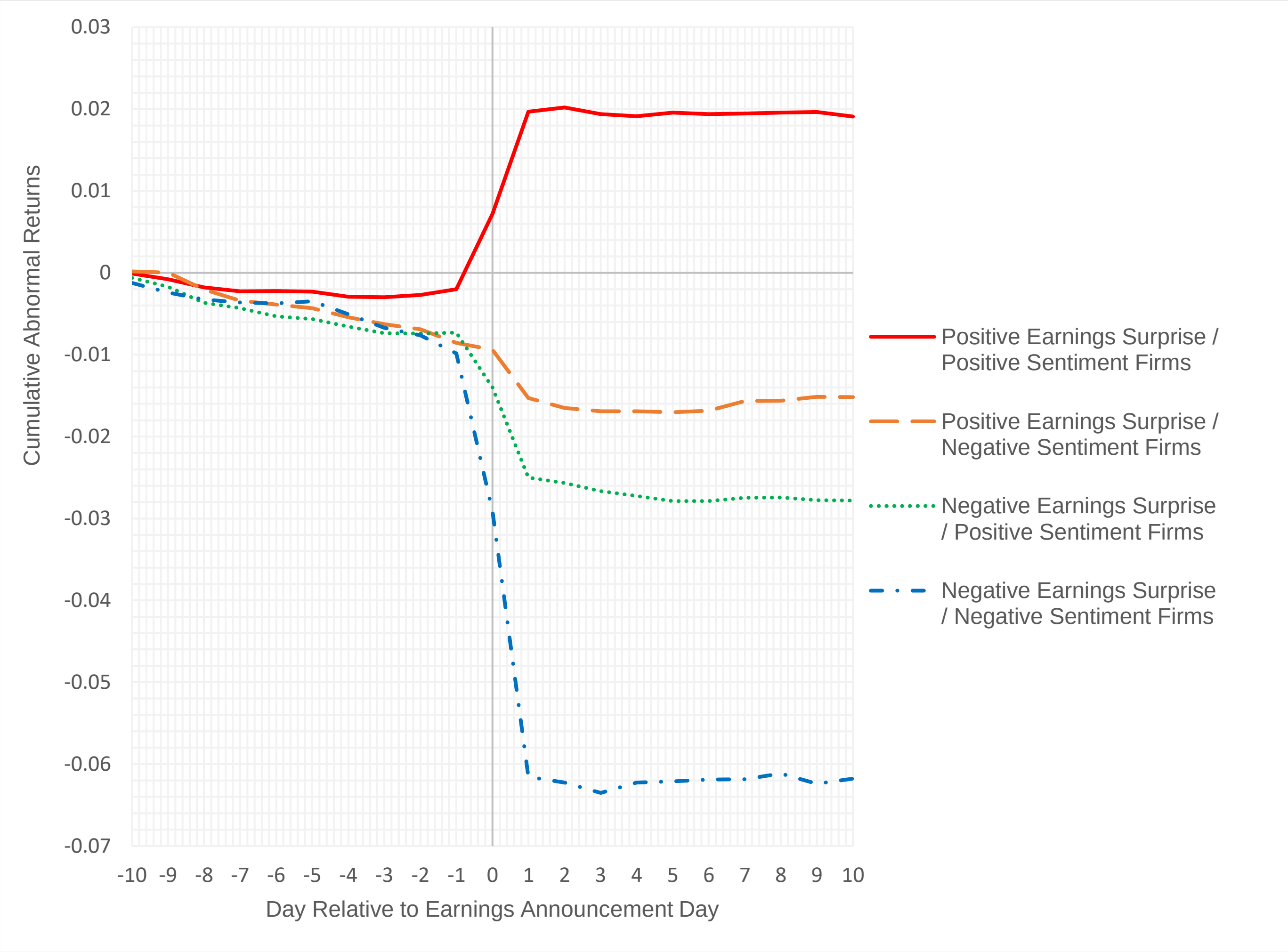

Table 3

Regression Results: The Effects of Stock-Specific and Market-Wide Investor Sentiment

This table compares the effects of stock-specific investor sentiment (CSI) and market-wide investor sentiment, Baker & Wurgler's (2006) sentiment index (B&W) on announcement-period abnormal returns (CAR). Cumulative abnormal return is measured related to value-weighted market return (panel A) and equally-weighted market return (panel B). See Appendix A for detailed definitions of the variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Model 1	Model 2	Variable	Model 3	Model 4
Panel A: CARs Value-Weighted					
$CSI_{(-2,0)}$	0.0161***	0.0130***	B&W	0.0146	0.0142*
	(28.23)	(23.81)		(1.65)	(1.69)
SUE		0.0056***	SUE		0.0063***
		(23.95)			(26.08)
Constant	-0.0213***	-0.0195***	Constant	-0.0135***	-0.0137***
	(-5.64)	(-5.38)		(-3.24)	(-3.48)
Year F.E	Yes	Yes	Year F.E	Yes	Yes
Sector F.E	Yes	Yes	Sector F.E	Yes	Yes
Obs	14658	14658	Obs	14658	14658
Adjusted R^2	0.0558	0.1187	Adjusted R^2	0.0031	0.0853

