The Stock Market's Twilight Zone: How Overnight Sentiment Affects Opening Returns*

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Abstract

This paper examines the relationship between overnight sentiment in social and news media and subsequent stock market behavior at market opening. Using high-frequency sentiment metrics, we find that sentiment from social media has a stronger impact on stock prices compared to traditional news sources. Highly positive sentiment in social media results in, on average, 4.75% excess returns annually, while highly negative sentiment results in -4.99% returns. News media sentiment shows weaker effects with 2.5% and -3.05% annual returns for highly positive and negative sentiment respectively. Our findings demonstrate that this effect is not explained by previous day price performance or fundamental news events such as earnings announcements, and highlight the need to employ more granular data, such as high-frequency sentiment metrics, to fully capture the impact of sentiment on the stock market.

Keywords: Investor Sentiment; Social Media; Overnight Return; High-frequency data; Thomson Reuters MarketPsych Indices (TRMI)

JEL: G17, C55, C58

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1 Introduction

In the never-ending search for alphas, the finance industry has turned to unconventional, unstructured, and irregular 'alternative data'. These alternative sources of data usually include narratives and posts in news and social media. Employing textual analysis and econometric models, financial economists are able to gauge the emotions to help anticipate price movement.[1] Curiously, O'Hara (2014) points out that one reason why nowadays high-frequency traders are so successful is that they use 'big data' and natural language processing to make decisions. We offer low-frequency traders a framework to better understand the market dynamics to help level the playing field with high-frequency traders. A survey of the literature reveals that the forecasting ability of sentiment is highly contentious,[2] and even less is known about what drives the stock price changes following substantial sentiment swings. Most studies concentrate on examining links between the aggregate market sentiment and the broad market indices (Baker and Wurgler, 2006, 2007; Barber et al., 2008; Berkman et al., 2012; Siganos et al., 2014; Stambaugh et al., 2012, 2014; Sun et al., 2016, to name a few). In contrast, there is less research focusing on firm-specific sentiment and individual stock returns (Groß-Klußmann and Hautsch, 2011; Sprenger et al., 2014; Bartov et al., 2018; Boudoukh et al., 2018).[3] In this paper, we investigate whether the company-related sentiment accrued during non-trading hours helps explain the price behaviour at the reopening.

The nature of overnight returns makes it a great tool to directly contrast the impact of information on the markets channelled through two distinct media types — the news vs social media. Intraday trading and trading at the close reflect trades that are not purely information-based; many of these trades are made to rebalance portfolios or are a result of institutional capital flows (Lou et al., 2019). Conversely, trading at the open are purely information-based. In fact, Berkman et al. (2012) show that attention-generating events often lead to higher trading from individual investors especially at the open of stock market in the next trading day. This creates temporary price pressure at the open, resulting from the imbalance of trading orders that are being placed before market opening. In turn, these

[1] Research of Antweiler and Frank (2004); Da et al. (2011); Bollen et al. (2011); Mao et al. (2011) have led the way in quantifying qualitative information on social media platforms such as internet message boards, Google Search and Twitter to predict stock variables. The literature in this realm is continuously expanding. For comprehensive summaries, see Kearney and Liu (2014) and Gentzkow et al. (2017).

[2] For instance, Azar and Lo (2016) shows that the content of tweets can be used to predict future returns following the Federal Open Markets Committee (FOMC) meeting. Heston and Sinha (2017) documents that daily Thomson Reuters News Analytics (TRNA) sentiment indices predict stock returns for one or two days, while weekly TRNA news sentiment predicts stock returns for one quarter. Sun et al. (2016) and Renault (2017) find that the changes of sentiment in the first half-hour of the trading day can forecast stock index returns in the last trading hour. In contrast, Behrendt and Schmidt (2018) finds that the out-of-sample forecast performance of high-frequency Twitter information is at negligible economical magnitudes, albeit statistically significant.

[3] This list of examples is far from exhaustive, interested readers are referred to Bukovina (2016) for a comprehensive survey.

trading orders are affected by the information releases during non-trading hours. Naturally, trading off-hours is accompanied by high liquidity costs; therefore, investors should do so only when they possess valuable new information about the firms to compensate the loss in liquidity (Barclay and Hendershott, 2003). The point at issue is which media type is considered as the primary source of this valuable new information?

In this study, we employ overnight tonality in the news and social media to contrast the price impacts at the open. Our analysis is performed on a granular 1-minute intraday sentiment derived from as many as 55,000 news sites and 4.5 million social media sites, blogs and tweets. By employing an approach akin to an intraday event study, we focus on differentiating the impact of news media sentiment from social media. Setting the market open time (9:30am EST) as the *event*, we accumulate sentiment data prior to the *event* and check its correspondence with the cumulative returns after the event. We find that only the top and bottom deciles of the cumulative sentiment exhibit significant explanatory power, while moderate changes in the sentiment tonality exert weak influence on the returns.

Benefiting from the availability of 1-minute intraday data, we focus our investigation on the impact of overnight sentiment for several reasons. Firstly, we are better positioned to disentangle the cause and effect with non-overlapping temporal aggregations of (i) sentiment just hours prior to market opening and (ii) the returns during the trading hours. Modern financial markets are efficient in reflecting all available, relevant information; the sentiment effect can be fleeting and easily missed even with daily data. Secondly, we are able to investigate and control for potential endogeneity in our analysis by considering the effects of previous day returns on the overnight sentiment that follows. Our analysis shows that the social and news media activity declines rapidly after 4pm following the market closure, reaching its lowest level in the hours from 2am to 5am and increasing steadily before it reaches its peak in the period from 9:30am to 10am.[4] Gathering overnight sentiment data hours following the market closing time or hours prior to market opening also has the advantage of generating a better signal-to-noise measure for what can be a very "noisy" proxy. Finally, as the majority of firm-specific announcements are scheduled outside regular trading hours (Birru, 2018), it stands to reason that the moods emanating from these announcements are best measured during the same period.[5]

Our study offers novel insights into the influence of news and social media on stock

[4] This intraday sentiment pattern is consistent with the pre-market and after-hours trading sessions from 4:00am to 9:30am and from 4:00pm to 8:00pm, respectively.

[5] Jiang et al. (2012) reveals that over 95% of their sample announcements are outside regular trading hours; Bagnoli et al. (2005) shows that only 27% of earnings announcements are scheduled during trading hours in the years 2000 to 2005, whereas this used to be 67% in the 1990s. Michaely et al. (2013) documents that only 5% of corporate earnings announcements occur during trading sessions from 2006 to 2009. Except for earnings announcements, Bradley et al. (2014) also finds that most analyst updates take place outside of trading hours.

returns. We find that both social and news media sentiment help explain the price behaviour of stocks. The results indicate that overnight sentiment and returns on the following day are highly concordant, in other words, overnight media sentiment helps predict the next day opening return. The correlation coefficient between social media sentiment on days in the 1st and the 10th deciles and the corresponding cumulative abnormal returns (CARs) during the trading hours that follow is as high as 0.79, while similarly, for the news sentiment it is 0.57.[6]

To test the longevity of sentiment predictive power, we exclude price data during the first minutes of trading. We find that the impact of overnight sentiment on average cumulative returns absent the opening session is substantially diminished compared with the average cumulative returns during the opening session. Our results remain consistent when we exclude the first half hour, first hour, and the entire morning session. In contrast to Aboody et al. (2018), which uses overnight return (close-to-open) as a proxy of firm-specific sentiment, our findings based on textual analysis of individual stock sentiment do not indicate overnight sentiment persistence.

Access to the 1-minute data allows us to contrast the behaviour of firm-specific sentiment from news and social media at the most granular level. Our results show that social media postings are more concentrated during trading hours while news media activity is more dispersed throughout the day. Both media sources display similar post-trading-hour patterns consistent with everyday routines, while social media's 'morning kinks' (a surge in postings just as people are waking up) tend to be more prominent than any similar effect in the news media. We find that moods formed in the three hours immediately prior to stock market opening have the greatest predictability on stock returns. Combining with our finding that social media sentiment is more influential on opening returns than news media, these results highlight the need to employ more granular data to capture the impact of sentiment on the stock market.

Our results indicate a stronger effect of the social media when compared with news media. We shed new light on the increasing influence of social media on the asset prices. The ever-increasing popularity of social media and its resultant influence is not just confined to popular culture, but increasingly permeates the financial markets. For example, in 2013, Carl Icahn tweeted that following a meeting with Tim Cook (Apple CEO), he bought "a large position" in Apple and believed that the company is "extremely undervalued".[7] This bullish tweet caused the market capitalization of Apple to jump by $12 billion. A recent study by Gan et al. (2019) documents how the transition of the influence has taken place.

[6] Both coefficients are significant at the 1% level.

[7] *"We currently have a large position in APPLE. We believe the company to be extremely undervalued. Spoke to Tim Cook today. More to come."* Source: https://twitter.com/carl_c_icahn/status/367350206993399808?lang=en, posted: 4:21am, Aug 14, 2013.

While once the news media was the dominant source of information and market sentiment, the sentiment in social media now has a leading effect over news media sentiment. This is not surprising considering that 4.2 billion people were using social media on mobile devices in January 2021, with a growth of 490 million new users — a year-on-year increase of more than 13.2 per cent (Kemp, 2021). Increasingly, news happens first on social media. Professional journalists embraced social media, and especially Twitter, as a new channel for information gathering (Moon and Hadley, 2014). One may recall that the news of Osama Bin Laden's death in May 2011 arrived first via Twitter from Keith Urbahn, the aide to former Defense Secretary Donald Rumsfeld. The tweet was retweeted by the New York Times resulting in the rapid spread of the news even before President Obama's official press conference (Rieder, 2011). These characteristics of social media offer us strong a prior motivation for comparing overnight sentiment between social media and news media.

We conduct a number of robustness tests to confirm the strength of our results. One concern with sentiment study is the potential for endogeneity, specifically the feedback loop that exists between microblog sentiment and related economic activities (Deng et al., 2018). We investigate whether messages in the media might simply rehash events in the market and find that investor sentiment after market closure is significantly positively related to the stocks' performance during previous trading session. The correlation between stock returns and after-hours social media sentiment on the top and bottom sentiment decile days is 0.4012; the correlation with the news media sentiment is similar at 0.4080. To resolve this endogeneity concern, we control for the previous day return performance and find that the the explanatory power of overnight social and news media sentiment persists after controlling for previous day returns. Further, we show that our findings are not driven by earnings announcement, thus we are not "cherry-picking" days that coincide with such occurrences. On average, less than 3% of overnight sentiment event-days (i.e., the top and bottom overnight sentiment decile days) in our sample overlap with earnings announcement days.

Our results hold for a number of model parameter specifications and controls. We demonstrate consistency of our findings to the variability in the length of pre-event window. The following day return predictability, however, does diverge depending on the length of overnight sentiment accumulation period. We assess the predictive accuracy of sentiment cumulated over various periods and find that using sentiment data from two to three hours prior to market opening results in the most accurate predictions of opening price directions. Windows shorter than two hours result in aggregation that is not sufficient for a volatile predictor such as 1-minute sentiment, hindering its predictive ability. Windows longer than five hours, however, utilise too much stale information, which dampens the accuracy of opening price prediction.[8]

Our study contributes to the literature in at least three ways. First, our study is directly related to research that use high-frequency textual analysis sentiment to forecast stock returns (Groß-Klußmann and Hautsch, 2011; Chouliaras, 2015; Sun et al., 2016; Renault, 2017). The existent work in this domain often neglects or absorbs sentiment accrued overnight, in other words, most papers have not explicitly examined the impact of overnight sentiment. For example, investigating the relation between news flow and stock return jumps, Jeon et al. (2021) rely on calendar day aggregation and close-to-close sentiment aggregation and find that using the latter method produces more significant overall results. In our opinion, this highlights the importance of the aggregation window choice which we investigate at length in this paper. We use close-to-open aggregation of sentiment and consider both news and social media to investigate the effect of the mood of the crowd on asset price behaviour while at the same time mitigating the feedback loop effects at times of active trading. In this respect, our paper is closely related to Boudoukh et al. (2018) that separates the overnight and intraday sessions, albeit in the analysis of return volatility. In a seemingly contradicting paper, Behrendt and Schmidt (2018) use 5-minute Twitter sentiment of DJIA constituent stocks and show that the relationship between Twitter moods and a stock's absolute return is economically negligible. By considering the absolute values of returns, however, the study focuses on stock return volatility rather than the direction of price movements.

Second, we identify the asymmetry between positive and negative sentiment effects more precisely than prior studies. A large body of empirical literature has shown that influences from negative investor sentiment prevail over positive side (e.g., Akhtar et al., 2012; Stambaugh et al., 2012, 2014; Sprenger et al., 2014, among others).[9] Akhtar et al. (2012) documents that negative consumer sentiment index surprise results in significant negative effects on the Dow Jones index and its corresponding futures returns. However, positive sentiment shocks do not generate similar positive effects. Stambaugh et al. (2012, 2014) corroborate that overpricing is more prevalent than underpricing following high investor sentiment, due to the impediments of short-sales. They provide evidence that the short-leg profits across 11 anomalies' long-short strategies are higher following enhanced sentiment, while sentiment exhibits no such impact on returns in the long legs. Conducting textual analysis on more than 400,000 tweets, Sprenger et al. (2014) finds that negative news that induce price reac-

[8] The complete set of robustness results is omitted for brevity but is available upon request.

[9] Lutz (2015) and Li et al. (2017) investigate a different type of asymmetry in investor sentiment. Lutz (2015) finds that during the sentiment contraction episode (peak-to-trough), high sentiment leads to low stock returns. During the sentiment expansion episode (trough-to-peak), high sentiment predicts high stock returns. Some also regard it as evidence that market-wide investor sentiment has certain synchronicity with business cycles. Similarly, using a conditional quantile causality test approach, Li et al. (2017) finds that market sentiment predicts stock market returns only in recession rather than expansion states. However, this type of investor sentiment asymmetry is beyond the scope of our research.

tion are largely confined to the event day, while positive news tend to suffer from information leakage before the announcement, suggesting higher shocks on the negative side of the news day. Although these studies have taken into account a plethora of behavioural bias, a major problem is that the sentiment measures they used were often defined as ordinal, in other words, either 'positive', 'neutral', or 'negative'. In contrast, using ratio scale data, we are able to quantify a more precise level of emotional scores that can be exploited to generate signals.

Last, we compliment the literature investigating informational aspects of market efficiency. Under the microscope of intraday data, our study sheds light on how information is propagated and incorporated into the market during trading and non-trading episodes. Prior studies in this domain include Morck et al. (2000), Dang et al. (2015), Engelberg et al. (2018), and Lou et al. (2019), to name a few. Using textual analysis, Boudoukh et al. (2018) and Jiang et al. (2019) differentiate news versus non-news to capture sentiment and its impact on stock market. Applying 15-minutes high-frequency RavenPack sentiment measures, Jiang et al. (2019) decomposes daily returns into news versus non-news driven components. They find that non-news driven returns precede a reversal whereas news-driven returns tend to exhibit a continuation, demonstrating that such effects are more prominent for overnight and weekend news among small, volatile, and illiquid firms that have low analysts coverage. Similarly, to measure the fundamental information component within overnight news, Boudoukh et al. (2018) classifies four hierarchical news days: non-news, unidentified news, identified news and complex news days. They find that stock price volatility is significantly higher in identified and complex news days. Taking a different stance, we distinguish our contribution in the following two ways. First, the prior two studies apply *news* relevance score, an index that is readily available from RavenPack and TRNA and often used in empirical research at lower data frequencies. We complement the missing piece by comparing effects from social media with the news. Second, our endogeneity analysis of media tonality generates new insights into how the abnormal stock returns and the overnight media coverage mutually influence each other — a point rarely addressed in the existing literature.

The rest of this paper proceeds as follows. Section 2 describes our sample data and methodology. The main results are provided in Section 3. In Section 4, we proceed with robustness tests and discussions about what drives our main findings. Section 5 concludes the paper.

2 Data and Methodology

We investigate and contrast the impact of sentiment on stock prices from the two different media types. We use 1-minute firm-specific sentiment polarity time-series based on *social media* as well as *news media* — the most granular data available — and 1-minute trades data on the Dow Jones Industrial Average (DJIA) constituents.

2.1 Sentiment Data

Increasing number of sentiment studies rely on commercial data. For example, Jeon et al. (2021) perform analysis on news articles from the Factiva database but in conducting robustness checks find consistent results based on commercially available news analytics data from RavenPack.

Our firm-specific sentiment data are from Thomson Reuters MarketPsych Indices (TRMI). Using its natural language processing algorithm, TRMI analyses news and social media in real-time to convert the quantity and variety of professional news and the internet messages into manageable information flows. TRMI draws its textual data from a wide variety of sources — including Internet news content from the top international and business news sources, regional news sources, and leading industry sources (for the news); Internet forums, finance-specific tweets and other finance-specific social media content of the top 30% of blogs, microblogs, and social media platforms based on popularity ranks measured by incoming links (for social media). TRMI emphasises that the measures focus on vetted, reputable, and credible sources that are likely to generate new information and insights for investors. The TRMI algorithm then scores the entity specific sentiment on social and news media based on over 2 million articles daily.[10] Since there is a vast distinction in communication styles between social and news media, MarketPsych uses differentiated text analytic models to improve sentiment scoring accuracy for news and social media sources including customised lexicons, superior disambiguation, context analysis, and optimised grammatical structures superseding the commonly adopted Loughran and McDonald (2011) financial dictionary lexicon method in (for specific details, see Peterson, 2016, Appendix A).

The data from TRMI track social and news media information across thousands of companies every minute of every hour 7 days a week, creating a firm-specific sentiment polarity time-series at 1-min frequency to provide insights on tonality of the news or public opinions on social media. Our sample period spans from 1 January 2011 to 30 November 2017, which covers a period of swift social media development.[11] In total, we analyse 10,485,413 firm-minute sentiment observations for 34 companies and examine overnight return reaction to social and news media sentiment accrued overnight. Table 2 summarises sentiment data availability and reports the total number of non-missing observations and average daily counts for social and news media for the DJIA and each of its constituents. Stocks delisted

[10] Markets and security coverage of TRMI include: over 12,000 companies, 36 commodities and energy subjects, 187 countries, 62 sovereign markets and 45 currencies since 1998, and more than 150 cryptocurrencies since 2009. A detailed summary of this dataset and description is provided in *Thomson Reuters MarketPsych Indices 2.2 User Guide*, 23 March 2016, Document Version 1.0.

[11] These data are provided by the Thomson Reuters Financial and Risk Team (re-structured as Refinitiv from 2019) as part of a TRMI product and is limited to November 2017 for academic research.

from the DJIA during the sample period are included.

Our choice to focus on the DJIA constituents helps mitigate sampling bias from missing observations in the 1-minute sentiment data and emanates from the discussion of stock 'saliency' (Akhtar et al., 2012). Stocks that are more 'salient' to investors are also more sensitive to sentiment. This does not necessarily imply that these are sentiment-prone stocks. Sentiment-prone stocks are small, young, unprofitable with high growth, highly volatile, and non-dividend paying, as characterised in Barber and Odean (2007). Salient stocks, however, are securities that are more prominent, or 'iconic'. Good candidates for salient stocks are large caps amply followed by analysts and are vastly discussed in the media.

Reflecting on the saliency of each stock based on Table 2, we observe substantial variability across stocks and media sources. Some companies are more salient in social media (AAPL, BAC, GE, CSCO), whereas others are covered more in the news media (MSFT, JPM, BA, IBM). Technology stocks, in general, enjoy considerable coverage in both social and news media compared to stocks from other sectors. For instance, Apple, Microsoft, Cisco and Intel have media coverage that is at least 40 times that of the least covered stock, The Travelers.[12]

Focusing on sentiment data at such high frequency inevitably restricts our company sample due to availability of news and social media coverage. Table 2 lists the companies ranked my media saliency. To no surprise, one can easily observe that Apple dominates the list with the average daily sentiment observations of 518 and 360 for social and news media, respectively. At the bottom of the table, Kraft Foods and The Travelers conclude the list with the average number of sentiment observations of around 2 per day, casting doubt on the appropriateness of such companies for our analysis. We investigated the data sparsity issue and found that while the average daily numbers may appear low, the observations typically cluster on specific days throughout the sample period which we find adequate for our proposed modelling framework. The one exception is Kraft Foods (KFT): With the average number of daily social media sentiment observations of 2.7, its news media coverage of 9 observations per day is more than 3 times that of social media with the majority of observations attributed to March 2015 when Kraft Foods Group announced that it would merge with the H.J. Heinz Company. Kraft's shares rose about 17 percent after the announcement of the deal. No sentiment data are available after the merger was completed in July 2015. Therefore, we excluded KFT from our analysis but retained it in Table 2 for illustrative purposes.

[12]The average daily count of social sentiment observations for Intel is 88.8, whereas for Travelers, it is 1.8. Similarly, the average news media counts for Intel and The Travelers are 81 and 2, respectively.

2.2 Stock Price Data

The DJIA index and constituent stock data are obtained from Thomson Reuters DataScope (TRTH). We extract the 1-minute closing, ask and bid prices from 1 January 2011 to 30 November 2017 to match the availability of our sentiment data while allowing for one additional day for the lead-lag analysis.

Days in the sample are indexed by $t = 1, ..., T$. Each day is divided into 1,440 1-minute intervals indexed by j, where it is often convenient to adopt HH:MM referencing in outlining the method constructs. Assets are indexed by i where $i = 0$ represents a broad market index benchmark, while $i = 1, ..., N$ denotes a stock. Once missing values in the price series are filled forward using the previous available observation, the continuously compounded return, $r_{i,t,j}$, is calculated as

$$r_{i,t,j} = \ln\left(\frac{P_{i,t,j}}{P_{i,t,j-1}}\right),$$

where $P_{i,t,j}$ is a mid-quote price.[13] In this setup, the overnight return corresponds to $j =$ 9:30am. Outlying return observations based on bid and ask quotes and prices are replaced with the preceding data points.[14]

2.3 Data Aggregation

Our sentiment variables range from -1 (maximally negative tone) to 1 (maximally positive tone), with a sentiment score of 0 representing neutral tonality. Heatmaps, day-of-the-week and time-of-day groupings enable visualisation of vast arrays of high-frequency sentiment and stock return data and help identify patterns and irregularities in our dataset. In Figure 1 (panels on the left), using Apple Inc (AAPL) as an example, we allot all the available 1-minute sentiment observations into pixelated heatmaps by time of day (horizontal axis) on each day of our sample (vertical axis). The horizontal axis spans from 12:00am to 11:59pm with 1,440 minutes in total and the vertical axis covers the entirety of our sample period totalling 2,526 days. Each pixel represents a single 1-minute observation — positive values are shown in red, negative values in blue and missing data are not plotted. A mixture of positive and negative sentiment scores brings out an overall purple hue. A strong tendency of social media to coincide with the exchange trading hours can be observed by contrasting saturations of social and news media data in the heatmaps. Coincidentally, such a pattern in the

[13]Mid-quotes are obtained through $P_{i,t,j} = \frac{1}{2}\left(Ask_{i,t,j} + Bid_{i,t,j}\right)$. In a set of unreported results, we computed returns using trades data last reported within the 1-minute interval. The results are similar and are available upon request.

[14]Observations that are more than three local scaled median absolute deviation (MADs) from the local median within a sliding window containing 1,440 past elements (window length corresponding to 24 hours of 1-minute data) are treated as outliers. The scaled MAD is defined as $c \times \mathbf{median}(|A - \mathbf{median}\,(A)|)$, where $c = -\frac{1}{\sqrt{2}\mathbf{erfc}^{-1}(3/2)}$ and $\mathbf{erfc}^{-1}\,(.)$ is the inverse complimentary error function. By way of example, for Apple Inc, we identified a single outlier corresponding to the stock split on a 7-for-1 basis on 9 June 2014.

news media is less obvious but with more pronounced threads weaved through each morning "on the hour" (i.e., pronounced ridges at 6:00, 7:00, 8:00 and 9:00 o'clock marks in the middle left panel). Panels on the right-hand side display proportions of non-missing observations corresponding to variables on the left-hand side and capture intraday and day-of-the-week patterns in variables including non-trading days (e.g., weekends and public holidays). Figure 1 provides a vivid illustration of irregular nature of sentiment data and discrepancies between the sources of sentiment which require a nontrivial approach in aggregating sentiment observations, especially in light of the asynchronicity with the returns.[15]

[Insert Figure 1 here]

The irregularity of sentiment data and its asynchronicity with the returns present a challenge for modelling their causal relation. A solution proposed in this paper benefits from the availability of 1-minute intraday data and focuses on the impact of accumulated overnight sentiment just before the market opens. Market opening and closing times offer logical anchors and allow unambiguous temporal separation of public sentiment and return performance. As a consequence, measuring sentiment during non-trading periods allows us to break the return-sentiment causality loop and effectively avoid endogeneity issues. If sentiment and returns are considered simultaneously, during trading hours, their effects are undoubtedly intertwined. It would be difficult, indeed, if not impracticable, to disentangle these effects. Coupled with the fact that the majority of firm-specific announcements are scheduled outside of trading hours (Bagnoli et al., 2005; Jiang et al., 2012; Michaely et al., 2013; Bradley et al., 2014; Birru, 2018), it stands to reason that the emotions and sentiment generated by these announcements would also be formed and best measured outside of trading hours. Whether the sentiment generated outside of trading hours has predictive capacity or simply reflects and follows the events of the previous trading session is the focal point of this study.

We concentrate on differentiating the impact of news media sentiment from social media using an intraday event study approach. Setting the market open time (9:30am EST) as the *event*, we accumulate sentiment data prior to the *event* and check for its correspondence with the cumulative returns after the *event*.[16] We define the abnormal return (AR) of stock

[15] The 1-minute mid-price return series are generally continuous over the trading hours; TRMI sentiment observations eventuate with the flow of social media or news service posts tagged with a company name or ticker. Therefore, returns are mainly confined between the trading hours of 9:30am to 4:00pm, while TRMI scores present irregularly round-the-clock.

[16] The classic event study methodology, akin to MacKinlay (1997), is used widely in measuring market reaction to certain type of corporate events (such as earnings announcements, merger and acquisitions, stock splits for individual stocks) or macroeconomic announcement events (such as sovereign debt rating downgrades and the federal fund rate changes). Although we do not consider specific announcements as events in this paper, we hypothesise that the diversity of investors' emotions is synthesised in the overall sentiment scores in response to such announcements.

i on day t at time j as:

$$AR_{i,t,j} = r_{i,t,j} - r_{0,t,j}, \tag{1}$$

where $r_{0,t,j}$ is the index return on day t at time j. The cumulative abnormal return (CAR) on stock i on day t over the intraday time interval $[\tau_1, \tau_2]$ is given by:

$$CAR_{i,t}\,[\tau_1, \tau_2] = \sum_{j=\tau_1}^{\tau_2} AR_{i,t,j}, \tag{2}$$

where τ_1 and τ_2 define the return cumulation window with $\tau_1 < \tau_2$. In this study, we investigate the impact of sentiment on two types of cumulative returns: the one inclusive of overnight return, $CAR_{i,t}\,[9{:}30, 16{:}00]$, and the one that excludes the overnight return, $CAR_{i,t}\,[9{:}31, 16{:}00]$.

Similarly, if $Sent_{i,t,j}$ is the 1-minute sentiment score for stock i on day t at time j, the cumulative sentiment (CSent) on day t is defined as:

$$CSent_{i,t}\,[\tau_{-1}, \tau_0] = \sum_{j=\tau_{-1}}^{\tau_0} Sent_{i,t,j}, \tag{3}$$

where, in defining the overnight sentiment aggregation window, we set $\tau_{-1} = 16{:}01$ on day $t-1$ and $\tau_0 = 9{:}29$ on day t. This allows us to focus on the sentiment accumulated from the market closing on the previous day to just before the market opens on day t. Where necessary, we replace missing sentiment observations with zeros (e.g., in calculating cumulative sentiment) but keep track of the number of non-missing observations (e.g., for calculating average sentiment scores for a given period to avoid diluting sentiment estimates with imputed data). Therefore, our primary variables of interest are *sentiment* scores from news and social media, which we refer to as $Sent^{(S)}$ and $Sent^{(N)}$, respectively. These variables offer a combined measure of both the quantity of coverage and the attitudes expressed in articles or posts.[17] We conduct several robustness checks by varying aggregation window lengths in later sections.

We find that only the top and bottom deciles of cumulative sentiment exhibit predictive power, while moderate changes in sentiment tonality provide a weak information signal and are inconsistent in predicting the returns. Indeed, it is reasonable to assume that only acute sentiment swings move the market, whereas neutral or mild sentiment fluctuation show little effect on the markets. In fact, past studies based on aggregate market data revealed a stronger influence of investors' moods on the stock market during extreme sentiment periods

[17]For convenience, Table 1 in the appendix lists all variable definitions, data sources and acronyms. To distinguish the two sources of sentiment data, variables based on social or news media are denoted with (S) or (N) superscripts, respectively.

(e.g., Chue et al., 2019; Yang et al., 2017; Lu et al., 2012). Given high signal-to-noise ratios in the top and bottom deciles of cumulative sentiment, we show that such sentiment exhibits better predictive power. Therefore, if $d_{i,x}$ are deciles of $CSent_{i,t}$, we define the collection of days where sentiment accumulated prior to trading hours falls between deciles $x-1$ and x as follows:

$$\mathcal{D}_{i,x} = \{t : d_{i,x-1} < CSent_{i,t}\,[\tau_{-1}, \tau_0] \leq d_{i,x}\}. \tag{4}$$

For example, $\mathcal{D}_{i,1}$ identifies a collection of days for a stock i with the most negative cumulative overnight sentiment, that is the bottom 10%. Similarly, $\mathcal{D}_{i,10}$ identifies a collection of days with the most positive cumulative overnight sentiment, that is the top 10%. We refer to the collection of days in $\mathcal{D}_{i,1}$ and $\mathcal{D}_{i,10}$ as *event-days*. The average cumulative sentiment in each decile x is, therefore,

$$\overline{CSent_{i,x}}\,[\tau_{-1}, \tau_0] = \frac{1}{|\mathcal{D}_{i,x}|} \sum_{t \in \mathcal{D}_{i,x}} CSent_{i,t}\,[\tau_{-1}, \tau_0]. \tag{5}$$

where $|\mathcal{D}_{i,x}| = \sum_{t \in \mathcal{D}_{i,x}} 1$ is the cardinality of $\mathcal{D}_{x,i}$ (i.e., the number of its elements). It follows that the average cumulative abnormal return may be conditioned on the sentiment accumulated prior to market opening as follows:

$$\overline{CAR_{i,x}}\,[\tau_1, \tau_2] = \sum_{t \in \mathcal{D}_x} CAR_{i,t}\,[\tau_1, \tau_2]. \tag{6}$$

In the next section, we accentuate the importance of $\overline{CAR_{i,1}}\,[9{:}30, 16{:}00]$ and $\overline{CAR_{i,10}}\,[9{:}30, 16{:}00]$, that is, the average cumulative returns following the most negative and positive sentiment amassed overnight, respectively. We contrast our findings with a similar set of results when the overnight returns are excluded, namely $\overline{CAR_{i,1}}\,[9{:}31, 16{:}00]$ and $\overline{CAR_{i,10}}\,[9{:}31, 16{:}00]$.

3 Findings

In this section, we explore how the firm-specific sentiment accrued during non-trading hours affects stocks' price behaviour at the reopening. For illustrative purposes, we detail our analysis using a single stock. We apply the same approach to the remaining assets summarising the results in a set of tables and figures to facilitate comparison. We find evidence of a greater impact of social media compared to traditional news outlets. We show that the impact of sentiment is asymmetric, with negative sentiment having a greater influence on opening returns and discuss the longevity of sentiment effect in predicting stock returns.

3.1 Opening Return Patterns

Tracking minute-by-minute changes in Cisco's social and news media tonality and stock prices, Figures 2 and 3 demonstrate the dynamics between the sentiment accrued overnight and the asset returns during the trading period that ensues. Specifically, on each trading day, we obtain cumulative overnight sentiment by aggregating 1-minute sentiment scores from the first minute past the market closure on the previous trading day and leading up to market open on the current day. The overnight cumulative sentiment series are then sorted into deciles representing the set of days with the most negative and positive overnight sentiment denoted by $\mathcal{D}_1$ and $\mathcal{D}_{10}$, respectively. Consequently, the average cumulative sentiment series conditional on $\mathcal{D}_x$ (depicted on the left-hand side) appear in descending order, by construction, where the most positive and negative sentiment are represented by blue and red curves, respectively. The right-hand side depicts the average cumulative abnormal returns corresponding to each sentiment decile and mapped to the same colour. The bootstrapped 99%, 95% and 90% confidence intervals around CARs are depicted by the grey-shaded bands and are based on the average CARs of n days randomly drawn M times from the entire sample unconditional on sentiment. We set n to match the size (in days) of each sentiment decile (i.e., the cardinality of $\mathcal{D}_x$) and perform $M = 2,000$ draws. The dashed black curves show the average sentiment and CARs across all T days.

Contrasting the overnight sentiment dynamics in Figures 2 and 3, we find a compelling distinction between social and news media. First, the overnight social media sentiment exhibits a time-sensitive effect with varying persistence. From 4:01pm to midnight, the sentiment accrues quickly, showing steeper slopes and waning down from midnight to early morning at around 6:00am-7:00am. This pattern, however, cannot be easily discerned in the overnight news media sentiment. A particularly prominent 'kink' in the negative social media sentiment at around 7:00am suggests that negative overnight emotions continue to intensify before the market open. This timeline is consistent with most social media users' daily routines.[18] Second, news media sentiment tends to be more positive compared with the social media. Figure 3 shows that both the average cumulative sentiment (black-dashed line) and most deciles of overnight news media sentiment (except for $\mathcal{D}_1$) are trending upward, accruing to positive sentiment values. The speed of such positive sentimental drift is accelerated after 6:00am and is strongest for $\mathcal{D}_{10}$. This is rather intuitive, since social media users, in general, are more prone to posting extremely negative comments and discussions than news article reporters, whose opinions ought to be based on facts and are typically moderated.

[18]Although the extent varies from stock to stock, this early morning 'kink' is a common characteristic among most stocks in our sample, especially in social media-based sentiment dynamics. For reasons of brevity, we report results for CSCO.OQ only and make similar graphs for the other 33 stocks available upon request.

[Insert Figure 2 and Figure 3 here]

The primary difference between the top and bottom panels in Figures 2 and 3 is the point of origin of conditional CARs. In the top panels, the CARs accrue from 9:30am, that is, inclusive of the overnight return. In contrast, the bottom panels reveal the dynamics of the average conditional CARs when the overnight return is excluded.

Spanning outside of the most conservative confidence band, only the CARs conditional on $\mathcal{D}_1$- and $\mathcal{D}_{10}$-deciles are statistically significant, however, when the overnight return is excluded, only the most negative overnight sentiment continues to exert a persistent negative effect on the returns throughout the trading session. This asymmetric impact of positive versus negative emotions is consistent across the social and news media: days with the most negative overnight sentiment ($\mathcal{D}_1$) experience stronger impacts, with CARs ranging from -30bps to -50bps daily, whereas days with the most positive overnight sentiment ($\mathcal{D}_{10}$) generate CARs between +20bps and +40bps daily. The boost to these dizzying CAR values emanates from the overnight returns: +35bps and -30bps conditional on the most positive and negative sentiment from social media and, equivalently, +20bps and -30bps from news media. The evidence of economic significance of the overnight return is striking but in line with Cooper et al. (2008) and Lou et al. (2019).[19] The comparison of overnight and intraday returns aids in our understanding of how information is impounded into stock prices and attests to the efficiency of the markets. We observe that the significant predictability of heightened overnight sentiment dissipates when overnight returns are excluded from CARs. Interestingly, only days with the most negative overnight sentiment continue to exhibit significantly negative CARs after the overnight return is removed. On the contrary, positive-sentiment-induced CARs no longer show significant results. Our analysis of the remaining stocks indicates that this pattern is consistent for both the social and news media sentiment.

The difference between overnight and intraday returns is of considerable interest. It brings to light the issues concerning the efficient market hypothesis, the process by which information is reflected in stock prices, as well as the relative merits of auction versus continuous trading. Many find overnight and intraday returns behave entirely differently, and overnight returns tend to outperform intraday returns. Specifically, Cooper et al. (2008) suggests that the US equity premium over the period 1993-2006 is solely due to overnight returns. This effect holds for individual stocks, equity indexes and futures contracts on equity indexes across the NYSE and Nasdaq exchanges. The authors find that overnight returns are consistently higher than intraday returns across days of the week, days of the month and months of the year, and argue that this effect is driven in part by high opening prices

[19] Lou et al. (2019) link investor heterogeneity to the strong persistence of the overnight and intraday returns. They find that the risk premium is earned entirely overnight for the largest stocks.

which subsequently decline in the first hour of trading. Similarly, for broad-based index exchange-traded funds, Kelly and Clark (2011) finds the overnight returns are on average larger than the intraday returns. In contrast, we find that on days with the most negative overnight sentiment, the overnight return is significantly lower than on any other days.

Our analysis of the remaining stocks reaffirms the absence of any discernible patterns between the intermediate overnight sentiment deciles and the associated CARs. Accordingly, in Tables 3 and 4, we report the results for the set of days in the two extreme sentiment deciles only. The average cumulative social and news media sentiment accrued overnight is reported in Columns (1) and (4).[20] The rest of the columns represent returns conditional on sentiment. Specifically, Columns (2) and (5) are the average cumulative abnormal returns aggregated from 9:30am to 4:00pm measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. Similarly, Columns (3) and (6) are the corresponding average cumulative abnormal returns but with the overnight return removed.[21]

[Insert Tables 3 and 4 here]

Hypothesising that the positive (negative) overnight media sentiment results in positive (negative) abnormal returns in the following trading session, for the panel of stocks in Tables 3–5 we calculate the misclassification rate as

$$\frac{1}{N}\sum_{i=1}^{N} \mathbb{1}\left[\operatorname{sgn}\left(\overline{CSent_{i,x}}\right) \neq \operatorname{sgn}\left(\overline{CAR_{i,x}}\right)\right] \times 100\%, \tag{7}$$

with $i = 1, ..., N$ denoting stocks. Among the stocks with the overall positive social media tonality, 4 out 34 stocks exhibit negative CARs (11.8% misclassification) while all but one out of 34 stocks feature negative average CARs on days with negative overnight sentiment (2.9% misclassification). The results for news media sentiment are less consistent with 7 out 34 stocks exhibiting negative (positive) average CARs across days with positive (negative) sentiment (20.6% misclassification in both cases).

Tables 3 and 4 reveal several compelling insights. First, the highest and lowest overnight sentiment is positively associated with cumulative excess return the following day with the

[20] Specifically, the numbers represent $\overline{CSent_{i,x}}\,[16{:}01, 9{:}29]$ as defined in Eq.(5). It should be noted that while $\overline{CSent}$ values are comparable across deciles for a given asset, they are not comparable across assets. This is due to the relative sparsity of sentiment data even among DJIA constituents. As reported in the appendix (Table 2), AAPL.OQ leads the list by the most number of media sentiment observations, while DD.N is one of the least 'talked about' stocks in our sample. Therefore, comparing average negative sentiment scores in Table 4 between AAPL (-34.25) and DD (-2.69) *does not* imply a more negative tonality for AAPL. Instead, these sentiment values are used to rank the days for a given asset taking into account not only the tonality of the sentiment but also its intensity.