Variable	Model 5	Model 6	Variable	Model 7	Model 8
Panel B: CARs Equally-Weighted					
$CSI_{(-2,0)}$	0.0161***	0.0130***	B&W	-0.0072	-0.0076
	(28.23)	(23.83)		(-0.82)	(-0.90)
SUE		0.0056***	SUE		0.0063***
		(24.04)			(26.17)
Constant	-0.0214***	-0.0195***	Constant	-0.0091**	-0.0092**
	(-5.65)	(-5.38)		(-2.17)	(-2.35)
Year F.E	Yes	Yes	Year F.E	Yes	Yes
Sector F.E	Yes	Yes	Sector F.E	Yes	Yes
Obs	14658	14658	Obs	14658	14658
Adjusted R^2	0.0556	0.1189	Adjusted R^2	0.0026	0.0853

Table 4

Regression Results: The Individual and Joint Effects of Stock Specific and Market-Wide Investor Sentiment

This table reports the results of regressions for investigating the individual and joint effects of stock-specific investor sentiment (CSI) and market-wide investor sentiment, Baker & Wurgler's (2006) sentiment index (B&W) on announcement-period abnormal returns (CAR). See Appendix A for detailed definitions of the variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Model 1	Model 2	Model 3
$CSI_{(-2,0)}$	0.0131***	0.0132***	0.0128***
	(23.84)	(23.77)	(23.04)
SUE	0.0056***	0.0056***	0.0056***
	(23.94)	(23.94)	(22.15)
B&W	0.0167**	0.0083	0.0068
	(2.01)	(0.81)	(0.64)
$CSI_{(-2,0)}$*B&W		0.0098*	0.0066
		(1.70)	(1.12)
Loss			-0.0070***
			(-2.61)
BM			0.0072***
			(3.55)
Size			0.0006
			(1.47)
Leverage			0.0121***
			(3.82)
ROA			-0.0078
			(-1.29)
$CAR_{(-205,-6)}$			-0.0038**
			(-2.08)
Constant	-0.0229***	-0.0224***	-0.0341***
	(-5.80)	(-5.64)	(-5.86)
Year F.E	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes
Obs	14658	14658	13936
Adjusted R^2	0.1189	0.1190	0.1217

Table 5

Regression Results: Variation in the Impact of Stock-Specific Investor Sentiment for Difficult/Easy to Value Firms

This table reports the results of regressions for relation of cumulative abnormal return (CAR) with cumulative stock-specific investor sentiment (CSI) for each subsample split by a given measure of uncertainty proxies. The measures of uncertainty include volatility (Volatility), market cap, stock style, and analyst coverage (Analyst). See Appendix A for detailed definitions of the variables. Top and bottom portfolios (quartiles 1&4) of volatility (Volatility) and analyst coverage (Analyst) are considered for analyse. Market cap and stock style are classified based on Morningstar Style Box. Statistical tests for differences of CSI between two groups are presented. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Stock style classifications are from Morningstar. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Volatility		Market Cap		Stock Style		Analyst Coverage	
	High	Low	Small	Large	Growth	Value	Low	High
$CSI_{(-2,0)}$	0.0180***	0.0075***	0.0147***	0.0076***	0.0153***	0.0102***	0.0132***	0.0101***
	(10.99)	(14.27)	(16.35)	(9.91)	(13.95)	(10.86)	(12.08)	(10.35)
SUE	0.0062***	0.0034***	0.0064***	0.0040***	0.0066***	0.0047***	0.0045***	0.0073***
	(10.07)	(12.40)	(17.95)	(9.80)	(13.85)	(11.90)	(12.16)	(14.19)
B&W	0.0121	-0.0082	0.0300*	-0.0310**	0.0715***	-0.0200	0.0122	0.0082
	(0.43)	(-0.69)	(1.71)	(-2.05)	(3.67)	(-1.06)	(0.57)	(0.49)
$CSI_{(-2,0)}$*B&W	0.0370**	0.0063	0.0021	0.0023	-0.0051	0.0040	0.0120	-0.0030
	(2.02)	(1.08)	(0.22)	(0.29)	(-0.42)	(0.43)	(0.98)	(-0.32)
Loss	-0.0179***	0.0070	-0.0105***	0.0092	-0.0058	-0.0087*	-0.0160***	0.0083
	(-3.47)	(1.59)	(-2.86)	(1.50)	(-1.15)	(-1.76)	(-4.15)	(1.39)
BM	0.0096**	0.0033	0.0048	0.0058*	0.0007	0.0062*	0.0064	0.0059*
	(2.16)	(1.28)	(1.49)	(1.86)	(0.13)	(1.73)	(1.64)	(1.70)
Size	0.0019	0.0001	-0.0008	0.0014	0.0017*	-0.0004	-0.0007	0.0019*
	(1.15)	(0.29)	(-0.67)	(1.40)	(1.93)	(-0.54)	(-0.75)	(1.89)
Leverage	0.0233**	0.0015	0.0139***	0.0004	0.0085	0.0099*	0.0132**	0.0146**
	(2.42)	(0.39)	(2.67)	(0.08)	(1.48)	(1.67)	(2.01)	(2.19)
ROA	-0.0195**	-0.0034	-0.0089	-0.0016	-0.0144	0.0036	-0.0115	-0.0198
	(-2.22)	(-0.18)	(-1.11)	(-0.08)	(-1.33)	(0.23)	(-1.39)	(-1.18)
$CAR_{(-205,-6)}$	-0.0038	-0.0090**	-0.0080***	-0.0077	-0.0000	-0.0133***	-0.0043	-0.0005
	(-1.50)	(-2.14)	(-3.10)	(-1.41)	(-0.00)	(-3.54)	(-1.51)	(-0.11)
Constant	-0.0614***	-0.0085	-0.0307**	-0.0215*	-0.0696***	-0.0099	-0.0300**	-0.0388***
	(-3.45)	(-1.11)	(-2.56)	(-1.82)	(-5.99)	(-0.93)	(-2.22)	(-3.28)
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	3274	3610	6489	2930	4360	3681	4296	3556
Adjusted R^2	0.1089	0.1435	0.1455	0.0974	0.1319	0.1150	0.1185	0.1198
Chow Test	37.95		35.97		12.68		4.52	
p-value	(0.000)		(0.000)		(0.000)		(0.034)	