[21] We performed robustness checks for a number of different CAR aggregation windows lengths and report the results for the CARs over the first half-hour (9:30am-10:00am), the first hour (9:30am-10:30am), and the morning session (9:30am-12:00pm) in Tables A.1-A.3 of the appendix. The results are qualitatively similar and do not affect our conclusion.

stronger relation for social media than for news. The correlation coefficient between social media based-series in Columns (1) and (2) is 0.79, while the correlation coefficient between news media-based series in Columns (4) and (5) is 0.57. After eliminating the overnight return from CARs, the coefficients are reduced substantially to 0.44 between Columns (1) and (3) and to 0.17 between Columns (4) and (6). A similar pattern emerges for CARs accrued to the first half-hour of a trading day, the first full hour and until noon as opposed to day close (see Table 5).[22] This evidence suggests that overnight sentiment from both media holds potential for the predictability of next-day returns, and that this potential appears to be greater for social media sentiment. Moreover, the economic magnitude of social media based returns, on average, is greater compared to news (19.03 vs 10.02 bps in Tables 3 and -19.97 vs -12.14 bps in Table 4).

It is helpful to appreciate this impact by considering annualised returns. Considering the top and bottom sentiment deciles, the number of effective trading days for each decile in a given year is 25. The average daily figures reported in bps in Tables 3-4, translate to average annualised excess returns of 4.75% for social media and 2.5% for the news when conditioned on highly positive sentiment tonality. Equivalently, the average annualised excess returns conditional on highly negative tonality are -4.99% and -3.05% for social media and the news, respectively. While the social media based strategy, on average, remains more prominent, the gains are substantially lower when the overnight returns are excluded.

[Insert Table 5 here]

Next, we identify the asymmetry between the positive and negative sentiment effects. Contrasting the returns conditional on the top and bottom sentiment from Columns (2) and (5) in Tables 3 and 4 we find that, on average, CARs contingent on the negative sentiment bolster higher economic magnitudes than CARs induced by positive sentiment. Taking CSCO.OQ as an example (Table 4, Column (2)) and conditioning on days with the most negative social media sentiment results in an average CAR of -43.19 bps. On days with the most positive social media sentiment (Table 3), an equivalent 33.23 bps CAR is attained. Overall, the evidence is suggestive of negative sentiment exhibiting greater impact on the opening return (Figure A.1 in the appendix). These results are consistent with Sprenger et al. (2014), Berkman et al. (2012), Stambaugh et al. (2012, 2014) and Barber et al. (2008) in that negative sentiment boasts a higher impact than positive sentiment. We discuss the asymmetry at length in Section 4.

Third, the information contained in overnight sentiment is swiftly reflected in the opening price, pointing to the efficiency of the market. Assessing CARs aggregated from 9:31am

[22] The details of these additional robustness checks are presented in the appendix (Tables A.1-A.3) and summarised in Table 5.

instead of 9:30am in Columns (3) and (6), we observe lower CAR magnitudes and a weaker association between overnight sentiment and the CARs. Continuing with CSCO.OQ as an example, on days with the most negative overnight social media sentiment, the average CARs are significantly negative at -43.19 and -11.93 bps depending on the inclusion of overnight returns. Similarly, on days with the most positive social media sentiment, the average CAR attains 33.23 bps compared to barely reaching 1.42 bps when the overnight return is omitted. Columns (5) and (6) in Table 3 display similar patterns for news media sentiment. Average CARs on days with negative news sentiment are -47.50 and -19.07 bps and on positive sentiment days these figures reach 18.99 and 0.60 bps.

Lastly, the relationship between overnight sentiment and opening return appears to be most prominent in the technology sector and in stocks with higher media coverage. For example, Apple, HP and IBM — stocks with unequivocally higher media coverage — have p-values that are statistically significant at 95% level in both the social and news media group tests. In contrast, the p-values of stocks with the least media coverage are not significant.[23] This finding is consistent with Sul et al. (2016) in that the emotional sentiment about a firm that involves larger numbers of followers on social media and contains more 'buzz', tends to be more contagious. As a result, media sentiment of these stocks is more likely to be impounded into their stock prices.

At the risk of belabouring our discussion above, we provide a visual summary of the results in this section in Figures 4 and 5. The overnight sentiment serves as a consistent predictor for the sign of the next-day returns, with predominantly positive (negative) CARs on days with the most positive (negative) sentiment tonality. The impact of overnight sentiment on the next-day returns is greater for social media compared to traditional news. This can be observed by contrasting the blue and red bars representing CARs of individual stocks. The average effect of social media sentiment across all stocks is at least doubled in magnitude compared to that of news media — this is represented by the horizontal dashed lines in the figures. Moreover, the importance of the opening returns is conspicuous when contrasting the top and bottom panels in the two figures.

[Insert Figure 4 and Figure 5 here]

3.2 After-Hours Media Sentiment Patterns

The important question to consider is whether the results obtained in our previous section could simply be driven by past stock performance? For example, could it be that a particularly bearish session is followed by a torrent of pessimistic commentary in the media that would simply reflect the continuation of the tone during the trading session? It is well

[23] In Figure A.3 in the appendix, we compute the average daily counts of sentiment scores from the social and news media to rank the stocks in our sample by their 'saliency'.

documented that articles and postings in news and social media comment and recap on the daytime trading activities after the market closure. Some have argued that sentiment carries little predictive power for the near-term stock returns, and in fact, it is the contrary — returns are more likely to drive future sentiment. For instance, based on more than 1,000 individual stocks' daily sentiment metrics from Bloomberg, Coqueret (2020) determines that returns are more likely to drive future sentiment than the other way around. Similarly, Brown and Cliff (2004) reveals that weekly changes and the level of survey-based sentiment have limited effects on subsequent returns. This feedback effect, the so-called sentiment-return causality loop, is reminiscent of the one mentioned by Olivier Blanchard in the aftermath of the 2008 financial crisis: *"Crises feed uncertainty. And uncertainty affects behaviour, which feeds the crisis"*.[24] On that account, we check whether a feedback effect exists in the intraday sentiment data. Specifically, to examine the reaction of overnight media sentiment to the daily market performance, we conduct an analysis akin to the one presented in Section 3.1 by swapping the sentiment and CAR variables.

Continuing with our illustrative example of CSCO.OQ, we demonstrate the method in Figure 6. In the estimation window spanning from 9:30am to 4:00pm, we calculate and sort CARs into deciles. In the evaluation window spanning from 4:01pm on the day to 9:29am the following day, we identify the corresponding cumulative sentiment scores. These 'after-hours' media patterns are depicted on the right-hand sides of the top and bottom panels in Figure 6 for the social and news media, respectively. Consistent with the figure legends in previous sections, thick blue curves indicate average sentiment in the highest deciles, that is, following the trading day sessions with the highest CARs. Similarly, thick red curves delineate sentiment following the trading day sessions with the lowest CARs. The bootstrapped 99%, 95% and 90% confidence intervals around cumulative sentiment are depicted by the grey-shaded bands and are based on the average cumulative sentiment of n days randomly drawn M times from the entire sample unconditional on CAR. We set n to match the size (in days) of each CAR decile and perform $M = 2,000$ draws.

[Insert Figure 6 here]

The intraday social media sentiment pattern tends to be consistent with daily routines. Following market closure and up to midnight, we observe a rapid build-up in social media sentiment. After midnight, social media activity subsides due to a lack of postings on social media platforms with the majority of users presumably asleep. As a result, the cumulative social media sentiment flattens as shown in the top panel of Figure 6. From around 7:00am,

[24] '(Nearly) nothing to fear but fear itself', 29 January 2009, *The Economist*, accessed on 8 July 2020, https://www.economist.com/finance-and-economics/2009/01/29/nearly-nothing-to-fear-but-fear-itself.

social media sentiment resumes its trend until the market opens. This is in striking contrast with the pattern observed for news media sentiment in the bottom panel of Figure 6.[25]

News media sentiment appears to be more congruent than that from social media. In the case of CSCO.OQ, on days with large positive or negative CARs, news media sentiment continues to reflect the previous day's performance (Figure 6, right-hand side of the bottom panel; the blue and red lines arched outside of the 99% confidence band indicate statistically significant effects). Only on the worst performing days does social media continue to exhibit significantly negative sentiment that spans outside of the 99% confidence band. Social media sentiment following the best performing trading sessions is at par with sentiment trends on any other days, suggesting inconsequential reactions to the previous day's top performance.[26]

The conditional sentiment expressed in the news media is more positive than the emotions divulged on social media—consistent with the unconditional sentiment patterns in Figures 2 and 3. Cumulative social media sentiment of CSCO ranges from -3 to -6 (top panel of Figure 6, right vertical axis), while the cumulative news media sentiment is bounded between +3 to +9.5 (bottom panel of Figure 6, right vertical axis). This pattern matches the user characteristics of the two different media. Generally, social media users tend to be less hesitant in publicizing negative commentary, complaints, and discussions unjustified by facts when compared to professional news article reporters.

[Insert Table 6 and Table 7 here]

We perform the analysis for all the stocks in our sample and summarise the findings in Tables 6 and 7. Our results confirm a degree of concordance between cumulative abnormal returns and the sentiment following trading sessions with excessive CARs. The findings across the social and news media are comparable, with the correlation between the CARs on the top (bottom) decile performing days and the after-hours sentiment that follows reported at 0.4012 (0.4080). This evidence suggests a 'causality loop' whereas trading session performance generates media sentiment following the market closing time, continues overnight, and may be reflected in the opening returns the following day. The existence of such a 'causality loop' exposes our results to strong endogeneity problem. We examine the causality loop in more detail and elaborate on other issues in Section 4.

4 Robustness Checks and Discussion

In this section, we assess the robustness of our main result by considering alternative model specifications, examine the overlap of event-days with the top and bottom sentiment tonali-

[25]Social and news media patterns observed in Figure 6 for CSCO.OQ are consistent with other stocks in our sample.

[26]Some stocks are more positive-driven, while others are more negative-driven as in our example of CSCO.OQ. For brevity, we present the detailed results for CSCO.OQ only. We generated similar plots for other stocks in our sample which we make available upon request.

ties and firms' earning announcements, and deliberate on the choice of estimation and event window lengths.

4.1 Tackling the Causality Loop

In assessing the predictive ability of sentiment on the opening returns, one wonders if other factors, omitted from the model, may exert additional explanatory power. If such factors exist and are omitted from the model, the estimated coefficients are likely to be biased. At daily frequencies, the most prominent factor to consider is previous day performance. In what follows, for each stock in our sample we contrast estimates from the two linear regressions — a baseline model and extended control model. The controlled model is designed to account for the chain reactions from the prior day's stock performance to the next day's opening returns via overnight media sentiment. The baseline model is:

$$CAR_{i,t}\left[\tau_1,\tau_2\right] = a_i + b_i \times CSent_{i,t}\left[\tau_{-1},\tau_0\right] + e_{i,t}, \tag{8}$$

where i denotes a firm, τ_1 and τ_2, as before, define the length of the return accumulation window, and $t \in \mathcal{D}_{i,x}$ as defined in Eq.(4). In fact, we consider three different event sets: (a) all days in our sample, $t = 1, ..., T$; (b) only days with the highest average overnight sentiment, $t \in \mathcal{D}_{i,10}$; (c) only days with the lowest average overnight sentiment, $t \in \mathcal{D}_{i,1}$. Further, the extended model is specified as follows:

$$CAR_{i,t}\left[\tau_1,\tau_2\right] = \alpha_i + \beta_i \times CSent_{i,t}\left[\tau_{-1},\tau_0\right] + \gamma_i \times CAR_{i,t-1}\left[\widetilde{\tau}_1,\widetilde{\tau}_2\right] + \epsilon_{i,t}, \tag{9}$$

where τ_1 and τ_2 as before. Specifically, for the dependent variable, we focus on the first-minute cumulative abnormal return on day t as the predictive ability of overnight sentiment is quickly diminished after the first trading minute (refer to Section 3). That is, on day t we set τ_1 to 9:30am and τ_2 to 9:31am. To account for the previous day performance, we set $\widetilde{\tau}_1$ to 9:30am and $\widetilde{\tau}_2$ to 4:00pm.

The focal regressor, $CSent_{i,t}\left[\tau_{-1},\tau_0\right]$ is the average cumulative sentiment based on either social or news media. We set τ_{-1} to 4:01pm on day $t-1$ and τ_0 to 9:29am on day t. It is computed by dividing $CSent_{i,t}$ in Eq.(3) by the total number of non-missing observations within the same time frame. This averaging adjustment is essential before running the regressions because cumulative media sentiment score is driven by the volume of media coverage overnight. For instance, the cumulative overnight sentiment range is $[-1048, 1048]$, assuming consistent minimum or maximum sentiment values (-1 or $+1$, respectively) are reported every minute from 4:01pm to 9:29am.[27] As a result, if not adjusted for the volume

[27] Theoretically, if every consecutive minute from 4:01pm to 9:29am contains the maximum score ($+1$), the accumulated sentiment score over the entire period equals 1,048, the total number of minutes in the 17 hours and 28 minutes. Similarly, the least possible cumulative sentiment scores would reach $-1,048$ overnight.

of media coverage, the CAR series and the $CSent$ series would be at incomparable scales, resulting in inconsistent estimates in Eq.(8) and Eq.(9).

[Insert Table 8 here]

In Table 8, we provide exemplars of regression results based on Eq.(8) and Eq.(9) for CSCO.OQ estimated for the social and news media sentiment separately. The results in Panel A are based on all event days, whereas the estimates in Panels B and C are obtained based on the data from the most positive and negative deciles of sentiment events. All three panels reveal statistically significant positive coefficients for overnight sentiment, $CSent$, ranging between 0.2206 and 1.2074. We find that heightened negative overnight sentiment exerts greater impact on daily CAR compared to positive sentiment. We also observe that the effect of social media is more pronounced compared to news media with a particular vivid distinction on days with the heightened sentiment (Panels B and C only).[28] In assessing R^2, the strength of the signal relative to the noise is highest in Panel C, on the days with the most negative overnight sentiment. Interestingly, a comparable R^2 on the days with the most positive sentiment is only evident for the social media.

In analysing the impact of overnight sentiment on daily returns, we find that the signal capturing information transmission from investor sentiment to asset returns is strongest on the days with heightened sentiment and that such signal is less contaminated by noise when based on social media rather than news media. Therefore, sentiment based on social media carries stronger predictability than news media derived sentiment. Furthermore, negative sentiment has a greater effect on the next day's opening return than positive sentiment for both social and news media.

We find no evidence of omitted variable bias when the previous day CARs are included in the regression. Moreover, all $\hat{\gamma}$s — the coefficients of the previous day's return, CAR_{t-1} in Eq.(9) — are negative, except for the social media group in Panel B where the coefficient is not statistically significant. This finding is suggestive of a price correction in the first minute of the abnormal returns following the previous day's overreaction. This price reversion is strongest in the negative news media group (-0.2823). In fact, most of the stocks in our sample behave in a similar way.[29] This is consistent with the evidence provided in the literature on the overnight and intraday return reversals.[30]

[28] Recall our reference to these occurrences as event-days.

[29] The findings for the other stocks in the sample are qualitatively similar. Moreover, in checking the robustness of the results to several combinations of τ_{-1}, τ_0, τ_1, and τ_2 in Eq.(8) and Eq.(9), we verified the persistence of the pattern identified. These results are available upon request.

[30] Branch and Ma (2012) refers to this phenomenon as the "negative autocorrelation" between the overnight and intraday returns. Cooper et al. (2008) and Berkman et al. (2012) provide consistent evidence that mean overnight stock return is positive while mean intraday return is negative, due to the net buying pressure at the market open, generated by retail investors who are most likely to be affected by sentiment and attention-grabbing events. Aboody et al. (2018) suggests that overnight return is suitable to serve as a measure of

[Insert Figure 7 here]

We perform the analysis for the remaining 33 stocks and provide a visual summary of the estimated coefficients in Figure 7. In the figure, the estimated coefficients from Eqs.(8) and (9) are contrasted to a 45-degree line and paired to highlight the prominence of the social media relative to the news media (Panels A and B), positive sentiment relative to negative sentiment (Panels C and D) and the robustness of the estimates to the omitted variables (Panels E and F).

Panels A and B in Figure 7 compare the effects of the social and news media on each stock after controlling for the previous day returns. To construct Panel A, for each stock, we estimate Eq.(9) using social or news media for $CSent_t$ and $t \in \mathcal{D}_{i,1}$ to obtain $\hat{\beta}^S$ or $\hat{\beta}^N$ on the days with the highest sentiment. Similarly, Panel B is constructed using data on the days with the lowest sentiment.[31] We observe that the majority of stocks are located below the 45-degree line, suggesting greater sensitivities to social media sentiment than to news sentiment (e.g., NKE.N, CSCO.OQ and CAT.N). Stocks positioned above the 45-degree line, such as MMM.N, GE.N and KO.N are more sensitive to news media sentiment.

Panels C and D in Figure 7 demonstrate the exploration of the asymmetry in the stocks' sensitivities to positive and negative media sentiment. For instance, the sensitivity of CSCO's opening return to positive social media sentiment is 0.8752 (Panel B of Table 8). This is lower than its sensitivity to negative social media sentiment, 1.2074 (Panel C of Table 8), placing CSCO above the 45-degree line in Panel C. Other stocks that exhibit greater sensitivity to negative social media sentiment include NKE.N, AA.N and GE.N. In contrast, stocks that are more sensitive to positive social media sentiment and placed below the 45-degree line include CAT.N, HPQ.N and BA.N. In Panel D, when we consider stock sensitivities to news media sentiment, we observe a greater uniformity and higher concentration around the 45-degree line. This implies that stocks' returns are less sensitive to polarized emotions from the news media than from the social media and that the asymmetry in the reaction to positive and negative sentiment is less pronounced in the news media.

Using social media sentiment, Panels E and F in Figure 7 allow us to check the robustness of the results by contrasting the estimates from the baseline and controlled models.[32] The x-axis displays $\hat{\beta}$s from the controlled model in Eq.(9) and the y-axis indicates $\hat{b}$s estimated

firm-specific investor sentiment, while Hendershott et al. (2020) finds that stock returns are positively related to beta overnight and negatively related to beta during the trading hours.

[31] As a way of example, consider CSCO and the estimated coefficients in Eq.(9) listed in the 'Controlled' column in Table 8. On the days with the highest sentiment, the sensitivities of CSCO returns to the social and news media are 0.8752 and 0.2538, respectively, representing the coordinates of the CSCO point in Figure 7 Panel A. Similarly, on the days with the lowest sentiment, the sensitivities of CSCO returns to the social and news media are 1.2074 and 0.7192, respectively, representing the coordinates of the CSCO point in Figure 7 Panel B.

[32] The respective news media sentiment plots are shown in Figure A.2 in the Appendix.

using the baseline model in Eq.(8). If there is an omitted variable bias due to the previous day return performance, the coefficients of sentiment will differ, diverging from the 45-degree line. Stocks above the 45-degree line would have their opening returns driven by the previous day returns. Stocks below the 45-degree line, in contrast, would manifest themselves as more easily swayed by the overnight media sentiment. Based on the evidence presented in Panels E and F as well as Figure A.2, we find that most stocks are clustering along the 45-degree line, implying that the differences in the coefficients are not substantial. Therefore, the effect of overnight sentiment on the opening price is not biased by the stock performance the previous day.

4.2 Investor Sentiment and Earnings Announcements

Beginning with Beaver (1968) and Ball and Brown (1968), earnings announcements have been shown to carry significant information content capable of explaining a substantial fraction of the increase in market response. Moreover, Beaver et al. (2020) show that information arrival at earnings announcement dates has increased significantly over the past two decades. In this section, we examine whether strong overnight sentiment coincides with earnings news. We omit market and macroeconomic announcements assuming that the information has been incorporated when we computed cumulative abnormal returns thus excluding market-wide returns.

We acquire quarterly earnings announcement data for each constituent of the DJIA from Compustat. To investigate if the strong overnight sentiment on the days with the highest and the lowest 10% cumulative sentiment is driven by corporate earnings announcements, we check how many days in the two deciles coincides with earnings announcement dates and calculate the overlapping rate for both the social and news media sentiment. To remain conservative, we take into account both the announcement and reporting dates. Our findings are summarised in Table 9.

[Insert Table 9 here]

In Table 9, we verify that the strong sentiment days, generally, do not coincide with earnings announcements. The highest overlap rate between strong sentiment and earnings announcement days is 4% for BAC with 7 out of 172 dates of the most positive sentiment coinciding with the BAC's earnings announcements. On average, however, only 1–2% of the sentiment event-days coincide with the earnings announcements. These findings alleviate our concerns about omitted effects of earnings announcements on the overnight sentiment, especially given that the proportion of earnings announcements scheduled outside of normal trading hours has increased in recent years.[33] To address the fact that earnings-related

[33] Refer to Jiang et al. (2012), Bagnoli et al. (2005), Michaely et al. (2013) and Bradley et al. (2014) as mentioned in Section 1.

price changes are not observed on the earnings announcement date, but one trading day later, as pointed out by Berkman and Truong (2009), we analyse the sentiment-event clustering around the earnings announcement dates and find no evidence that the distribution of heightened positive and negative sentiment is linked to earnings announcements.[34]

Our findings suggest that the sentiment measured by TRMI and the overnight sentiment derived in this study capture emotions expressed in the social and news media, which are materially different from the sentiment measures used in other studies, such as Baker and Wurgler (2006) (BW), or other survey-based consumer confidence sentiment. The correlation between BW sentiment and TRMI sentiment measures (reported in Table A.5 of the appendix) demonstrate commonalities between TRMI sentiment indicators and the BW index, yet, the magnitude of correlation coefficients are indicative of divergence in these two measures, suggesting the TRMI sentiment indices capture different investor sentiment from BW's.

4.3 Event window choice

We perform robustness checks, analyse alternative event windows and consider several combinations of the pre-event (τ_{-1}) and post-event (τ_2) times. We keep the end time of the overnight sentiment accumulation (τ_0) fixed at 9:29am. Our findings are consistent with those previously discussed. One issue, however, remains unresolved: What is the 'optimal' combination of τ_{-1} and τ_2? In other words, what would be the optimal period before the market opens and how long does the predictability of sentiment lasts in assessing returns? We address this issue using a quasi-percentile approach. This approach and the relevant interpretation are well established in Welch (2021, p. 40, Fig. 2).

We depict our analysis of the optimal τ_{-1} and τ_2 for CSCO.OQ in Figure 8 for the case of social media. Treating market opening time as an 'event', Panel (a) in Figure 8 illustrates the average cumulative abnormal returns for each decile x, $\overline{CAR_{i,x}}\,[9{:}30, 9{:}31]$, conditional on a range of τ_{-1} values used to aggregate sentiment prior to the market opening. That is, keeping τ_0 fixed at 9:29am, we consider five-hour, three-hour, two-hour, one-hour, 30-minute and 15-minute windows prior to the market opening, for example, $\overline{CSent_{i,x}}\,[\tau_{-1}, 9{:}29]$. In Panel (b), we examine the persistence of overnight sentiment in gauging cumulative abnormal returns after the market opens by keeping the sentiment cumulation period fixed at the six-hour period prior to the market open and considering CARs after 15 minutes, 30 minutes, one hour, two hours, three hours and five hours following the market opening.[35]

Similar to a quantile function, horizontal axes in both panels show percentiles of the

[34] An exemplar of sentiment-event clustering and earnings announcements overlap is provided in the Supplementary Online Appendix in Figure A.4 for Apple, Inc. Similar figures for the remaining DJIA constituents are available upon request.

[35] Figure 9 in the Appendix shows the results based on the news media sentiment. Our conclusion based on the news media sentiment is qualitatively similar to the social media results.

sorting variable, cumulative sentiment. It starts from the most negative sentiment, the lowest 10%, to the most positive sentiment, the highest 10%, or cumulatively, 100%. The thick blue curves in both panels display the percentile distribution of $\overline{CSent_{i,x}}$ [3:29, 9:29], the cumulative social media sentiment for CSCO.OQ, aggregated from 3:29am to 9:29am, in other words, six hours before the market open. While the sentiment axes are on the left and are indicated by blue colour, the cumulative abnormal return axes are on the right and are indicated in red. The red thick curves represent the first-minute returns conditioned on the sentiment. The curves with varying grey colour gradients demonstrate our exploration of different pre-event (τ_{-1}, Panel (a)) and post-event (τ_2, Panel (b)) windows ranging among 15 minutes, 30 minutes, one hour, two hours, three hours, five hours and six hours. The shaded bands mark the upper and lower bounds of the 90% confidence interval of the unconditional CARs estimated with 2,000 bootstrap simulations.

We verify the robustness of our main results and confirm that our findings are consistent across a number of different specifications. Panel (a) in Figure 8 provides convincing evidence that our results are rigorous across different pre-event windows (τ_{-1}). Aggregating sentiment at 15-minute intervals (the most diluted curve) tends to generate a more volatile result than other event windows, suggesting that relying on merely 15 minutes of sentiment prior to the market open does not seem to incorporate enough information to make precise predictions. Sentiment is a noisy measure — more observations are required to cancel out the noise and tease out a stable signal.[36] Panel (b) in Figure 8 shows that varying the intervals of CARs of longer than 15 minutes mitigate the precision of sentiment predictability. Intuitively, CAR evaluated at longer time intervals is analogous to computing a moving average at longer lags—the longer the lag in the moving average estimate, the more it will dampen the initial effect. In that respect, we mainly focus on the first minute of the trading hours, the 1-minute CARs.

This 'percentile sentiment' analysis presents us with further evidence that social media sentiment is more negatively driven, while the news media is prone to be more positive. In particular, as shown in Figure 8, the 10th percentile of $CSent^S$ is equal to -0.021, while the 100th percentile of $CSent^S$ equals $+0.014$, the lowest and highest values on the left axes, respectively. On the other hand, as demonstrated in Figure 9, the 10th percentile of $CSent^N$ is -0.009, while the 100th percentile of $CSent^N$ is $+0.014$.

Another benefit of this framework is the ability to precisely pinpoint the exact percentile of the tailed cumulative sentiment that could predict returns at the specified significance level. This allows us to consider alternative definitions of heightened sentiment values instead of relying on ad hoc decile splits. We will follow this avenue of research in our upcoming

[36]In the unreported set of results, we find that an estimation window of less than 30 minutes does not provide precise results, predominantly due to the sparsity of observations within the short time interval.

studies.

5 Conclusion

In this study, we provide the most comprehensive analysis to date on intraday firm-specific investor sentiment. Using minute-to-minute sentiment scores based on textual analysis of over two million blogs, internet message boards, social and news media sites, we show that the sentiment distilled from these two media types display distinctive characteristics. Social media postings are concentrated during trading hours while news media activity is more dispersed throughout the day. Both media sources display similar post-trading-hour patterns that are consistent with everyday routines, while social media 'morning kinks' (a surge in postings just as people are waking up) tend to be more prominent than any similar effect in the news media.

We find that the accumulated sentiment from overnight non-trading period can predict the opening stock return. Our results indicate that the cumulative abnormal returns of these stocks are positively related to the top and bottom decile overnight sentiment from social and news media. In contrast to the prior literature, we do not find persistence in this sentiment-return relation. We show that if we remove the first trading minute from cumulative abnormal returns, the relationship between overnight sentiment and the next day's abnormal returns quickly diminishes. The fast dissipating effect implies that overnight sentiment is swiftly impounded into stock prices in the first minutes of opening, most likely through orders submitted at the pre-opening sessions. It is noteworthy, however, that this short-lived effect is asymmetric. The asymmetry between positive and negative sentiment is a recurrent theme in our findings. We show that, on average, negative sentiment exert a higher economic impact on stock prices than positive sentiment. Our finding that positive and negative sentiment affects the market differently is consistent with several cognitive and psychological biases of noise traders. We therefore provide investors with a set of tools to understand the novel dynamics of the market in this fast-paced digital era.

We offer new insights into the optimal time frame to gauge emotions and generate a reliable predictive signal before the market opening. We find that sentiment accumulated from as early as six hours to 15 minutes before the market opening has a statistically significant impact on the opening price. Moreover, sentiment cumulated in the two to three hour period immediately prior to the opening of the market provides the most accurate predictions of opening returns. Unlike previous studies, the use of overnight sentiment during non-trading hours enables the analysis to break up the sentiment-return causality loop. Our robustness tests show that the inclusion of returns from the previous trading day does not have any impact on the significant relationship between overnight sentiment and opening returns. Further, we verify that the sources of sentiment variations do not coincide with earnings announcements — the corporate news events most pertinent to company valuation.

Overall, using stock-specific rather than market-wide sentiment measures, this paper contributes to the literature investigating overnight investor sentiment and intraday return patterns. Our results suggest that opinions and investor moods are incorporated into prices swiftly. With the rapid expansion of social media platforms in the past decade, especially in the US, stock prices are becoming increasingly sensitive to social media sentiment. And while the influence of text-based investor sentiment on stock markets has been established in the literature, the majority of the studies remain US-centred or focus on a single source of sentiment. Future research shall focus on contrasting the effects of social and news media to investigate how sentiment from these two sources impacts markets in other countries.

References

Aboody, D., Even-Tov, O., Lehavy, R., and Trueman, B. (2018). Overnight returns and firm-specific investor sentiment. *Journal of Financial and Quantitative Analysis*, 53(2):485–505.

Akhtar, S., Faff, R., Oliver, B., and Subrahmanyam, A. (2012). Stock salience and the asymmetric market effect of consumer sentiment news. *Journal of Banking & Finance*, 36(12):3289–3301.

Antweiler, W. and Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, 59(3):1259–1294.

Azar, P. D. and Lo, A. W. (2016). The wisdom of twitter crowds: Predicting stock market reactions to FOMC meetings via twitter feeds. *The Journal of Portfolio Management*, 42(5):123–134.

Bagnoli, M., Clement, M. B., and Watts, S. G. (2005). Around-the-clock media coverage and the timing of earnings announcements. *Working Paper*.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4):1645–1680.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2):129–152.

Ball, R. and Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, 6(2):159.

Barber, B. M. and Odean, T. (2007). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2):785–818.

Barber, B. M., Odean, T., and Zhu, N. (2008). Do retail trades move markets? *The Review of Financial Studies*, 22(1):151–186.

Barclay, M. J. and Hendershott, T. (2003). Price discovery and trading after hours. *Review of Financial Studies*, 16(4):1041–1073.

Bartov, E., Faurel, L., and Mohanram, P. S. (2018). Can twitter help predict firm-level earnings and stock returns? *The Accounting Review*, 93(3):25–57.

Beaver, W. H. (1968). The information content of annual earnings announcements. *Journal of Accounting Research*, 6:67.

Beaver, W. H., McNichols, M. F., and Wang, Z. Z. (2020). Increased market response to earnings announcements in the 21st century: An empirical investigation. *Journal of Accounting and Economics*, 69(1):101244.

Behrendt, S. and Schmidt, A. (2018). The Twitter myth revisited: Intraday investor sentiment, Twitter activity and individual-level stock return volatility. *Journal of Banking & Finance*, 96:355–367.

Berkman, H., Koch, P. D., Tuttle, L., and Zhang, Y. J. (2012). Paying attention: overnight returns and the hidden cost of buying at the open. *Journal of Financial and Quantitative Analysis*, 47(4):715–741.

Berkman, H. and Truong, C. (2009). Event day 0? After-hours earnings announcements. *Journal of Accounting Research*, 47(1):71–103.

Birru, J. (2018). Day of the week and the cross-section of returns. *Journal of Financial Economics*, 130(1):182–214.

Bollen, J., Mao, H., and Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8.

Boudoukh, J., Feldman, R., Kogan, S., and Richardson, M. (2018). Information, trading, and volatility: Evidence from firm-specific news. *The Review of Financial Studies*, 32(3):992–1033.

Bradley, D., Clarke, J., Lee, S., and Ornthanalai, C. (2014). Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delays. *The Journal of Finance*, 69(2):645–673.

Branch, B. and Ma, A. (2012). Overnight return, the Invisible Hand Behind Intraday Returns? *Journal of Applied Finance*, 22(2):90–100.

Brown, G. W. and Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, 11(1):1–27.

Bukovina, J. (2016). Social media big data and capital markets—an overview. *Journal of Behavioral and Experimental Finance*, 11:18–26.

Chouliaras, A. S. (2015). High frequency newswire textual sentiment: Evidence from international stock markets during the European financial crisis. Technical report.

Chue, T. K., Gul, F. A., and Mian, G. M. (2019). Aggregate investor sentiment and stock return synchronicity. *Journal of Banking & Finance*, 108:105628.

Cooper, M. J., Cliff, M. T., and Gulen, H. (2008). Return differences between trading and non-trading hours: Like night and day. Available at SSRN: https://ssrn.com/abstract=1004081.

Coqueret, G. (2020). Stock-specific sentiment and return predictability. *Quantitative Finance*, 0(0):1–21.

Da, Z., Engelberg, J., and Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5):1461–1499.

Dang, T. L., Moshirian, F., and Zhang, B. (2015). Commonality in news around the world. *Journal of Financial Economics*, 116(1):82–110.

Deng, S., , Huang, Z. J., Sinha, A. P., Zhao, H., , and and (2018). The interaction between microblog sentiment and stock returns: An empirical examination. *MIS Quarterly*, 42(3):895–918.

Engelberg, J., McLean, R. D., and Pontiff, J. (2018). Anomalies and news. *The Journal of Finance*, 73(5):1971–2001.

Gan, B., Alexeev, V., Bird, R., and Yeung, D. (2019). Sensitivity to sentiment: News vs social media. *International Review of Financial Analysis*, page 101390.

Gentzkow, M., Kelly, B. T., and Taddy, M. (2017). Text as data. Technical report, National Bureau of Economic Research.

Groß-Klußmann, A. and Hautsch, N. (2011). When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. *Journal of Empirical Finance*, 18(2):321–340.

Hendershott, T., Livdan, D., and Rösch, D. (2020). Asset pricing: A tale of night and day. *Journal of Financial Economics.*

Heston, S. L. and Sinha, N. R. (2017). News vs sentiment: predicting stock returns from news stories. *Financial Analysts Journal*, 73(3):67–83.

Jeon, Y., McCurdy, T. H., and Zhao, X. (2021). News as sources of jumps in stock returns: Evidence from 21 million news articles for 9000 companies. *Journal of Financial Economics.*

Jiang, C. X., Likitapiwat, T., and McInish, T. H. (2012). Information content of earnings announcements: Evidence from after-hours trading. *Journal of Financial and Quantitative Analysis*, 47(6):1303–1330.

Jiang, H., Li, S. Z., and Wang, H. (2019). News momentum. Technical report.

Kearney, C. and Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, 33:171–185.

Kelly, M. A. and Clark, S. P. (2011). Returns in trading versus non-trading hours: The difference is day and night. *Journal of Asset Management*, 12(2):132–145.

Kemp, S. (2021). Digital 2021 Global Overview Report: The latest insights into how people around the world use the internet, social media, mobile devices, and e-commerce.

Li, H., Guo, Y., and Park, S. Y. (2017). Asymmetric relationship between investors' sentiment and stock returns: Evidence from a quantile non-causality test. *International Review of Finance*, 17(4):617–626.

Lou, D., Polk, C., and Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, 134(1):192–213.

Loughran, T. and McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, 66(1):35–65.

Lu, X., Lai, K. K., and Liang, L. (2012). Dependence between stock returns and investor sentiment in chinese markets: A copula approach. *Journal of Systems Science and Complexity*, 25(3):529–548.

Lutz, C. (2015). The impact of conventional and unconventional monetary policy on investor sentiment. *Journal of Banking & Finance*, 61:89–105.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, 35(1):13–39.

Mao, H., Counts, S., and Bollen, J. (2011). Predicting financial markets: Comparing survey, news, twitter and search engine data. *arXiv preprint arXiv:1112.1051*.

Michaely, R., Rubin, A., and Vedrashko, A. (2013). Corporate governance and the timing of earnings announcements. *Review of Finance*, 18(6):2003–2044.

Moon, S. J. and Hadley, P. (2014). Routinizing a new technology in the newsroom: Twitter as a news source in mainstream media. *Journal of Broadcasting & Electronic Media*, 58(2):289 – 305.

Morck, R., Yeung, B., and Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, 58(1-2):215–260.

O'Hara, M. (2014). High-frequency trading and its impact on markets. *Financial Analysts Journal*, 70(3):18–27.

Peterson, R. L. (2016). *Trading on sentiment: The power of minds over markets*. John Wiley & Sons.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the US stock market. *Journal of Banking & Finance*, 84:25–40.

Rieder, R. (2011). Passing on rumors. *American Journalism Review*.

Siganos, A., Vagenas-Nanos, E., and Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior & Organization*, 107:730–743.

Sprenger, T. O., Sandner, P. G., Tumasjan, A., and Welpe, I. M. (2014). News or noise? using twitter to identify and understand company-specific news flow. *Journal of Business Finance & Accounting*, 41(7-8):791–830.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, 104(2):288–302.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2014). The long of it: Odds that investor sentiment spuriously predicts anomaly returns. *Journal of Financial Economics*, 114(3):613–619.

Sul, H. K., Dennis, A. R., and Yuan, L. I. (2016). Trading on Twitter: Using social media sentiment to predict stock returns. *Decision Sciences*, 48(3):454–488.

Sun, L., Najand, M., and Shen, J. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance*, 73:147–164.

Welch, I. (2021). Simple better market betas. *SSRN Electronic Journal*, Last revised: 22 Jun 2021.

Yang, S. Y., Liu, A., Chen, J., and Hawkes, A. (2017). Applications of a multivariate hawkes process to joint modeling of sentiment and market return events. *Quantitative Finance*, 18(2):295–310.

Appendix

Figure 1: **Visual representation of sentiment and return data for Apple Inc.** Panels on the left are heatmaps representing all available 1-minute sentiment data based on social media (top), news media (middle), and mid-quote returns (bottom). The data are arranged by time-of-day (horizontal axis) on each day of the sample (vertical axis). Each pixel represents a single 1-minute observation — positive values are shown in red, negative values in blue, missing data appear white in the heatmaps. Right-hand side panels display proportions of non-missing observations corresponding to variables on the left and capture intraday and day-of-the-week patterns.