Table 6

Regression Results: Variation in the Impact of Stock-Specific Investor Sentiment for High/Low Limits to Arbitrage Firms

This table reports the results of regressions for relation of cumulative abnormal return (CAR) with cumulative stock-specific investor sentiment (CSI) for each subsample split by a given measure of limits to arbitrage proxies. The measures of limits to arbitrage include Amihud (2002) illiquidity (Illiquidity), number of institutional shareholders (InstOwner), dollar trading volume ($Volume), and bid-ask spread (Bid-Ask). See Appendix A for detailed definitions of the variables. Top and bottom quartiles (1&4) of Amihud (2002) illiquidity (Illiquidity), number of institutional shareholders (InstOwner), dollar trading volume ($Volume), and bid-ask spread (Bid-Ask) are considered for analyse. Statistical tests for differences of CSI between two groups are presented. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Institutional ownership records come from Thomson Reuters. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Amihud Illiquidity		No of Institutional Shareholders		Dollar Trading Volume		Bid-Ask Spread	
	High	Low	Low	High	Low	High	High	Low
$CSI_{(-2,0)}$	0.0156***	0.0083***	0.0147***	0.0074***	0.0144***	0.0099***	0.0123***	0.0097***
	(11.17)	(10.59)	(9.84)	(9.10)	(11.09)	(11.09)	(9.88)	(9.63)
SUE	0.0054***	0.0045***	0.0047***	0.0053***	0.0055***	0.0055***	0.0052***	0.0054***
	(10.63)	(11.49)	(8.61)	(13.14)	(11.89)	(12.73)	(10.06)	(11.46)
B&W	0.0228	0.0173	0.0274	-0.0182	0.0245	0.0131	0.0795***	-0.0145
	(0.85)	(1.07)	(1.02)	(-1.12)	(0.96)	(0.79)	(3.30)	(-0.84)
$CSI_{(-2,0)}$*B&W	0.0066	-0.0022	0.0181	0.0071	0.0026	0.0013	0.0037	0.0024
	(0.41)	(-0.27)	(1.09)	(0.85)	(0.18)	(0.14)	(0.25)	(0.23)
Loss	-0.0219***	0.0059	-0.0195***	0.0113**	-0.0175***	0.0050	-0.0185***	-0.0059
	(-4.72)	(1.21)	(-3.65)	(2.03)	(-3.89)	(0.91)	(-3.34)	(-1.25)
BM	0.0060	0.0055	0.0044	0.0027	0.0037	0.0085**	0.0095*	0.0087***
	(1.36)	(1.64)	(0.89)	(0.80)	(0.83)	(2.35)	(1.65)	(2.66)
Size	-0.0006	0.0020**	-0.0010	0.0011	-0.0013	0.0029***	0.0001	0.0010
	(-0.37)	(2.08)	(-0.68)	(1.13)	(-0.84)	(2.59)	(0.10)	(1.23)
Leverage	0.0140*	0.0119**	0.0173**	0.0126**	0.0148*	0.0218***	0.0131*	0.0106**
	(1.66)	(2.24)	(2.12)	(2.30)	(1.94)	(3.30)	(1.71)	(1.97)
ROA	-0.0168*	-0.0163	-0.0124	-0.0142	-0.0116	0.0152	-0.0101	-0.0220
	(-1.91)	(-0.84)	(-1.26)	(-0.70)	(-1.23)	(0.70)	(-0.74)	(-1.43)
$CAR_{(-205,-6)}$	-0.0022	-0.0009	-0.0018	-0.0024	-0.0024	-0.0023	0.0048	-0.0156***
	(-0.80)	(-0.19)	(-0.65)	(-0.49)	(-0.78)	(-0.55)	(1.48)	(-4.14)
Constant	-0.0260	-0.0349***	-0.0314	-0.0232*	-0.0242	-0.0550***	-0.0504***	-0.0282**
	(-1.47)	(-3.00)	(-1.58)	(-1.95)	(-1.44)	(-4.17)	(-3.63)	(-2.34)
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	3285	3609	2893	3201	3375	3582	3123	3640
Adjusted R^2	0.1310	0.0896	0.1062	0.1107	0.1321	0.1003	0.1152	0.1090
Chow Test	21.01		18.29		8.30		2.71	
p-value	(0.000)		(0.000)		(0.004)		(0.099)	

Table 7

Robustness Check: Predicting Post-Announcement Abnormal Returns

This table relates announcement-period stock-specific investor sentiment (CSI) to post-announcement abnormal returns (ARs and CARs). Abnormal returns are measured related to value-weighted market returns over the following +2 to +6 days after the earnings announcements. Cumulative abnormal returns are measured related to value-weighted market returns over the windows (+3,+4), (+3,+6), and (+3,+10), where day 0 is the day of the earnings announcements. See Appendix A for detailed definitions of the variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The p-values are reported in parentheses. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively. The statistical significance of the coefficients on $CSI_{(-2,0)}$ is reported based on one-tailed p-values.

Variable	$AR_{(+2)}$	$AR_{(+3)}$	$AR_{(+4)}$	$AR_{(+5)}$	$AR_{(+6)}$	$CAR_{(+3,+4)}$	$CAR_{(+3,+6)}$	$CAR_{(+3,+10)}$
$CSI_{(-2,0)}$	0.0002	-0.0002*	-0.0003**	0.0002	-0.0002*	-0.0005**	-0.0006**	-0.0008**
	(0.844)	(0.094)	(0.044)	(0.905)	(0.054)	(0.018)	(0.032)	(0.031)
SUE	0.0001	0.0000	0.0001	0.0000	0.0001	0.0001	0.0002**	0.0000
	(0.102)	(0.627)	(0.119)	(0.774)	(0.191)	(0.102)	(0.035)	(0.828)
$CAR_{(-1,+1)}$	0.0136***	0.0021	-0.0041	-0.0030	-0.0022	-0.0043	-0.0103*	0.0052
	(0.001)	(0.529)	(0.146)	(0.306)	(0.402)	(0.320)	(0.098)	(0.518)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	13934	13933	13933	13933	13931	13933	13931	13931
Adjusted R^2	0.0039	0.0052	0.0037	0.0048	0.0041	0.0073	0.0142	0.0187

Table 8

Robustness Check: Daily Market-Wide Investor Sentiment

This table reports the results of regressions for relation of cumulative abnormal return (CAR) with cumulative stock-specific investor sentiment (CSI) while the effect of daily market-wide investor sentiment is controlled. NASDAQ100 and S&P500 Mood Indexes are considered as proxies for market-wide investor sentiment. See Appendix A for detailed definitions of the variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Model 1	Model 2	Model 3
$CSI_{(-2,0)}$	0.0130***	0.0130***	0.0127***
	(23.77)	(21.89)	(21.62)
SUE	0.0056***	0.0056***	0.0056***
	(23.92)	(23.92)	(22.15)
$CSI_{ndx(-2,0)}$	0.0018***	0.0018***	0.0016***
	(4.13)	(3.12)	(2.74)
$CSI_{spx(-2,0)}$	0.0002	0.0001	0.0001
	(0.35)	(0.14)	(0.22)
$CSI_{(-2,0)}$*$CSI_{ndx(-2,0)}$		-0.0000	-0.0000
		(-0.03)	(-0.08)
$CSI_{(-2,0)}$*$CSI_{spx(-2,0)}$		0.0001	-0.0000
		(0.20)	(-0.08)
Loss			-0.0068**
			(-2.51)
BM			0.0073***
			(3.58)
Size			0.0005
			(1.18)
Leverage			0.0123***
			(3.87)
ROA			-0.0076
			(-1.26)
$CAR_{(-205,-6)}$			-0.0039**
			(-2.16)
Constant	-0.0207***	-0.0207***	-0.0321***
	(-5.71)	(-5.71)	(-5.66)
Year F.E	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes
Obs	14658	14658	13936
Adjusted R^2	0.1199	0.1198	0.1224

Table 9

Robustness Check: Seasonal Random Walk Model Earnings Surprises

This table reports the results of regressions for relation of cumulative abnormal return (CAR) with cumulative stock-specific investor sentiment (CSI) while earnings surprise is measured by seasonal random walk model. Seasonal random walk model standardized unexpected earnings (RW SUE) is the difference between actual earnings and actual earnings lagged four quarters, scaled by stock price at the end of the quarter. See Appendix A for detailed definitions of other variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
$CSI_{(-2,0)}$	0.0150***		0.0150***	0.0152***	0.0151***
	(23.36)		(23.37)	(23.21)	(23.05)
RW SUE	0.3627***	0.4319***	0.3616***	0.3610***	0.3301***
	(8.03)	(8.99)	(8.00)	(7.99)	(7.09)
B&W		0.0171*	0.0199**	0.0135	0.0108
		(1.72)	(2.04)	(1.09)	(0.86)
$CSI_{(-2,0)}$*B&W				0.0071	0.0061
				(1.09)	(0.94)
Loss					-0.0161***
					(-4.97)
BM					0.0084***
					(3.40)
Size					0.0011**
					(2.05)
Leverage					0.0045
					(1.17)
ROA					-0.0141*
					(-1.89)
$CAR_{(-205,-6)}$					-0.0074***
					(-3.13)
Constant	-0.0166***	-0.0104**	-0.0206***	-0.0203***	-0.0337***
	(-3.91)	(-2.22)	(-4.42)	(-4.29)	(-4.76)
Year F.E	Yes	Yes	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes	Yes	Yes
Obs	10137	10137	10137	10137	10064
Adjusted R^2	0.0597	0.0129	0.0600	0.0600	0.0668