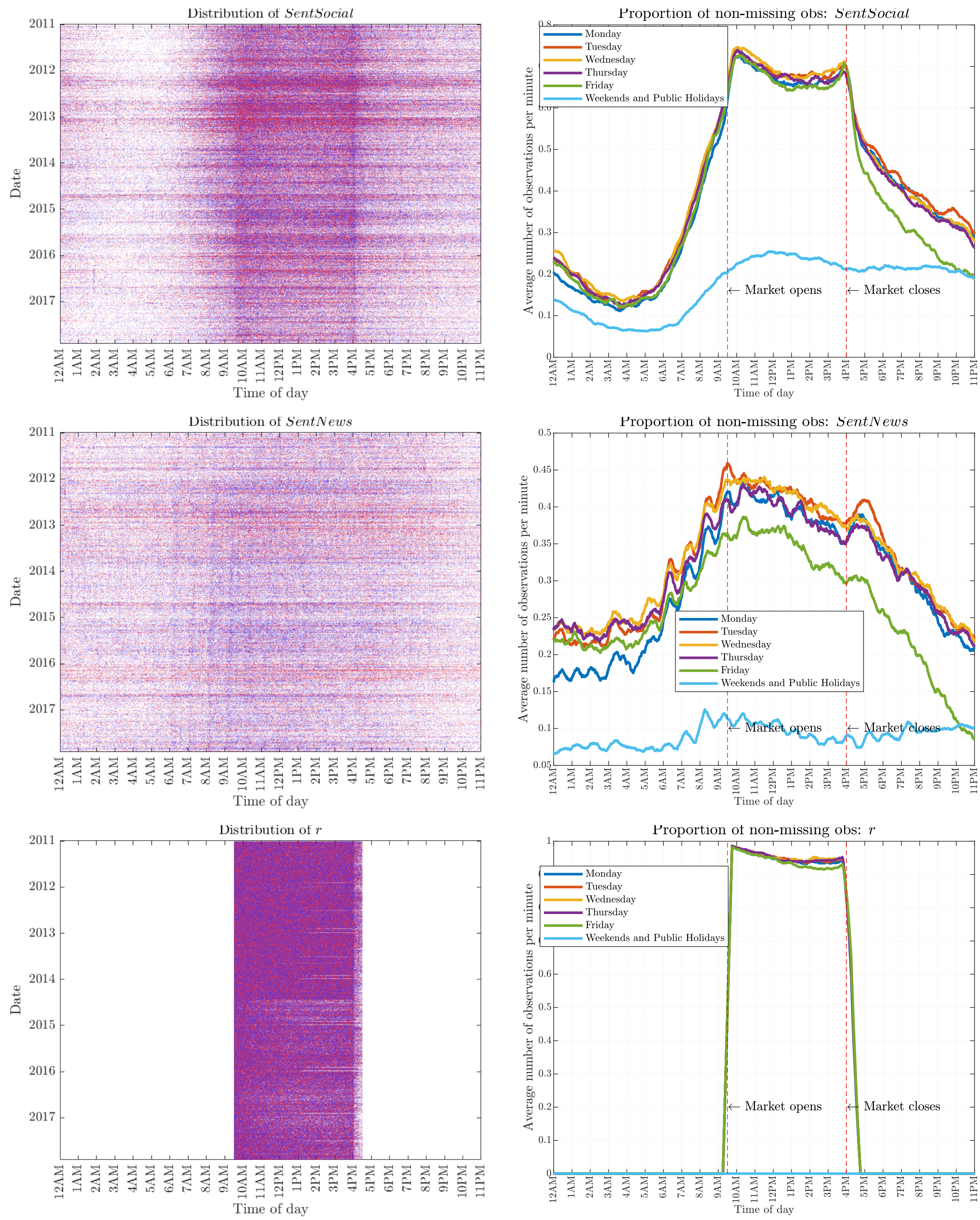


Figure 2: Social Media: Overnight Sentiment and Opening Returns (CSCO.OQ) Sentiment and return data are at 1-minute frequency from 1 January 2011 to 30 November 2017. Overnight sentiment is cumulated daily from previous day close to current day open (i.e., from 4:01pm to 9:29am). Cumulative sentiment is sorted into deciles and the average cumulative sentiment scores for each decile are presented on the left axes. Average cumulative abnormal returns on the corresponding days are depicted in matching colours on the right axes. The red colour represents decile 1, the most negative sentiment prior to market opening and the corresponding returns during the trading hours. Similarly, the blue colour depicts decile 10, days with the most positive overnight sentiment and the corresponding stock returns. The difference between the panels is the aggregation starting point in the abnormal returns: in the top panel, the aggregation starts from 9:30am, while in the bottom panel, it starts from 9:31am, omitting overnight returns. The grey-shaded 99%, 95% and 90% confidence bands are based on average cumulative returns on n days randomly drawn M times from the entire sample of T days *without* conditioning on sentiment. Specifically, n is 174 to match the size (in days) of each sentiment decile (i.e., the cardinality of $\mathcal{D}_{x,i}$) and the number of simulations is set to $M = 2,000$.

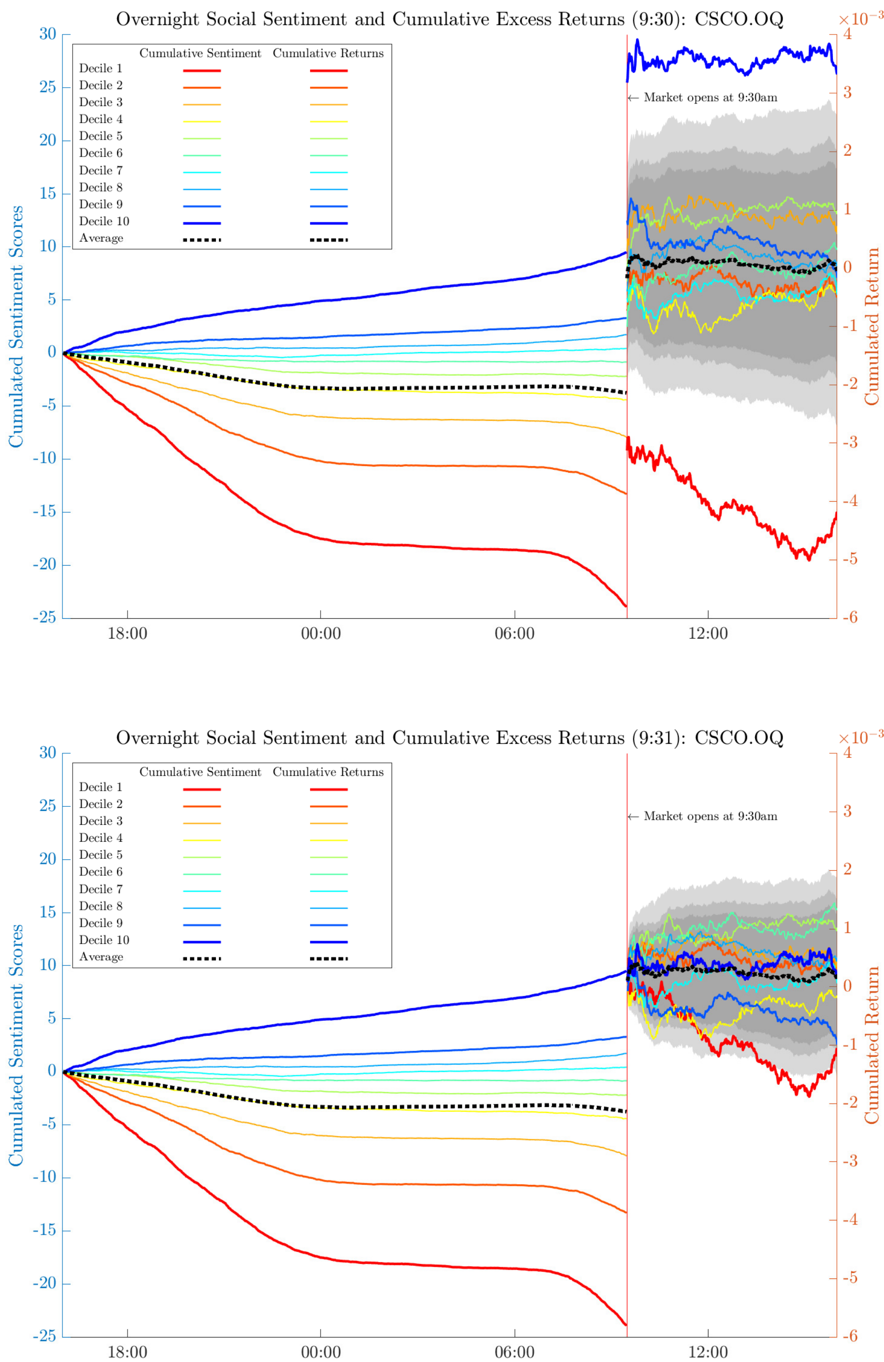
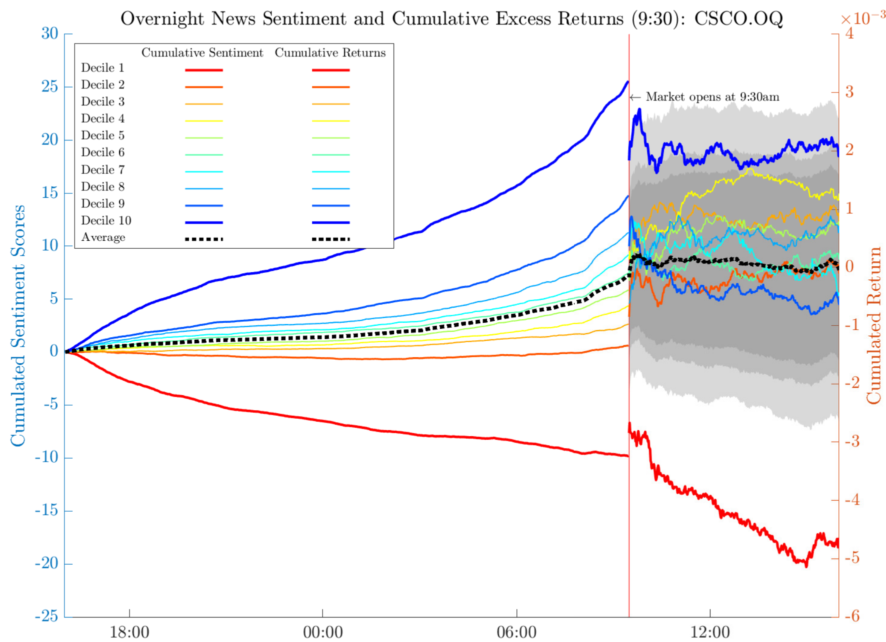


Figure 3: NEWS MEDIA: OVERNIGHT SENTIMENT AND OPENING RETURNS (CSCO.OQ) Sentiment and return data are at 1-minute frequency from 1 January 2011 to 30 November 2017. Overnight sentiment is cumulated daily from previous day close to current day open (i.e., from 4:01pm to 9:29am). Cumulative sentiment is sorted into deciles and the average cumulative sentiment scores for each decile are presented on the left axes. Average cumulative abnormal returns on the corresponding days are depicted in matching colours on the right axes. The red colour represents decile 1, the most negative sentiment prior to market opening and the corresponding returns during the trading hours. Similarly, the blue colour depicts decile 10, days with the most positive overnight sentiment and the corresponding stock returns. The difference between the panels is the aggregation starting point in the abnormal returns: in the top panel, the aggregation starts from 9:30am, while in the bottom panel, it starts from 9:31am, omitting overnight returns. The grey-shaded 99%, 95% and 90% confidence bands are based on average cumulative returns on n days randomly drawn M times from the entire sample of T days *without* conditioning on sentiment. Specifically, n is 174 to match the size (in days) of each sentiment decile (i.e., the cardinality of $\mathcal{D}_{x,i}$) and the number of simulations is set to $M = 2,000$.



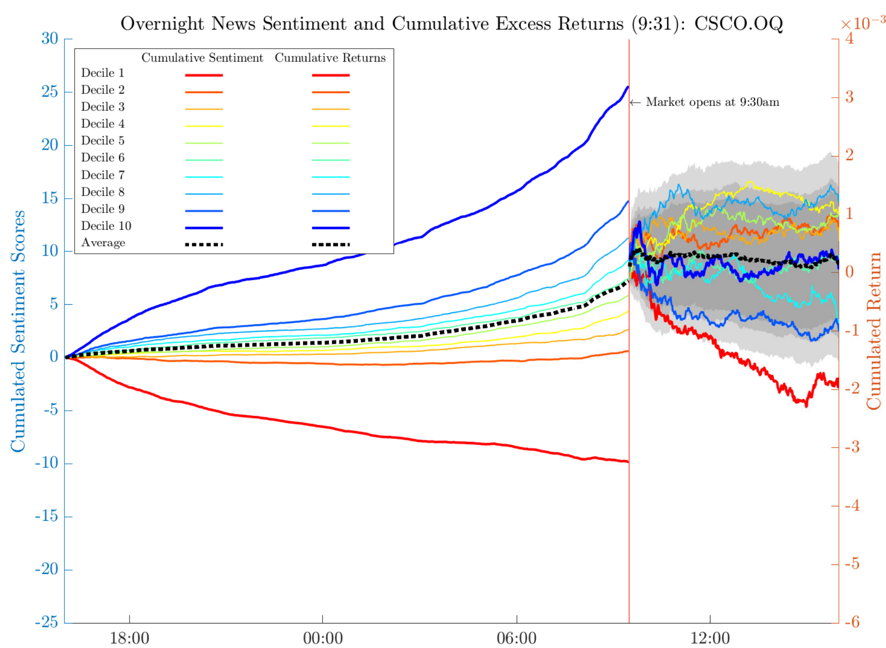


Figure 4: Average Cumulative Abnormal Returns Conditioned on Top Sentiment. The figure reports the average cumulative abnormal returns, in bps, conditional on the most positive decile of overnight sentiment. The plotted values represent returns conditional on social media sentiment (blue), on news media sentiment (red) and, for comparison, the average returns across all stocks (dashed lines). The top panel depicts returns aggregated from 9:30am to 4:00pm measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. Similarly, the bottom panel depicts the corresponding average returns but aggregated from 9:31am to 4:00pm instead, omitting overnight returns.

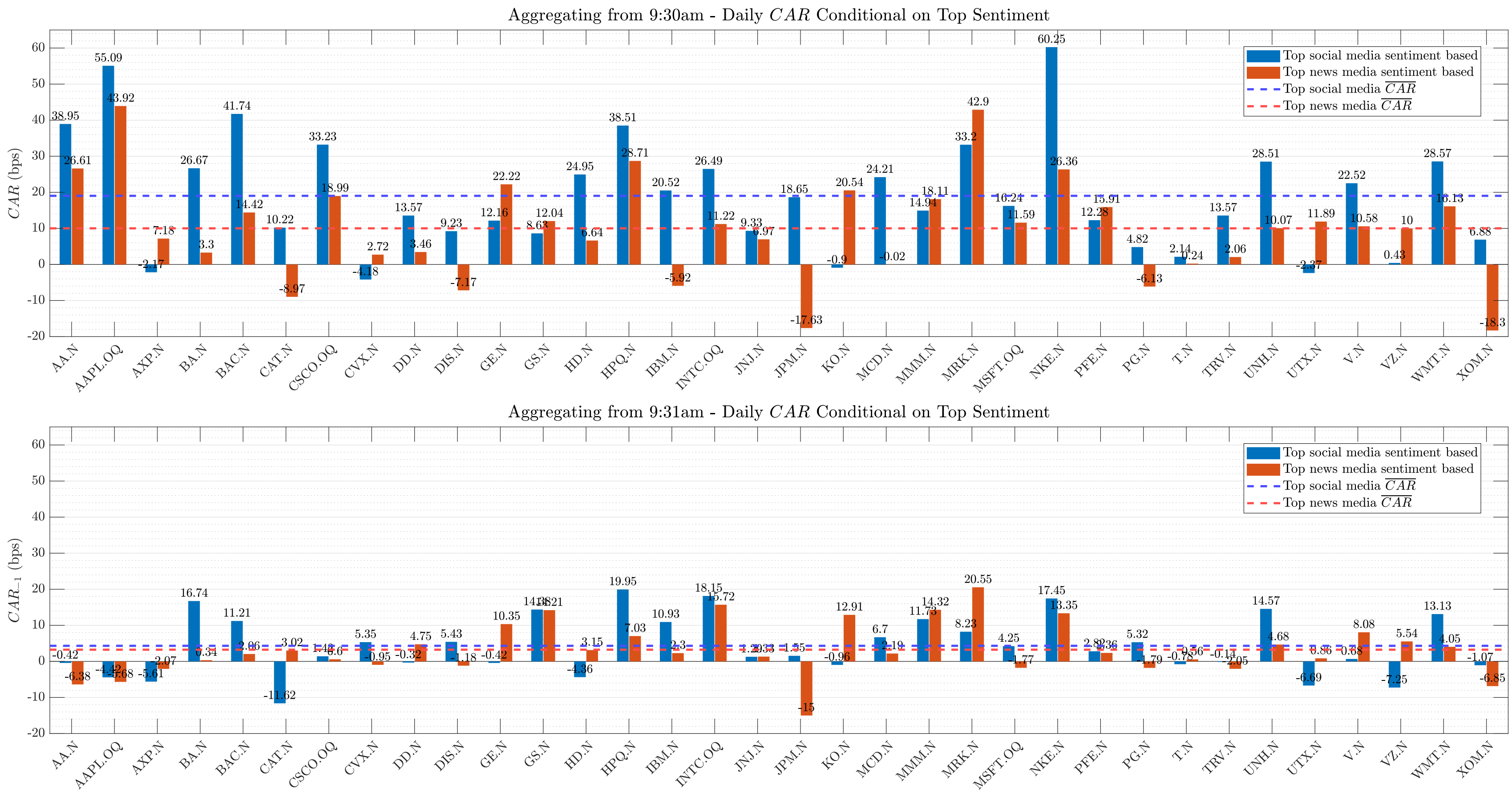


Figure 5: Average Cumulative Abnormal Returns Conditioned on Bottom Sentiment. The figure reports the average cumulative abnormal returns, in bps, conditional on the most negative decile of overnight sentiment. The plotted values represent returns conditional on social media sentiment (blue), on news media sentiment (red) and, for comparison, the average returns across all stocks (dashed lines). The top panel depicts returns aggregated from 9:30am to 4:00pm measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. Similarly, the bottom panel depicts the corresponding average returns but aggregated from 9:31am to 4:00pm instead, omitting overnight returns.

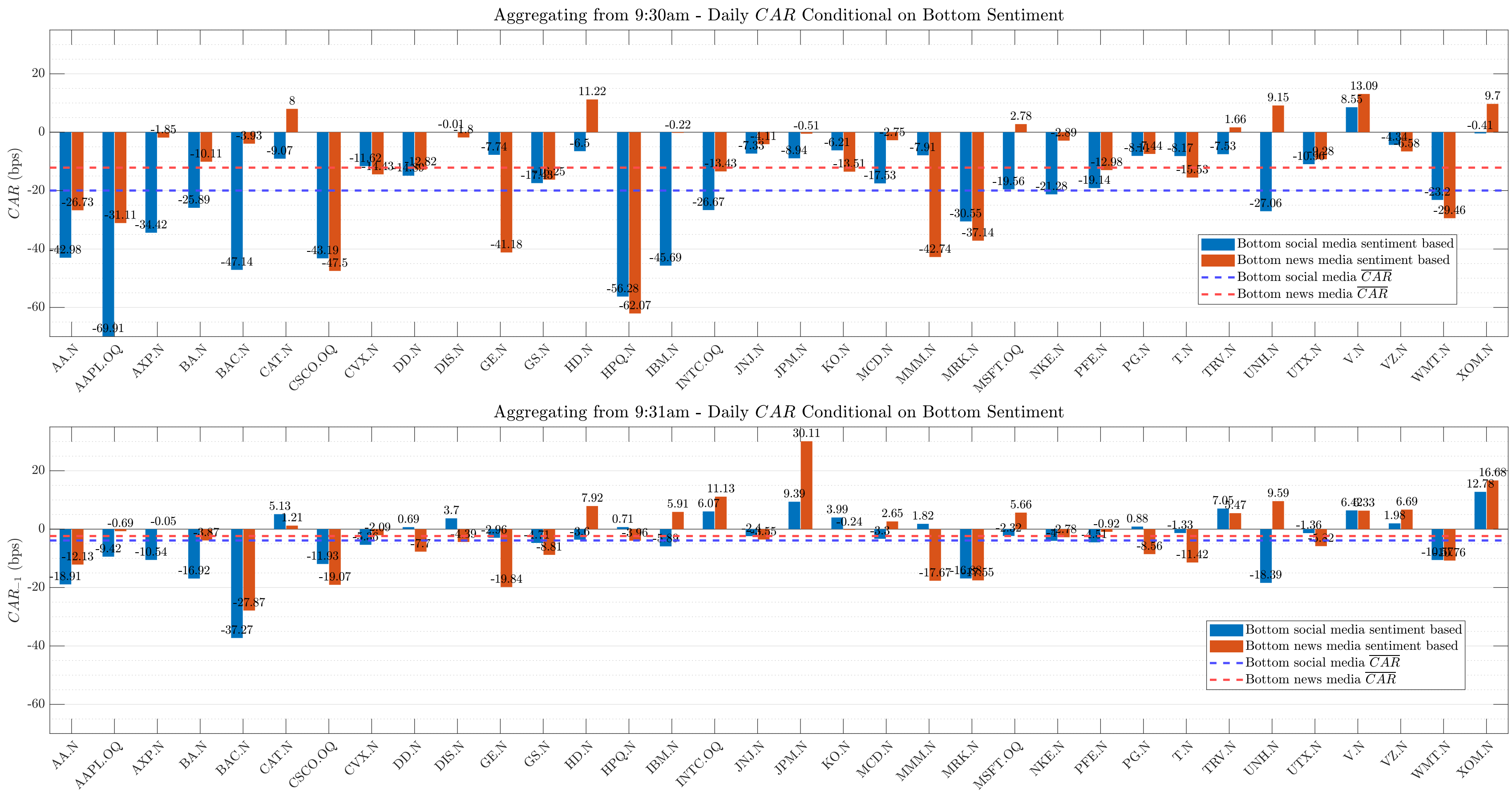
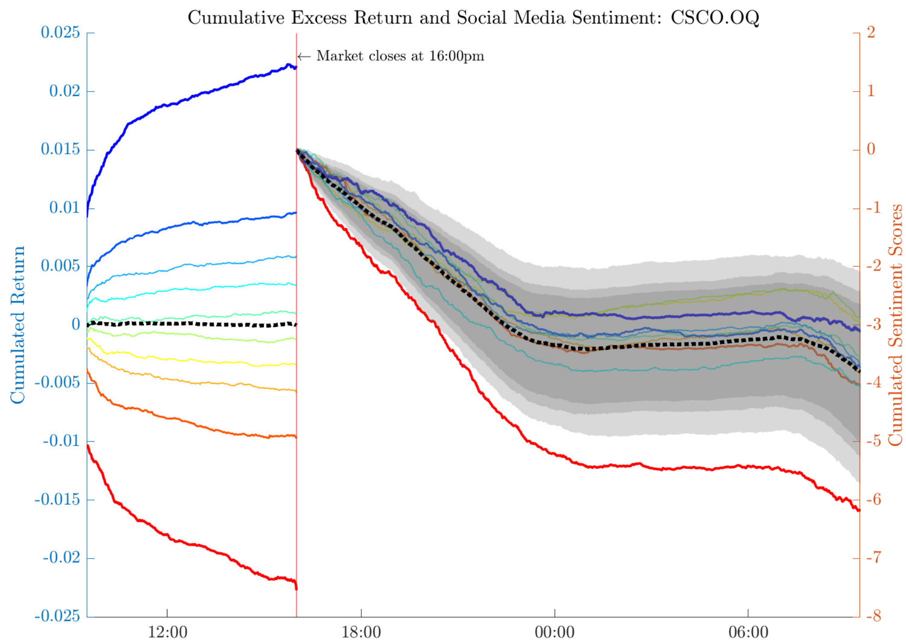


Figure 6: Cumulative Returns and Ensuing Sentiment (CSCO.OQ) Sentiment and return data are at 1-minute frequency from 1 January 2011 to 30 November 2017. Abnormal returns are cumulated daily from market open to close (from 9:30am to 4:00pm on each trading day). The cumulative abnormal returns (CARs) are then sorted into deciles. The average CAR for each decile are presented on the left axes. The average cumulative sentiment on the corresponding days are depicted in matching colours on the right axes. The red colour represents decile 1 — days with the most negative CARs and the corresponding sentiment from the market close at 4:01pm to 9:29am the following day. Similarly, the blue colour depicts decile 10 — days with the most positive CARs and the corresponding sentiment. The top panel depicts CAR-conditioned social media sentiment, while the bottom panel details CAR-conditioned news media sentiment. The grey-shaded 99%, 95% and 90% confidence bands are based on average cumulative sentiment on n days randomly drawn M times from the entire sample of T days *without* conditioning on CAR. Specifically, n is 174 to match the size (in days) of each CAR decile and the number of simulations is set to $M = 2,000$.