Appendix A: Variable Definitions and Sources

Variable	Definitions	Source
$CAR_{(-1,+1)}$	Cumulative Abnormal Return relative to value-weighted market return over the three-day window centred on the earnings announcement date.	CRSP
$CSI_{(-2,0)}$	Cumulative stock-specific investor sentiment Index over the three-day window from 2 days before the earnings announcement date until the date of announcement, where Sentiment Index (SI) is measured as natural logarithm of (1+Bulish 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 forecast errors.	I/B/E/S
B&W	Baker & Wurgler's (2006) Index of investor sentiment (market-wide) for the month of the earnings announcement. Baker and Wurgler's Index is available up to the end of September, 2015 from Jeffrey Wurgler's website. Holt–Winters non-seasonal smoothing method is used to forecast the index for October, November, and December, 2015 (based on the index values over the period of January, 2011 to September, 2015).	http://people.stern.nyu.edu/jwurgler/
$CSI_{(-2,0)}$*B&W	An interaction variable of investor sentiment indexes, between cumulative stock-specific investor sentiment Index, $CSI_{(-2,0)}$, and market-wide investor sentiment, B&W.	PsychSignal & 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 prior the earnings announcement.	Compustat
Size	The natural logarithm of share price times shares outstanding in the year prior the earnings announcement.	Compustat
Leverage	The sum of long term debt and the debt in current liabilities divided by total assets in the year prior the earnings announcement.	Compustat
ROA	The ratio of net income to total assets in the year prior the earnings announcement.	Compustat
$CAR_{(-205,-6)}$	Cumulative Abnormal Return related to value-weighted market return over the (-205,-6) day interval prior the earnings announcement.	CRSP
Volatility	Standard deviation of stock daily abnormal return related to value-weighted market return over the (-205,-6) day interval prior the earnings announcement.	CRSP
Analyst	The number of analysts providing one year ahead EPS forecast in the month prior the earnings announcement.	I/B/E/S
Illiquidity	Amihud (2002) illiquidity measured as the average ratio of the absolute daily return to the dollar trading volume on that day over the (-205,-6) day interval prior the earnings announcement.	CRSP
InstOwner	The number of institutional shareholders holding a firm's shares at the year prior the earnings announcement.	Thomson Reuters
$Volume	Dollar trading volume measured as the average of daily share trading volume times closing price over the (-205,-6) day interval prior the earnings announcement.	CRSP
Bid-Ask	Average daily bid-ask spread over the (-205,-6) day interval prior the earnings announcement.	CRSP
Small/Large Stocks	Market cap classification based on Morningstar style box in the month prior the earnings announcement.	Morningstar
Growth/Value Stocks	Stock style classification based on Morningstar style box in the month prior the earnings announcement.	Morningstar

Appendix B: PsychSignal's Textual Sentiment Measures

We use a commercial organization, PsychSignal, as the source of our stock-specific investor sentiment and daily sentiment index data, which is based on stock related messages that are extracted from Twitter and StockTwits. PsychSignal is a leading provider of real-time trader sentiment data covering more than 10,000 individual securities including all stocks in the NASDAQ100 and S&P500[22].

PsychSignal has created a highly specialized natural language processing (NLP) engine, which analyses millions of tweets every day in order to quantify the public mood about the universe of stocks it covers. The NLP engine uses a sophisticated linguistic based approach to sentiment mining that is able to correctly extract, interpret, and score online conversations in the context of stock related comments. PsychSignal has developed its NLP engine based on the Linguistic Inquiry and Word Count (LIWC) application (the most recent evolution, LIWC2015 (Pennebaker, Booth, Boyd, & Francis, 2015)). The PsychSignal NLP engine uses LIWC textual analysis methods to determine the degree to which any text contains positive or negative emotions, self-references, causal words, and other language dimensions.[23] The NLP engine processes the language used for stocks and securities' names the same way a professional trader would do as it uses an enormous lexicon of n-grams evaluated, scored, and filtered by hundreds of trading professionals. It is programmed in such a way as to locate the subtle yet specific language nuances used by professionals on the trading floors instead of trying to guess sentiment by using the

[22] The definitions and descriptions in this Appendix are based on documents and information provided by PsychSignal. For further detains see https://psychsignal.com/.
[23] For further details about the LIWC application refer to "The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods" (Tausczik & Pennebaker, 2010) and "The Development and Psychometric Properties of LIWC2015" (Pennebaker, Boyd, Jordan, & Blackburn, 2015).

language of the general public or even a financial dictionary. PsychSignal's specialized NLP engine, along with its smart filtering and quantification algorithms, allows it to recognize, categorize, and specifically quantify the meaning behind each word communicated in the nuanced language used on Twitter and StockTwits. As a result, it is claimed that PsychSignal's system can correctly score messages like "$MSFT is ripping right now", "it's a Dead cat bounce on NFLX", or "loading the boat with SPY". The NLP engine's potential for the codification and extraction of the psychological meaning of words along with PsychSignal's access to the full firehose datafeeds from its business partners like Twitter and StockTwits gives it a critical advantage over other companies in this field enabling it to give its subscribers the most granular financial sentiment faster and more accurately than other sources.