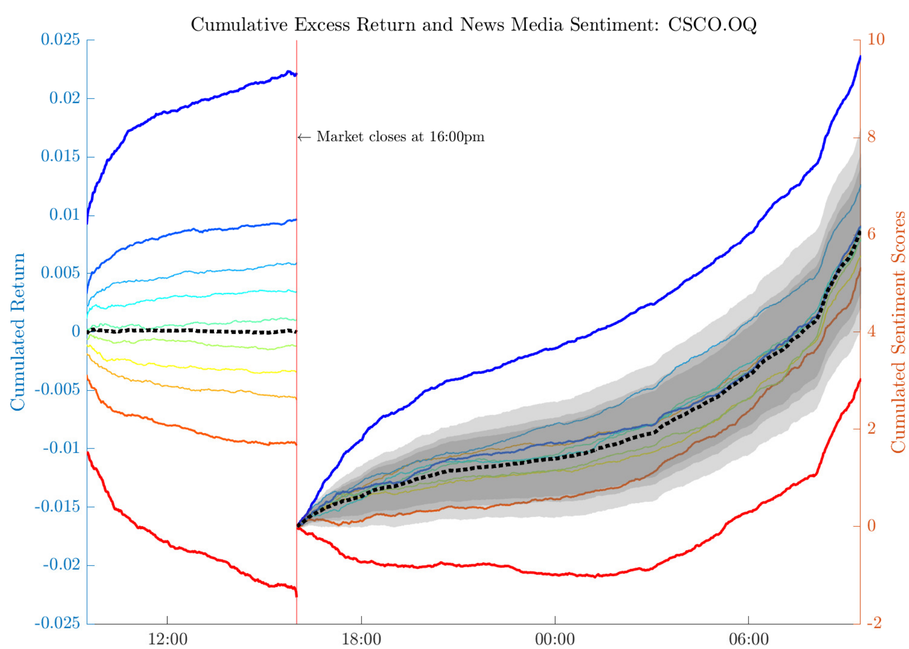


Figure 7: Sensitivity to Sentiment The figure contrasts stock sensitivities to sentiment between different media types (Panels A and B), between sentiment polarities (Panels C and D) and between the baseline and controlled models in Eqs. (8) and (9) (Panels E and F). Each scatter point represents an intersection of the two slope coefficients from Eq.(8) and/or Eq.(9). For example, the scatter points for CSCO.OQ in all the panels are constructed based on the regression output reported in Table 8. The scatter points are labelled with stock tickers if at least one of the coefficients is significant at the 10% level. Panels A and B contrast sensitivity to the social and news media sentiment after controlling for the previous day return, CAR_{t-1}. In Panel A (and B), points below the 45-degree line indicate that the corresponding stocks are more sensitive to social media sentiment when the sentiment is positive (negative). Panel C (and D) contrasts sensitivities to the positive and negative sentiment from social (and news) media. Panels E and F consider the effect of controlling for the previous day return in the social media sentiment. Sensitivity comparison for the baseline and controlled model results for the news media sentiment is depicted in Figure A.2 in the appendix.

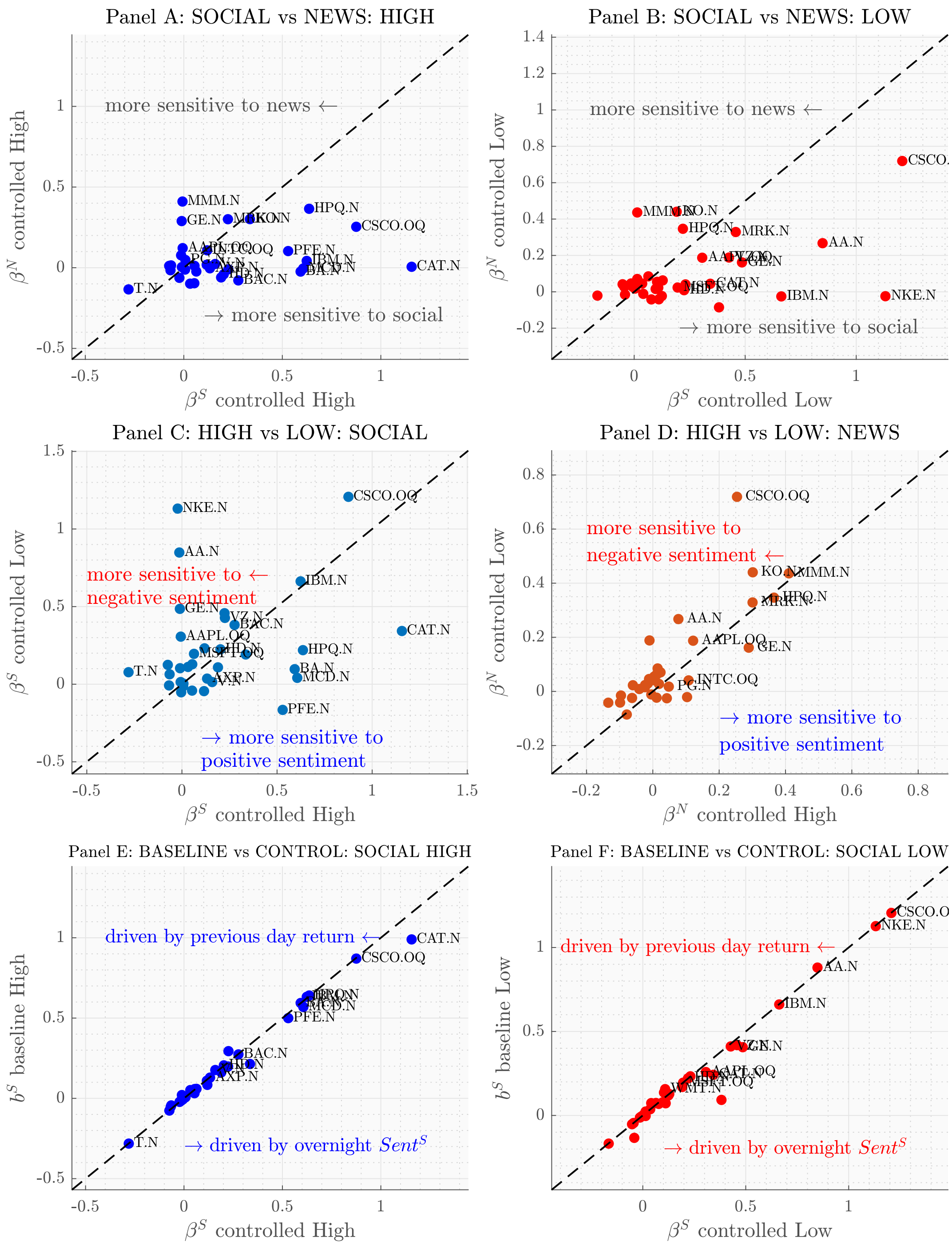
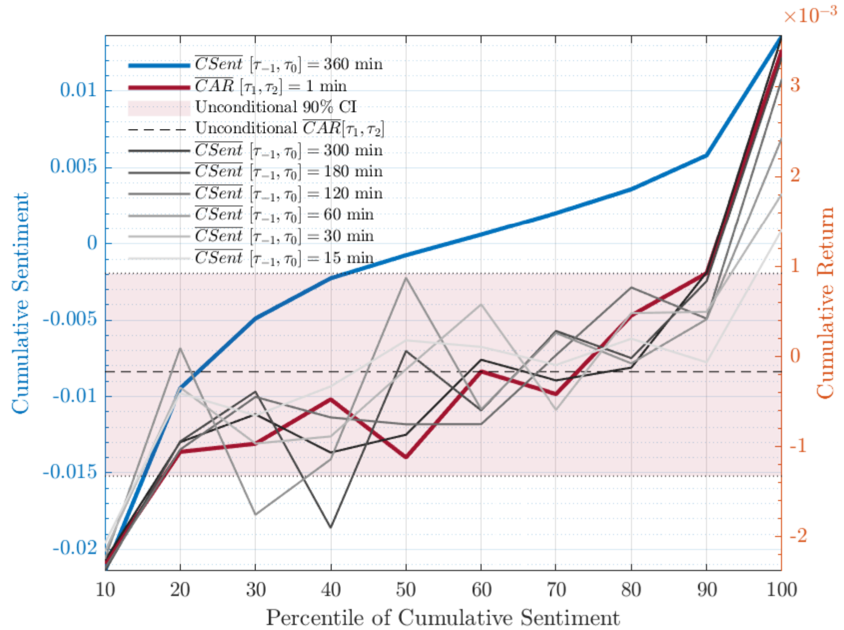
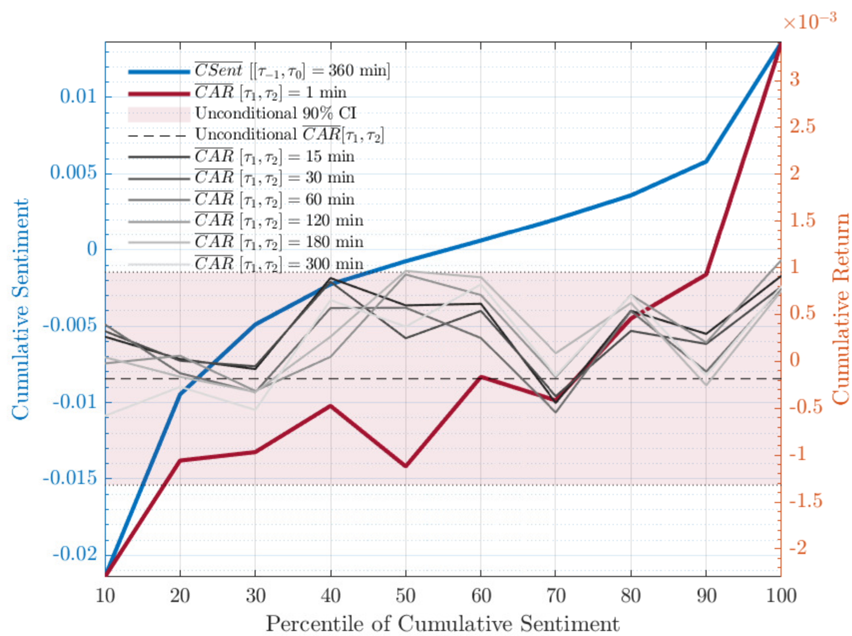


Figure 8: ALTERNATIVE EVENT WINDOW LENGTHS: THE CASE OF SOCIAL MEDIA FOR CSCO.OQ. This figure demonstrates how we determine the optimal pre- and post-event windows ($[\tau_{-1}, \tau_0]$ and $[\tau_1, \tau_2]$). The horizontal axis shows percentiles of the sorting variable, the cumulative sentiment based on social media, starting at the most negative sentiment (the average of $\mathcal{D}_{CSCO,1}$) to the most positive sentiment (the average of $\mathcal{D}_{CSCO,10}$). The blue curve and its scale (shown on the left vertical axis) display the distribution of cumulative sentiment. The red curve is the conditional variable, namely, $\overline{CAR}$s. The curves with varying grey colour gradients demonstrate our exploration of different pre-event ($[\tau_{-1}, \tau_0]$, Panel (a)) and post-event ($[\tau_1, \tau_2]$, Panel (b)) windows ranging among 15 minutes, 30 minutes, one hour, two hours, three hours, five hours and six hours. The shaded bands mark the upper and lower bounds of the 90% confidence interval from 2,000 bootstrap simulations.

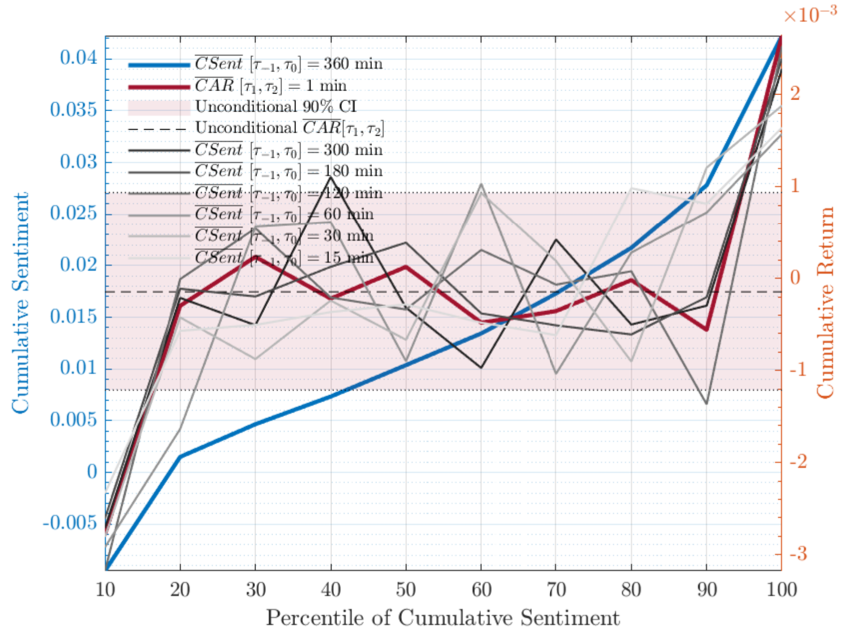


(a) Optimal $[\tau_{-1}, \tau_0]$

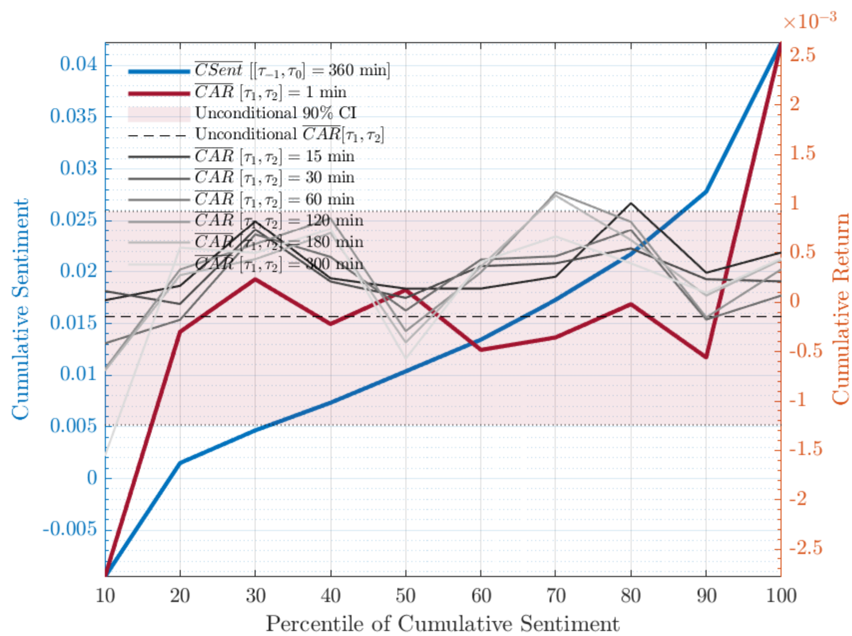


(b) Optimal $[\tau_1, \tau_2]$

Figure 9: Alternative event window lengths: The case of news media for CSCO.OQ. This figure demonstrates how we determine the optimal pre- and post-event windows ($[\tau_{-1}, \tau_0]$ and $[\tau_1, \tau_2]$). The horizontal axis shows percentiles of the sorting variable, the cumulative sentiment based on news media, starting at the most negative sentiment (average of $\mathcal{D}_{CSCO,1}$) to the most positive sentiment (average of $\mathcal{D}_{CSCO,10}$). The blue curve and its scale (shown on the left vertical axis) display the distribution of cumulative sentiment. The red curve is the conditional variable, namely, $\overline{CAR}$s. The curves with varying grey colour gradients demonstrate our exploration of different pre-event ($[\tau_{-1}, \tau_0]$, Panel (a)) and post-event ($[\tau_1, \tau_2]$, Panel (b)) windows ranging among 15 minutes, 30 minutes, one hour, two hours, three hours, five hours and six hours. The shaded bands mark the upper and lower bounds of the 90% confidence interval from 2,000 bootstrap simulations.



(a) Optimal $[\tau_{-1}, \tau_0]$



(b) Optimal $[\tau_1, \tau_2]$

Table 1: **List of acronyms, data sources, and variable definitions**

Acronym	Description
DJIA	Dow Jones Industrial Average
ETF	Exchange-Traded Funds
LSE	London Stock Exchange
Nasdaq	National Association of Securities Dealers Automated Quotations Stock Market
NYSE	New York Stock Exchange
S&P	Standard and Poor
TRMI	Thomson Reuters MarketPsych Indices
TRNA	Thomson Reuters News Analytics
TRTH	Thomson Reuters Tick History
US	United States
DataScope	Thomson Reuters/Refinitiv DataScope
RavenPack	A data analytics provider for financial services

Symbol	Description
$P_{i,t,j}$	Mid-quote price for asset i on day t at time j, i.e. $P_{i,t,j} = \frac{1}{2}\left(Ask_{i,t,j} + Bid_{i,t,j}\right)$
$i = 1, ..., N$	Asset indexation with $i = 0$ reserved for a broad market index or a benchmark
$t = 1, ..., T$	Index of days in the sample
j	Each day is divided into equidistant one-minute mesh indexed by j
$r_{i,t,j}$	Continuously compounded returns
$x^{(S)}$	Superscript denotes **s**ocial media-based variables
$x^{(N)}$	Superscript denotes **n**ews media-based variables
$AR_{i,t,j}$	Asset i's abnormal return on day t at time j, i.e., $AR_{i,t,j} = r_{i,t,j} - r_{0,t,j}$
$CAR_{i,t}[\tau_1, \tau_2]$	Asset i's cumulative abnormal return, i.e., $CAR_{i,t}[\tau_1, \tau_2] = \sum_{j=\tau_1}^{\tau_2} AR_{i,j,t}$
$Sent^S_{i,j,t}$	One-minute **s**ocial media sentiment score for stock i on day t at time j
$Sent^N_{i,j,t}$	One-minute **n**ews media sentiment score for stock i on day t at time j
$CSent_{i,t}[\tau_{-1}, \tau_0]$	Cumulative sentiment on day t, computed as: $CSent_{i,t}[\tau_{-1}, \tau_0] = \sum_{j=\tau_{-1}}^{\tau_0} Sent_{i,j,t}$
$\mathcal{D}_{i,x}$	A collection of days of stock i with the x-th decile sentiment
Event-days	Sentiment event-days is the collection of days identified in $\mathcal{D}_{i,1}$ and $\mathcal{D}_{i,10}$ for each stock i, that is the set of days with the lowest and highest cumulative overnight sentiment.
$\lvert\mathcal{D}_{i,x}\rvert$	Number of elements in (the cardinality of) decile x
$\overline{CAR_{i,x}}\,[\tau_1, \tau_2]$	Average cumulative abnormal return conditional on the x-th decile of cumulative overnight sentiment
$\overline{CSent_{i,x}}[\tau_{-1}, \tau_0]$	Average cumulative sentiment in decile x

Table 2: Sentiment Data Availability. The total number of non-missing 1-minute observations and average daily counts are presented for the social and news media for the Dow Jones Industrial Average Index ('.DJI') and each of its constituents. Securities traded on the New York Stock Exchange and Nasdaq have their tickers suffixed with '.N' and '.OQ', respectively. Stocks delisted from the DJIA during the sample period are included. Calculations are based on the Thomson Reuters MarketPsych Indices (TRMI) social and news media *Sentiment* scores at 1-minute frequency for the period from 1 January 2011 to 30 November 2017, totaling 2,526 days. The rows are sorted by the total number of non-missing sentiment scores from social media.

RIC	**Social**		**News**	
	Total	**Daily**	**Total**	**Daily**
.DJI	**2,593,029**	**1026.5**	**2,449,177**	**969.6**
AAPL.OQ	1,310,025	518.6	910,719	360.5
BAC.N	400,181	158.4	195,850	77.5
GE.N	390,059	154.4	173,480	68.7
MSFT.OQ	361,855	143.3	507,409	200.9
CSCO.OQ	300,459	118.9	132,024	52.3
GS.N	291,235	115.3	320,741	127.0
INTC.OQ	224,186	88.8	204,624	81.0
WMT.N	212,873	84.3	212,538	84.1
JPM.N	192,823	76.3	311,167	123.2
BA.N	168,487	66.7	292,763	115.9
T.N	159,040	63.0	151,011	59.8
HPQ.N	146,304	57.9	170,659	67.6
VZ.N	116,153	46.0	154,311	61.1
IBM.N	112,768	44.6	198,993	78.8
XOM.N	109,729	43.4	151,723	60.1
PFE.N	94,373	37.4	89,748	35.5
MCD.N	83,752	33.2	130,989	51.9
KO.N	69,217	27.4	126,629	50.1
AA.N	64,063	25.4	50,369	19.9
JNJ.N	57,250	22.7	68,966	27.3
CAT.N	57,194	22.6	55,463	22.0
MRK.N	56,075	22.2	63,800	25.3
NKE.N	52,647	20.8	57,582	22.8
CVX.N	43,411	17.2	97,178	38.5
HD.N	41,674	16.5	54,084	21.4
DIS.N	33,652	13.3	38,117	15.1
PG.N	33,208	13.1	58,429	23.1
MMM.N	30,326	12.0	52,848	20.9
V.N	27,532	10.9	19,075	7.6
AXP.N	22,970	9.1	49,300	19.5
DD.N	19,965	7.9	6,592	2.6
UTX.N	15,836	6.3	30,595	12.1
UNH.N	13,058	5.2	25,630	10.1
KFT.OQ	6,726	2.7	22,658	9.0
TRV.N	4,520	1.8	5,107	2.0
Mean	152,104	60	148,319	59
Median	69,217	27	97,178	38

Table 3: Positive Overnight Sentiment Days. The table reports the average overnight sentiment scores and the corresponding cumulative returns over the set of days with the most positive overnight sentiment (i.e., conditional on the highest sentiment decile for each stock, $\mathcal{D}_{i,10}$). Columns (1) and (4) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01pm the previous day to 9:29am. That is, $\overline{CSent_{i,x}}\,[16{:}01, 9{:}29]$ as defined in Eq.(5). Columns (2) and (5) are the average cumulative abnormal returns aggregated from 9:30am to 4:00pm measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. That is, $\overline{CAR_{i,x}}\,[9{:}30, 16{:}00]$ as defined in Eq.(6). Similarly, Columns (3) and (6) are the corresponding average cumulative abnormal returns but aggregated from 9:31am to 4:00pm instead, with the overnight return removed. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are constructed from bootstrap simulations of cumulative returns unconditional on sentiment. Misclassification rates are based on Eq. (7).

	Social Media			News Media		
Asset	(1) $CSent$	(2) CAR	(3) CAR_{-1}	(4) $CSent$	(5) CAR	(6) CAR_{-1}
AA.N	6.72	38.95***	−0.42	10.84	26.61**	−6.38
AAPL.OQ	46.34	55.09***	−4.42	62.32	43.92***	−5.68
BA.N	10.11	26.67***	16.74**	26.51	3.30	0.34
BAC.N	9.01	41.74***	11.21*	13.91	14.42	2.06
CAT.N	5.61	10.22	−11.62	10.88	−8.97	3.02
CSCO.OQ	9.49	33.23***	1.42	25.59	18.99*	0.60
CVX.N	5.28	−4.18	5.35	11.51	2.72	−0.95
DD.N	2.33	13.57*	−0.32	2.15	3.46	4.75
DIS.N	5.62	9.23	5.43	6.79	−7.17	−1.18
GE.N	7.74	12.16**	−0.42	25.34	22.22***	10.35**
GS.N	8.68	8.63	14.38	20.31	12.04	14.21
HD.N	9.62	24.95**	−4.36	19.32	6.64	3.15
HPQ.N	8.77	38.51***	19.95	19.70	28.71**	7.03
IBM.N	11.05	20.52***	10.93*	31.32	−5.92	2.30
INTC.OQ	15.13	26.49***	18.15**	29.58	11.22	15.72*
JNJ.N	7.02	9.33**	1.29	12.51	6.97*	1.33
JPM.N	8.28	18.65*	1.55	19.48	−17.63**	−15.00**
KO.N	6.49	−0.90	−0.96	15.41	20.54***	12.91***
MCD.N	6.44	24.21***	6.70	11.04	−0.02	2.19
MMM.N	4.68	14.94*	11.73	10.25	18.11**	14.32*
MRK.N	6.27	33.20***	8.23*	11.63	42.90***	20.55***
MSFT.OQ	24.92	16.24	4.25	49.02	11.59	−1.77
NKE.N	9.68	60.25***	17.45**	9.32	26.36***	13.35
PFE.N	6.81	12.28	2.82	13.26	15.91**	2.36
PG.N	4.94	4.82	5.32	9.35	−6.13	−1.79
T.N	11.62	2.14	−0.78	17.58	0.24	0.56
TRV.N	1.39	13.57*	−0.14	1.76	2.06	−2.05
UNH.N	4.31	28.51***	14.57*	8.29	10.07	4.68
UTX.N	3.52	−2.37	−6.69	6.89	11.89*	0.86
V.N	5.72	22.52**	0.68	6.65	10.58	8.08
VZ.N	9.92	0.43	−7.25	18.71	10.00**	5.54
WMT.N	10.90	28.57***	13.13**	19.27	16.13**	4.05
XOM.N	6.34	6.88*	−1.07	14.75	−18.30*	−6.85
Average		19.03	4.33		10.02	3.25
#Neg/#Pos		4/30	13/21		7/27	10/24
Misclassification rate		11.8%	38.2%		20.6%	29.4%

Table 4: Negative Overnight Sentiment Days. The table reports the average overnight sentiment scores and the corresponding cumulative returns over the set of days with the most negative overnight sentiment (i.e., conditional on the lowest sentiment decile for each stock, $\mathcal{D}_{i,1}$). Columns (1) and (4) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01pm the previous day to 9:29am. That is, $\overline{CSent_{i,x}}\,[16{:}01, 9{:}29]$ as defined in Eq.(5). Columns (2) and (5) are the average cumulative abnormal returns aggregated from 9:30am to 4:00pm measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. That is, $\overline{CAR_{i,x}}\,[9{:}30, 16{:}00]$ as defined in Eq.(6). Similarly, Columns (3) and (6) are the corresponding average cumulative abnormal returns but aggregated from 9:31am to 4:00pm instead, with the overnight return removed. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are constructed from bootstrap simulations of cumulative returns unconditional on sentiment. Misclassification rates are based on Eq. (7).

	Social Media			News Media		
Asset	(1) $CSent$	(2) CAR	(3) CAR_{-1}	(4) $CSent$	(5) CAR	(6) CAR_{-1}
AA.N	−6.39	−42.98***	−18.91	−17.84	−26.73*	−12.13
AAPL.OQ	−34.25	−69.91***	−9.42	−43.22	−31.11***	−0.69
AXP.N	−3.39	−34.42***	−10.54*	−5.42	−1.85	−0.05
BA.N	−13.32	−25.89***	−16.92***	−34.09	−10.11*	−3.87
BAC.N	−31.27	−47.14***	−37.27***	−25.58	−3.93	−27.87**
CAT.N	−6.51	−9.07	5.13	−14.12	8.00	1.21
CSCO.OQ	−23.94	−43.19***	−11.93**	−9.80	−47.50***	−19.07***
CVX.N	−5.44	−11.62	−5.36	−19.31	−14.43	−2.09
DD.N	−2.69	−14.89*	0.69	−1.56	−12.82	−7.70
DIS.N	−2.91	−0.01	3.70	−5.15	−1.80	−4.39
GE.N	−26.82	−7.74	−2.96	−10.46	−41.18***	−19.84***
GS.N	−18.98	−17.43**	−4.71	−42.88	−16.25*	−8.81*
HD.N	−3.60	−6.50*	−3.60	−5.64	11.22	7.92
HPQ.N	−13.69	−56.28***	0.71	−21.47	−62.07***	−3.96
IBM.N	−10.33	−45.69***	−5.89	−12.16	−0.22	5.91
INTC.OQ	−10.16	−26.67***	6.07	−15.52	−13.43	11.13
JNJ.N	−3.81	−7.33	−2.40	−7.55	−4.11	−3.55
JPM.N	−17.47	−8.94	9.39	−37.77	−0.51	30.11***
KO.N	−6.19	−6.21	3.99	−11.09	−13.51*	−0.24
MCD.N	−9.20	−17.53***	−3.30	−15.45	−2.75	2.65
MMM.N	−2.71	−7.91	1.82	−6.82	−42.74***	−17.67***
MRK.N	−4.29	−30.55***	−16.88**	−8.52	−37.14***	−17.55**
MSFT.OQ	−17.66	−19.56***	−2.32	−10.14	2.78	5.66
NKE.N	−4.99	−21.28***	−4.00	−7.00	−2.89	−2.78
PFE.N	−6.87	−19.14***	−4.51	−13.15	−12.98**	−0.92
PG.N	−3.07	−8.11	0.88	−6.45	−7.44	−8.56**
T.N	−8.22	−8.17	−1.33	−12.99	−15.53*	−11.42*
TRV.N	−1.24	−7.53	7.05	−1.22	1.66	5.47
UNH.N	−1.94	−27.06***	−18.39***	−4.29	9.15	9.59
UTX.N	−2.84	−10.96*	−1.36	−6.54	−9.28	−5.82
V.N	−2.18	8.55	6.42	−3.06	13.09	6.33
VZ.N	−7.68	−4.34	1.98	−13.36	−6.58	6.69*
WMT.N	−12.82	−23.20***	−10.57**	−24.15	−29.46***	−10.76**
XOM.N	−10.06	−0.41	12.78**	−24.39	9.70**	16.68***
Average		−19.97	−3.88		−12.14	−2.36
#Pos/#Neg		1/33	13/21		7/27	12/22
Misclassification rate		2.9%	38.2%		20.6%	35.3%

Table 5: Conditional CARs for varied window lengths. The table summarises the average cumulative abnormal returns across all stocks in the sample conditional on the days with the highest (top decile) and lowest (bottom decile) overnight sentiment from social and news media for varied periods of return accumulation. Results based on inclusion ('Incl.') and exclusion ('Excl.') of overnight returns are contrasted. The values in Panel D are from the last rows of Tables 3 and 4. Misclassification rates based on Eq. (7) are reported in brackets. Similarly, Panels A to C provide summaries for alternative return accumulation windows with detailed information on firm-specific results available in the appendix (Tables A.1-A.3).

Sentiment Condition	**Conditional CARs**			
	Social Media		**News Media**	
Overnight returns:	Incl.	Excl.	Incl.	Excl.
Panel A: First half hour, 9:30am-10:00am				
Top sentiment decile	18.36	3.67	8.86	2.09
	[5.9%]	[32.4%]	[20.6%]	[38.2%]
Bottom sentiment decile	−19.21	−3.12	−12.54	−2.77
	[2.9%]	[41.2%]	[20.6%]	[29.4%]
Panel B: First hour, 9:30am-10:30am				
Top sentiment decile	18.44	3.75	9.33	2.56
	[11.8%]	[29.4%]	[23.5%]	[41.2%]
Bottom sentiment decile	−19.08	−2.99	−12.51	−2.74
	[5.9%]	[35.3%]	[20.6%]	[23.5%]
Panel C: Morning session, 9:30am-12:00pm				
Top sentiment decile	17.60	2.91	9.70	2.93
	[11.8%]	[41.2%]	[23.5%]	[41.2%]
Bottom sentiment decile	−18.63	−2.54	−12.44	−2.66
	[5.9%]	[50.0%]	[20.6%]	[38.2%]
Panel D: Open-to-close, 9:30am-4:00pm				
Top sentiment decile	19.03	4.33	10.02	3.25
	[11.8%]	[38.2%]	[20.6%]	[29.4%]
Bottom sentiment decile	−19.97	−3.88	−12.14	−2.36
	[2.9%]	[38.2%]	[20.6%]	[35.3%]

Table 6: Positive Return Days. The table reports the average CARs (in bps) for the top CAR deciles in Column (1). The corresponding cumulative sentiment from the market close to the next trading day open for the social and news media are presented in Columns (2) and (3), respectively. That is, the CARs are aggregated from 9:30am to 4:00pm on day t using the 1-minute mid-price log returns for each stock subtracting the mid-price log return of the DJIA index. The cumulative sentiment scores are aggregated from 4:01pm on day t to 9:29am on day $t+1$. 'Top' represent the average CARs in the highest CAR deciles. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are constructed from bootstrap simulations of cumulative sentiment unconditional on CAR. Misclassification rates are based on Eq. (7).

			Social Media	News Media
		(1)	**(2)**	**(3)**
Asset	**Decile**	***CAR***	***CSent***	***CSent***
AA.N	Top	384.97	1.23***	1.53***
AAPL.OQ	Top	252.52	17.58***	22.94***
AXP.N	Top	243.90	0.88***	1.90
BA.N	Top	225.11	−0.56	4.68***
BAC.N	Top	354.98	−5.57***	−5.50***
CAT.N	Top	289.12	1.14***	−0.32
CSCO.OQ	Top	222.04	−3.12	9.69***
CVX.N	Top	207.90	0.25**	1.78***
DD.N	Top	228.71	−0.14	−0.01
DIS.N	Top	202.69	1.46**	0.56
GE.N	Top	210.80	−8.94***	8.39***
GS.N	Top	249.94	−3.08	−5.68
HD.N	Top	206.29	2.40***	5.55***
HPQ.N	Top	324.41	−0.74	1.37
IBM.N	Top	164.27	2.16***	11.82***
INTC.OQ	Top	225.97	4.24***	10.45***
JNJ.N	Top	145.50	2.19***	4.79***
JPM.N	Top	257.63	−2.16*	−0.28***
KO.N	Top	177.19	1.00***	1.24
MCD.N	Top	153.35	0.62***	−0.90
MMM.N	Top	206.81	0.76**	0.86
MRK.N	Top	229.48	1.18**	1.64
MSFT.OQ	Top	221.76	2.99	22.34**
NKE.N	Top	238.41	2.36***	3.19***
PFE.N	Top	189.12	0.79***	3.29***
PG.N	Top	146.79	0.78*	1.09
T.N	Top	157.82	0.62	4.16***
TRV.N	Top	216.14	0.13**	0.31**
UNH.N	Top	252.33	0.60***	0.77
UTX.N	Top	208.01	0.50***	1.05*
V.N	Top	270.82	1.23**	0.11
VZ.N	Top	176.56	2.02***	5.92***
WMT.N	Top	167.76	1.48***	4.40***
XOM.N	Top	223.26	−0.83	1.15***
Average			0.75	3.65
#Neg/#Pos			9/25	6/28
Misclassification Rate			26.5%	17.6%

Table 7: Negative Return Days. The table reports the average CARs (in bps) for the bottom CAR deciles in Column (1). The corresponding cumulative sentiment from the market close to the next trading day open for the social and news media are presented in Columns (2) and (3), respectively. That is, the CARs are aggregated from 9:30am to 4:00pm on day t using the 1-minute mid-price log returns for each stock subtracting the mid-price log return of the DJIA index. The cumulative sentiment scores are aggregated from 4:01pm on day t to 9:29am on day $t+1$. 'Bottom' represent the average CARs in the lowest CAR deciles. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are constructed from bootstrap simulations of cumulative sentiment unconditional on CAR. Misclassification rates are based on Eq. (7).