Every day PsychSignal rolls up 24 hours of data and releases mood data at approximately 12:01 AM EST. Its technology works as follows: it ingests social media firehoses, categorizes conversations by security, analyses mood,[24] aggregates mood scores for each security based upon the total volume and mood intensity, and outputs trading signals. In fact, PsychSignal provides trading signals before the opening of the stock markets on a daily basis. The outputs clarify how the public sentiment surrounding stocks and securities is trending so that PsychSignal users are able to predict market moves in advance. This allows them to execute reliable algorithmic trading strategies which incorporate a real-time view into the public psychology about stocks and markets.

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[24] PsychSignal's NLP engine detects the online community's mood, bullishness and bearishness and also scores the mood intensity.

We use both PsychSignal's stock-specific mood data and PsychSignal's market-wide mood data in this study. PsychSignal market-wide Mood Indexes are real-time aggregate sentiment indexes which measure traders' sentiment on the NASDAQ100 and S&P500 stock market indexes. The stock mood data is numerical raw data containing symbol, timestamp (UTC), bullish-intensity, bearish-intensity, bull-minus-bear, bull-scored-messages, bear-scored-messages, bull-bear-msg-ratio, and total-scanned-messages. The volume measures and sentiment analytics are defined as:

Bull-scored-messages: total count of bullish sentiment messages scored by PsychSignal's algorithm.

Bear-scored-messages: total count of bearish sentiment messages scored by PsychSignal's algorithm.

Bullish-intensity: score for each message's language for the strength of the bullishness that is contained in the messages on a 0-4 scale. A high score indicates a high bullish investor sentiment and *vice versa*.

Bearish-intensity: score for each message's language for the strength of the bearishness that is contained in the messages on a 0-4 scale. A high score indicates a high bearish investor sentiment and *vice versa*.

Total-scanned-messages: number of messages coming through PsychSignal's feeds and are related to a stock symbol regardless of whether the PsychSignal sentiment engine can score them for bullish or bearish intensity.

The total message count includes natural messages, which do not contain bullish or bearish emotion, and are therefore not active components of the sentiment measures.

Appendix C: Additional Empirical Results

Table C.1

Correlation Matrix

This table presents correlations of variables, cumulative abnormal return (CAR), cumulative stock-specific investor sentiment (CSI), standardized unexpected earnings (SUE), Baker & Wurgler's (2006) sentiment index (B&W), loss (Loss), book-to-market ratio (BM), firms size (Size), leverage (Leverage), return on assets (ROA), as well as the proxies of uncertainty including volatility (Volatility) and analyst coverage (Analyst), and proxies of limits to arbitrage including Amihud (2002) illiquidity (Illiquidity), number of institutional shareholders (InstOwner), dollar trading volume ($Volume), and bid-ask spread (Bid-Ask). See Appendix A for detailed definitions of the variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Institutional ownership records come from Thomson Reuters. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers.

Variable	$CAR_{(-1,+1)}$	$CSI_{(-2,0)}$	SUE	B&W	Loss	BM	Size	Leverage	ROA	$CAR_{(-205,-6)}$	Volatility	Analyst	Illiquidity	InstOwner	$Volume	Bid-Ask
$CAR_{(-1,+1)}$	1.0000															
$CSI_{(-2,0)}$	0.2243	1.0000														
SUE	0.2891	0.1570	1.0000													
B&W	0.0082	-0.0360	0.0026	1.0000												
Loss	-0.1037	-0.0654	-0.2236	0.0021	1.0000											
BM	0.0086	0.0165	-0.0557	0.0245	-0.0236	1.0000										
Size	0.0268	-0.0388	0.0715	-0.0163	-0.4147	-0.1599	1.0000									
Leverage	0.0124	0.0387	-0.0944	-0.0084	-0.1086	-0.0287	0.1340	1.0000								
ROA	0.0411	0.0128	0.0761	-0.0047	-0.6066	0.0488	0.4386	0.0834	1.0000							
$CAR_{(-205,-6)}$	0.0001	0.0676	0.0247	-0.0369	-0.0208	0.0519	-0.0303	0.0100	-0.0634	1.0000						
Volatility	-0.0439	-0.0980	-0.0341	0.0260	0.5212	-0.0533	-0.5821	-0.2290	-0.5405	-0.0165	1.0000					
Analyst	0.0244	-0.1103	0.0738	-0.0099	-0.2553	-0.1383	0.6752	0.0025	0.2489	-0.0087	-0.2841	1.0000				
Illiquidity	-0.0114	0.0074	-0.0334	0.0142	0.2357	0.0597	-0.3629	-0.0833	-0.2902	0.0798	0.2902	-0.2200	1.0000			
InstOwner	0.0141	-0.0893	0.0501	-0.0362	-0.2751	-0.0728	0.7911	0.0736	0.2705	0.0052	-0.4350	0.6544	-0.2278	1.0000		
$Volume	0.0068	-0.1405	0.0383	-0.0147	-0.1742	-0.0744	0.6750	0.0260	0.1764	-0.0111	-0.2300	0.6491	-0.1468	0.8531	1.0000	
Bid-Ask	-0.0177	0.0144	-0.0392	-0.0181	0.1181	-0.1045	-0.2066	-0.1121	-0.0948	-0.0041	0.1760	-0.1923	0.4431	-0.2361	-0.1130	1.0000

Table C.2

Robustness Check: Equally-Weighted Abnormal Returns

This table reports the results of regressions for investigating the individual and joint effects of stock-specific investor sentiment (CSI) and market-wide investor sentiment, Baker & Wurgler's (2006) sentiment index (B&W) on announcement-period abnormal returns (CAR) while cumulative abnormal return (CAR) is related to equally-weighted market return. See Appendix A for detailed definitions of other variables. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Model 1	Model 2	Model 3
$CSI_{(-2,0)}$	0.0130***	0.0131***	0.0128***
	(23.80)	(23.71)	(22.96)
SUE	0.0056***	0.0056***	0.0056***
	(24.04)	(24.04)	(22.26)
B&W	-0.0051	-0.0131	-0.0137
	(-0.62)	(-1.28)	(-1.31)
$CSI_{(-2,0)}$*B&W		0.0092	0.0064
		(1.61)	(1.08)
Loss			-0.0065**
			(-2.42)
BM			0.0072***
			(3.53)
Size			0.0006
			(1.36)
Leverage			0.0118***
			(3.73)
ROA			-0.0085
			(-1.41)
$CAR_{(-205,-6)}$			-0.0042**
			(-2.29)
Constant	-0.0184***	-0.0180***	-0.0291***
	(-4.66)	(-4.52)	(-4.97)
Year F.E	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes
Obs	14658	14658	13936
Adjusted R^2	0.1189	0.1190	0.1215

Table C.3

Robustness Check: Equally-Weighted Abnormal Returns

This table reports the results of regressions for relation of cumulative abnormal return (CAR) with cumulative stock-specific investor sentiment (CSI) for each subsample split by a given measure of uncertainty proxies while cumulative abnormal return (CAR) is related to equally-weighted market return. The measures of uncertainty include volatility (Volatility), market cap, stock style, and analyst coverage (Analyst). See Appendix A for detailed definitions of the variables. Top and bottom quartiles (1&4) of volatility (Volatility) and analyst coverage (Analyst) are considered for analyse. Market cap and stock style are classified based on Morningstar Style Box. Statistical tests for differences of CSI between two groups are presented. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Stock style classifications are from Morningstar. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Volatility		Market Cap		Stock Style		Analyst Coverage	
	High	Low	Small	Large	Growth	Value	Low	High
$CSI_{(-2,0)}$	0.0181***	0.0076***	0.0147***	0.0078***	0.0152***	0.0103***	0.0131***	0.0101***
	(11.04)	(14.30)	(16.32)	(10.00)	(13.78)	(10.84)	(12.09)	(10.39)
SUE	0.0062***	0.0034***	0.0064***	0.0040***	0.0066***	0.0047***	0.0045***	0.0073***
	(10.23)	(12.25)	(18.05)	(9.77)	(13.90)	(11.90)	(12.22)	(14.33)
B&W	-0.0143	-0.0218*	0.0082	-0.0427***	0.0476**	-0.0331*	-0.0080	-0.0114
	(-0.52)	(-1.82)	(0.47)	(-2.78)	(2.46)	(-1.75)	(-0.38)	(-0.68)
$CSI_{(-2,0)}$*B&W	0.0375**	0.0054	0.0023	0.0018	-0.0056	0.0033	0.0118	-0.0037
	(2.06)	(0.91)	(0.24)	(0.22)	(-0.47)	(0.35)	(0.98)	(-0.39)
Loss	-0.0172***	0.0069	-0.0098***	0.0088	-0.0049	-0.0084*	-0.0155***	0.0090
	(-3.36)	(1.54)	(-2.71)	(1.40)	(-0.99)	(-1.71)	(-4.04)	(1.55)
BM	0.0094**	0.0032	0.0049	0.0057*	0.0008	0.0064*	0.0065*	0.0053
	(2.15)	(1.22)	(1.54)	(1.85)	(0.15)	(1.83)	(1.65)	(1.54)
Size	0.0021	0.0001	-0.0008	0.0014	0.0016*	-0.0005	-0.0007	0.0021**
	(1.32)	(0.27)	(-0.68)	(1.36)	(1.83)	(-0.71)	(-0.76)	(1.99)
Leverage	0.0218**	0.0017	0.0137***	0.0001	0.0085	0.0096	0.0129*	0.0133**
	(2.26)	(0.44)	(2.65)	(0.01)	(1.48)	(1.61)	(1.94)	(2.04)
ROA	-0.0206**	-0.0060	-0.0098	-0.0067	-0.0142	0.0012	-0.0123	-0.0221
	(-2.34)	(-0.33)	(-1.23)	(-0.33)	(-1.33)	(0.08)	(-1.49)	(-1.32)
$CAR_{(-205,-6)}$	-0.0039	-0.0107***	-0.0080***	-0.0099*	0.0002	-0.0143***	-0.0040	-0.0015
	(-1.51)	(-2.71)	(-3.12)	(-1.86)	(0.06)	(-3.76)	(-1.41)	(-0.36)
Constant	-0.0559***	-0.0051	-0.0251**	-0.0186	-0.0624***	-0.0059	-0.0261*	-0.0347***
	(-3.14)	(-0.65)	(-2.08)	(-1.54)	(-5.34)	(-0.55)	(-1.93)	(-2.90)
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	3274	3610	6489	2930	4360	3681	4296	3556
Adjusted R^2	0.1084	0.1452	0.1445	0.1004	0.1294	0.1167	0.1176	0.1196
Chow Test	37.79		34.07		11.55		4.32	
p-value	(0.000)		(0.000)		(0.001)		(0.038)	

Table C.4

Robustness Check: Equally-Weighted Abnormal Returns

This table reports the results of regressions for relation of cumulative abnormal return (CAR) with cumulative stock-specific investor sentiment (CSI) for each subsample split by a given measure of limits to arbitrage proxies while cumulative abnormal return (CAR) is related to equally-weighted market return. The measures of limits to arbitrage include Amihud (2002) illiquidity (Illiquidity), number of institutional shareholders (InstOwner), dollar trading volume ($Volume), and bid-ask spread (Bid-Ask). See Appendix A for detailed definitions of the variables. Top and bottom quartiles (1&4) of Amihud (2002) illiquidity (Illiquidity), number of institutional shareholders (InstOwner), dollar trading volume ($Volume), and bid-ask spread (Bid-Ask) are considered for analyse. Statistical tests for differences of CSI between two groups are presented. The data set is related to stocks traded on the NYSE and NASDAQ exchanges over the period of 2011-2015. Stock-specific sentiment data comes from PsychSignal and Baker and Wurgler sentiment data is from Wurgler's website. Analyst data is from the Institutional Brokers' Estimate System (I/B/E/S). Stock prices data comes from the Center for Research in Security Prices (CRSP). Accounting data is taken from Compustat. Institutional ownership records come from Thomson Reuters. Variables are winsorized at 1% and 99% of the respective distribution to mitigate the impact of outliers. All regressions control for year and sector fixed effects whose coefficients are suppressed. The t-statistics reported in parentheses are adjusted for stocks clustering. *, **, and *** indicate significant at the 10, 5, and 1% level, respectively.

Variable	Amihud Illiquidity		No of Institutional Shareholders		Dollar Trading Volume		Bid-Ask Spread	
	High	Low	Low	High	Low	High	High	Low
$CSI_{(-2,0)}$	0.0155***	0.0084***	0.0146***	0.0076***	0.0143***	0.0099***	0.0122***	0.0097***
	(11.18)	(10.71)	(9.76)	(9.26)	(11.01)	(11.18)	(9.86)	(9.65)
SUE	0.0055***	0.0045***	0.0047***	0.0053***	0.0056***	0.0055***	0.0052***	0.0054***
	(10.73)	(11.49)	(8.67)	(13.10)	(12.01)	(12.77)	(10.21)	(11.43)
B&W	0.0033	-0.0020	0.0046	-0.0346**	0.0065	-0.0064	0.0547**	-0.0291*
	(0.12)	(-0.13)	(0.17)	(-2.09)	(0.26)	(-0.39)	(2.29)	(-1.70)
$CSI_{(-2,0)}$*B&W	0.0066	-0.0024	0.0187	0.0059	0.0021	0.0005	0.0050	0.0028
	(0.42)	(-0.29)	(1.13)	(0.71)	(0.15)	(0.06)	(0.35)	(0.26)
Loss	-0.0216***	0.0072	-0.0189***	0.0118**	-0.0171***	0.0059	-0.0178***	-0.0050
	(-4.63)	(1.50)	(-3.52)	(2.17)	(-3.80)	(1.08)	(-3.25)	(-1.06)
BM	0.0058	0.0049	0.0044	0.0025	0.0036	0.0082**	0.0091	0.0081**
	(1.32)	(1.47)	(0.90)	(0.72)	(0.81)	(2.32)	(1.57)	(2.52)
Size	-0.0007	0.0020**	-0.0010	0.0011	-0.0014	0.0028**	0.0002	0.0009
	(-0.40)	(2.11)	(-0.66)	(1.14)	(-0.87)	(2.49)	(0.17)	(1.14)
Leverage	0.0129	0.0118**	0.0170**	0.0126**	0.0143*	0.0212***	0.0127*	0.0095*
	(1.53)	(2.20)	(2.07)	(2.28)	(1.86)	(3.28)	(1.66)	(1.76)
ROA	-0.0177**	-0.0178	-0.0134	-0.0167	-0.0127	0.0141	-0.0110	-0.0230
	(-2.02)	(-0.91)	(-1.37)	(-0.81)	(-1.35)	(0.65)	(-0.82)	(-1.50)
$CAR_{(-205,-6)}$	-0.0019	-0.0021	-0.0015	-0.0032	-0.0020	-0.0036	0.0051	-0.0167***
	(-0.69)	(-0.44)	(-0.54)	(-0.66)	(-0.67)	(-0.85)	(1.58)	(-4.39)
Constant	-0.0199	-0.0316***	-0.0260	-0.0206*	-0.0183	-0.0499***	-0.0454***	-0.0231*
	(-1.12)	(-2.69)	(-1.30)	(-1.71)	(-1.08)	(-3.77)	(-3.27)	(-1.91)
Year F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	3285	3609	2893	3201	3375	3582	3123	3640
Adjusted R^2	0.1303	0.0893	0.1040	0.1126	0.1310	0.0997	0.1130	0.1098
Chow Test	20.12		16.79		7.64		2.51	
p-value	(0.000)		(0.000)		(0.006)		(0.113)	