			Social Media	**News Media**
		(1)	**(2)**	**(3)**
Asset	**Decile**	$\boldsymbol{CAR}$	$\boldsymbol{CSent}$	$\boldsymbol{CSent}$
AA.N	Bottom	-396.44	-1.03^{***}	-5.30^{***}
AAPL.OQ	Bottom	-253.38	-10.56^{***}	-9.82^{***}
AXP.N	Bottom	-245.75	-0.33^{***}	1.20
BA.N	Bottom	-208.38	-3.96^{***}	-0.04
BAC.N	Bottom	-347.40	-19.98^{***}	-8.11^{***}
CAT.N	Bottom	-297.60	-1.58^{***}	-1.10^{*}
CSCO.OQ	Bottom	-227.21	-6.18^{***}	3.04^{**}
CVX.N	Bottom	-212.87	-1.41^{***}	-10.97^{***}
DD.N	Bottom	-237.26	-0.52^{***}	0.02
DIS.N	Bottom	-186.81	0.39	0.02
GE.N	Bottom	-209.30	-13.95^{***}	-0.13^{***}
GS.N	Bottom	-253.52	-7.25^{***}	-19.54^{***}
HD.N	Bottom	-181.86	0.69^{***}	3.66
HPQ.N	Bottom	-330.28	-4.21^{***}	-4.71^{***}
IBM.N	Bottom	-180.74	-1.08^{***}	3.66^{***}
INTC.OQ	Bottom	-220.86	-0.66^{***}	0.95^{***}
JNJ.N	Bottom	-130.97	0.34^{**}	0.88
JPM.N	Bottom	-243.01	-7.96^{***}	-21.48^{***}
KO.N	Bottom	-188.18	-0.02^{*}	0.68
MCD.N	Bottom	-151.68	-1.56^{***}	-2.32
MMM.N	Bottom	-215.55	0.31^{**}	1.61^{*}
MRK.N	Bottom	-227.59	0.00^{***}	0.84
MSFT.OQ	Bottom	-201.58	-0.09^{***}	17.93
NKE.N	Bottom	-229.57	0.30^{*}	0.12
PFE.N	Bottom	-180.70	-1.27^{***}	-2.54^{***}
PG.N	Bottom	-143.00	0.04^{***}	1.49^{*}
T.N	Bottom	-181.24	-0.93^{***}	-2.02^{***}
TRV.N	Bottom	-207.44	-0.09^{*}	-0.20^{**}
UNH.N	Bottom	-221.79	0.01^{***}	0.87
UTX.N	Bottom	-208.61	-0.08^{*}	0.53
V.N	Bottom	-238.23	0.44^{**}	0.48
VZ.N	Bottom	-177.10	-0.12^{***}	-1.12^{***}
WMT.N	Bottom	-173.92	-3.08^{***}	-8.60^{***}
XOM.N	Bottom	-220.13	-3.32^{***}	-9.29^{***}
Average			-2.61	-2.04
#Pos/#Neg			8/26	17/17
Misclassification Rate			23.5%	50.0%

Table 8: Sentiment as a Predictor for Returns. The table contains representative regression output for the case of CSCO.OQ based on Eq.(8) and Eq.(9). The dependent variable is $CAR_{i,t}\,[9{:}30, 9{:}31]$, that is the cumulative abnormal return on CSCO.OQ in excess of the DJIA on day t from 9:30am to 9:31am. The sample period is from 1 January 2011 to 30 November 2017 and, excluding non-trading days, contains 1,741 observations. $CSent_{i,t}\,[16{:}01, 9{:}29]$ is the overnight cumulative sentiment averaged over the number of non-empty observations from 4:01pm on the previous day to 9:29am on day t. The controlled variable, $CAR_{i,t-1}\,[9{:}30, 16{:}00]$, is the cumulative abnormal return of CSCO.OQ on day $(t-1)$ from 9:30am to 4:00pm. The HAC robust t-statistics are in parentheses while *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively. Panel A lists the estimates based on all the days in the sample period. Panels B and C show estimated coefficients when only the observations on the days with the highest and lowest sentiment, respectively, are considered. For brevity, we do not report the regression output for the entirety of our stock sample but make it available upon request.

	Social Media		News Media	
	Baseline	Controlled	Baseline	Controlled
Panel A: All days ($\forall t$)				
$CSent_{i,t}$	0.2827***	0.2849***	0.2281***	0.2406***
	(4.044)	(4.018)	(3.592)	(3.507)
$CAR_{i,t-1}$		-0.0187		-0.0447
		(-0.742)		(-1.520)
No.Obs.	1,741	1,740	1,741	1,740
R^2	0.0414	0.0417	0.0335	0.0354
F-stat	75	37.8	60.3	31.9
Panel B: Days with the highest average overnight sentiment ($t \in \mathcal{D}_{i,10}$)				
$CSent_{i,t}$	0.8704***	0.8752***	0.2206	0.2538
	(5.681)	(6.044)	(1.233)	(1.286)
$CAR_{i,t-1}$		-0.1732**		-0.0789
		(-1.979)		(-1.283)
No.Obs.	174	174	174	174
R^2	0.1787	0.1964	0.0361	0.0469
F-stat	37.4	20.9	6.45	4.21
Panel C: Days with the lowest average overnight sentiment ($t \in \mathcal{D}_{i,1}$)				
$CSent_{i,t}$	1.2058***	1.2074***	0.5717***	0.7192***
	(2.380)	(2.376)	(3.343)	(3.795)
$CAR_{i,t-1}$		0.0104		-0.2823***
		(0.204)		(-3.089)
No.Obs.	174	174	174	174
R^2	0.2373	0.1964	0.1690	0.2300
F-stat	52.1	25.9	34.9	25.5

Table 9: Coincidence between earnings announcement days and strong sentiment days. The table reports the number of days in the most negative ($\mathcal{D}_{i,1}$) and the most positive ($\mathcal{D}_{i,10}$) deciles of cumulative social and news media sentiment, as well as the number of days that overlap with the earnings announcements (*Earnings*). The rates of overlap (*Rate*) in each decile are displayed. Quarterly earnings announcement data from 2011 to 2017 are obtained from Compustat. Both earnings announcement days and earnings reporting days are taken into account.

Asset, i	No.days	**Social Media sentiment**				**News Media sentiment**			
		$\mathcal{D}_{i,1}$		$\mathcal{D}_{i,10}$		$\mathcal{D}_{i,1}$		$\mathcal{D}_{i,10}$	
		Earnings	Rate	Earnings	Rate	Earnings	Rate	Earnings	Rate
AA.N	172	3	2%	2	1%	0	0%	0	0%
AAPL.OQ	174	2	1%	2	1%	2	1%	3	2%
AXP.N	201	0	0%	5	2%	2	1%	4	2%
BA.N	174	3	2%	5	3%	4	2%	0	0%
BAC.N	172	3	2%	2	1%	2	1%	7	4%
CAT.N	201	1	0%	3	1%	2	1%	5	2%
CSCO.OQ	174	1	1%	4	2%	1	1%	3	2%
CVX.N	174	1	1%	3	2%	1	1%	3	2%
DD.N	225	1	0%	5	2%	0	0%	4	2%
DIS.N	174	0	0%	2	1%	2	1%	1	1%
GE.N	174	1	1%	6	3%	5	3%	3	2%
GS.N	174	1	1%	1	1%	1	1%	3	2%
HD.N	174	1	1%	4	2%	4	2%	2	1%
HPQ.N	174	2	1%	3	2%	3	2%	1	1%
IBM.N	174	6	3%	2	1%	1	1%	1	1%
INTC.OQ	174	2	1%	4	2%	2	1%	2	1%
JNJ.N	174	1	1%	0	0%	2	1%	4	2%
JPM.N	174	0	0%	2	1%	1	1%	1	1%
KO.N	201	3	1%	2	1%	0	0%	2	1%
MCD.N	174	1	1%	2	1%	3	2%	2	1%
MMM.N	201	1	0%	3	1%	1	0%	3	1%
MRK.N	201	3	1%	4	2%	3	1%	0	0%
MSFT.OQ	174	2	1%	3	2%	2	1%	1	1%
NKE.N	174	6	3%	5	3%	7	4%	3	2%
PFE.N	174	1	1%	2	1%	1	1%	3	2%
PG.N	174	1	1%	2	1%	2	1%	0	0%
T.N	174	4	2%	2	1%	3	2%	3	2%
TRV.N	200	0	0%	3	2%	2	1%	4	2%
UNH.N	228	4	2%	5	2%	4	2%	2	1%
UTX.N	228	2	1%	2	1%	3	1%	2	1%
V.N	200	5	3%	2	1%	4	2%	3	2%
VZ.N	174	4	2%	4	2%	2	1%	3	2%
WMT.N	174	1	1%	5	3%	0	0%	3	2%
XOM.N	201	0	0%	2	1%	1	0%	0	0%
Average	185	1.97	1%	3.03	2%	2.15	1%	2.38	1%

A Supplementary Appendix

A.1 Robustness of the results under alternative event windows

Table A.1: 30 Minutes Window. This table reports the top (Panel A) and bottom (Panel B) deciles of overnight cumulative sentiment for each sample stock and the corresponding cumulative abnormal returns 30 minutes after the market opening. Columns (1) and (4) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01pm the previous day to 9:29am. That is, $\overline{CSent_{i,x}}$ [16:01, 9:29] as defined in Eq.(5). Columns (2) and (5) are the average cumulative abnormal returns aggregated from 9:30am to 10:00am measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. That is, $\overline{CAR_{i,x}}$ [9:30, 10:00] as defined in Eq.(6). Similarly, Columns (3) and (6) are the corresponding average cumulative abnormal returns but aggregated from 9:31am to 10:00am instead, with the overnight return removed. The $\overline{CAR}$s are conditional on the highest (lowest) sentiment decile, $\mathcal{D}_{i,10}$ ($\mathcal{D}_{i,1}$). The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are constructed from bootstrap simulations of cumulative returns unconditional on sentiment.

Panel A: Top decile, 30 minutes after market open

		Social Media			News Media		
Asset	Decile	(1) *CSent*	(2) *CAR*	(3) CAR_{-1}	(4) *CSent*	(5) *CAR*	(6) CAR_{-1}
AA.N	Top	6.72	32.93***	−6.44	10.84	25.57**	−7.42
AAPL.OQ	Top	46.34	58.41***	−1.09	62.32	40.91***	−8.69***
AXP.N	Top	4.03	5.05	1.62	10.31	4.36	−4.89*
BA.N	Top	10.11	18.50**	8.56	26.51	3.94	0.99
BAC.N	Top	9.01	46.49***	15.96***	13.91	15.46	3.10
CAT.N	Top	5.61	21.44***	−0.40	10.88	−7.06	4.93
CSCO.OQ	Top	9.49	34.91***	3.10	25.59	21.55**	3.16
CVX.N	Top	5.28	−10.21	−0.68	11.51	2.24	−1.43
DD.N	Top	2.33	20.40***	6.51**	2.15	−1.69	−0.40
DIS.N	Top	5.62	16.16**	12.36***	6.79	−9.33*	−3.34
GE.N	Top	7.74	11.40**	−1.18	25.34	8.81**	−3.06
GS.N	Top	8.68	10.00	15.76*	20.31	11.40	13.58
HD.N	Top	9.62	32.03***	2.72	19.32	4.94	1.45
HPQ.N	Top	8.77	31.53***	12.97	19.70	26.45***	4.77
IBM.N	Top	11.05	19.05***	9.46**	31.32	−11.44	−3.22
INTC.OQ	Top	15.13	19.45***	11.11**	29.58	10.94**	15.43***
JNJ.N	Top	7.02	6.88***	−1.16	12.51	4.03	−1.61
JPM.N	Top	8.28	24.08***	6.98	19.48	0.29	2.92
KO.N	Top	6.49	1.10	1.04	15.41	15.12***	7.48***
MCD.N	Top	6.44	19.23***	1.72	11.04	0.21	2.42
MMM.N	Top	4.68	11.88**	8.67*	10.25	16.00***	12.20**
MRK.N	Top	6.27	31.56***	6.59**	11.63	39.93***	17.59***
MSFT.OQ	Top	24.92	1.90	−10.09***	49.02	13.98*	0.61
NKE.N	Top	9.68	49.35***	6.55	9.32	17.71**	4.70
PFE.N	Top	6.81	8.29	−1.18	13.26	16.63***	3.08
PG.N	Top	4.94	6.86**	7.37*	9.35	0.71	5.05
T.N	Top	11.62	0.61	−2.30	17.58	−7.30	−6.98
TRV.N	Top	1.39	15.65***	1.94	1.76	0.78	−3.33
UNH.N	Top	4.31	19.70***	5.75	8.29	6.57	1.18
UTX.N	Top	3.52	4.20	−0.12	6.89	19.81***	8.77**
V.N	Top	5.72	27.25***	5.40	6.65	6.52	4.02
VZ.N	Top	9.92	−6.62	−14.30**	18.71	−1.32	−5.77
WMT.N	Top	10.90	24.46***	9.02***	19.27	16.59***	4.51
XOM.N	Top	6.34	10.41***	2.46	14.75	−12.22	−0.77
Average			18.36	3.67		8.86	2.09
#Neg/#Pos			2/32	11/23		7/27	13/21
Misclassification Rate			5.9%	32.4%		20.6%	38.2%

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Panel B: Bottom decile, 30 minutes after market open							
		Social Media			News Media		
		(1)	(2)	(3)	(4)	(5)	(6)
Asset	Decile	*CSent*	*CAR*	CAR_{-1}	*CSent*	*CAR*	CAR_{-1}
AA.N	Bottom	-6.39	-65.86^{***}	-41.80^{***}	-17.84	-37.85^{***}	-23.24^{**}
AAPL.OQ	Bottom	-34.25	-50.32^{***}	10.17^{**}	-43.22	-20.43^{***}	9.99^{**}
AXP.N	Bottom	-3.39	-31.92^{***}	-8.04^{***}	-5.42	-5.40	-3.61
BA.N	Bottom	-13.32	-19.41^{***}	-10.45^{***}	-34.09	-9.96^{**}	-3.73
BAC.N	Bottom	-31.27	-23.86^{***}	-14.00^{***}	-25.58	16.01	-7.93^{*}
CAT.N	Bottom	-6.51	-25.18^{***}	-10.97	-14.12	1.77	-5.02
CSCO.OQ	Bottom	-23.94	-31.10^{***}	0.16	-9.80	-28.21^{***}	0.22
CVX.N	Bottom	-5.44	-18.68^{**}	-12.42^{**}	-19.31	-18.66^{**}	-6.33
DD.N	Bottom	-2.69	-11.32^{*}	4.25	-1.56	-6.79	-1.66
DIS.N	Bottom	-2.91	-1.78	1.93	-5.15	3.10	0.52
GE.N	Bottom	-26.82	-0.15	4.64	-10.46	-22.81^{***}	-1.47
GS.N	Bottom	-18.98	-14.51^{**}	-1.79^{*}	-42.88	-8.79^{*}	-1.35^{*}
HD.N	Bottom	-3.60	-2.78^{*}	0.11	-5.64	6.14	2.84
HPQ.N	Bottom	-13.69	-61.52^{***}	-4.53	-21.47	-63.55^{***}	-5.44
IBM.N	Bottom	-10.33	-38.71^{***}	1.09	-12.16	1.62	7.76^{*}
INTC.OQ	Bottom	-10.16	-30.18^{***}	2.55	-15.52	-21.62^{***}	2.94
JNJ.N	Bottom	-3.81	-10.79^{*}	-5.86	-7.55	-4.52	-3.96
JPM.N	Bottom	-17.47	-13.08^{**}	5.25	-37.77	-24.82^{***}	5.80
KO.N	Bottom	-6.19	-13.34^{*}	-3.13	-11.09	-20.55^{***}	-7.28^{**}
MCD.N	Bottom	-9.20	-12.16^{***}	2.07	-15.45	-5.57	-0.17
MMM.N	Bottom	-2.71	-5.64	4.09	-6.82	-34.51^{***}	-9.43^{***}
MRK.N	Bottom	-4.29	-26.17^{***}	-12.50^{***}	-8.52	-33.75^{***}	-14.16^{***}
MSFT.OQ	Bottom	-17.66	-21.14^{***}	-3.90	-10.14	-3.89	-1.00
NKE.N	Bottom	-4.99	-22.10^{***}	-4.83	-7.00	-5.77	-5.66^{*}
PFE.N	Bottom	-6.87	-3.74	10.89^{***}	-13.15	-16.95^{***}	-4.89
PG.N	Bottom	-3.07	-4.52	4.47^{*}	-6.45	-1.76	-2.88
T.N	Bottom	-8.22	-10.10	-3.25	-12.99	-11.86	-7.75
TRV.N	Bottom	-1.24	-13.84^{**}	0.75	-1.22	-7.28	-3.47
UNH.N	Bottom	-1.94	-11.75^{**}	-3.09	-4.29	0.39	0.83
UTX.N	Bottom	-2.84	-11.83^{**}	-2.23	-6.54	-5.69	-2.23
V.N	Bottom	-2.18	1.78	-0.34	-3.06	15.70^{*}	8.93^{**}
VZ.N	Bottom	-7.68	-12.82	-6.50	-13.36	-20.31^{**}	-7.04
WMT.N	Bottom	-12.82	-15.80^{***}	-3.17	-24.15	-25.83^{***}	-7.13^{**}
XOM.N	Bottom	-10.06	-18.97^{**}	-5.79	-24.39	-4.10	2.88
Average			-19.21	-3.12		-12.54	-2.77
#Pos/#Neg			1/33	14/20		7/27	10/24
Misclassification Rate			2.9%	41.2%		20.6%	29.4%

Table A.2: One Hour Window. This table reports the top (Panel A) and bottom (Panel B) deciles of overnight cumulative sentiment for each sample stock and the corresponding cumulative abnormal returns one hour after the market opening. Columns (1) and (4) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01pm the previous day to 9:29am. That is, $\overline{CSent_{i,x}}\,[16{:}01, 9{:}29]$ as defined in Eq.(5). Columns (2) and (5) are the average cumulative abnormal returns aggregated from 9:30am to 10:30am measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. That is, $\overline{CAR_{i,x}}\,[9{:}30, 10{:}30]$ as defined in Eq.(6). Similarly, Columns (3) and (6) are the corresponding average cumulative abnormal returns but aggregated from 9:31am to 10:30am instead, with the overnight return removed.The $\overline{CAR}$s are conditional on the highest (lowest) sentiment decile, $\mathcal{D}_{i,10}$ ($\mathcal{D}_{i,1}$). The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are constructed from bootstrap simulations of cumulative returns unconditional on sentiment.

Panel A: Top decile, one hour after market open							
		Social Media			News Media		
		(1)	(2)	(3)	(4)	(5)	(6)
Asset	Decile	*CSent*	*CAR*	CAR_{-1}	*CSent*	*CAR*	CAR_{-1}
AA.N	Top	6.72	37.20***	−2.17	10.84	21.87**	−11.13
AAPL.OQ	Top	46.34	58.64***	−0.87	62.32	41.52***	−8.07**
AXP.N	Top	4.03	4.33	0.89	10.31	4.99	−4.26
BA.N	Top	10.11	22.19***	12.26*	26.51	1.83	−1.13
BAC.N	Top	9.01	42.28***	11.76*	13.91	9.49	−2.87
CAT.N	Top	5.61	22.95***	1.11	10.88	−9.19	2.79
CSCO.OQ	Top	9.49	35.32***	3.51	25.59	18.56 * *	0.17
CVX.N	Top	5.28	−6.71	2.81	11.51	−0.17	−3.84
DD.N	Top	2.33	17.23***	3.34	2.15	−1.00	0.30
DIS.N	Top	5.62	16.65**	12.84***	6.79	−9.07	−3.08
GE.N	Top	7.74	10.37**	−2.21	25.34	13.53***	1.67
GS.N	Top	8.68	8.18	13.94	20.31	10.64	12.81
HD.N	Top	9.62	35.41***	6.09	19.32	10.31	6.82
HPQ.N	Top	8.77	31.81***	13.24	19.70	31.89***	10.21
IBM.N	Top	11.05	18.85***	9.27*	31.32	−9.96	−1.74
INTC.OQ	Top	15.13	21.63***	13.29**	29.58	13.42**	17.92***
JNJ.N	Top	7.02	5.96**	−2.08	12.51	2.87*	−2.76
JPM.N	Top	8.28	19.85**	2.75	19.48	−2.42	0.21
KO.N	Top	6.49	−1.31	−1.37	15.41	20.65***	13.02***
MCD.N	Top	6.44	20.31***	2.80	11.04	4.46	6.67
MMM.N	Top	4.68	11.37**	8.17	10.25	18.20***	14.41***
MRK.N	Top	6.27	32.80***	7.84**	11.63	43.33***	20.98***
MSFT.OQ	Top	24.92	3.20	−8.80**	49.02	12.06	−1.30
NKE.N	Top	9.68	47.06***	4.26	9.32	19.38**	6.37
PFE.N	Top	6.81	9.14	−0.33	13.26	17.46***	3.91
PG.N	Top	4.94	5.26	5.76	9.35	1.59	5.93
T.N	Top	11.62	−2.31	−5.22	17.58	−7.50	−7.18
TRV.N	Top	1.39	14.71***	1.00	1.76	0.56	−3.55
UNH.N	Top	4.31	21.80***	7.86	8.29	10.20	4.80
UTX.N	Top	3.52	1.72	−2.60	6.89	17.44***	6.41
V.N	Top	5.72	27.36***	5.51	6.65	5.82	3.32
VZ.N	Top	9.92	−4.41	−12.09	18.71	2.17	−2.29
WMT.N	Top	10.90	27.36***	11.92***	19.27	17.69***	5.61
XOM.N	Top	6.34	10.84***	2.89	14.75	−15.55*	−4.10
Average			18.44	3.75		9.33	2.56
#Neg/#Pos			4/30	10/24		8/26	14/20
Misclassification Rate			11.8%	29.4%		23.5%	41.2%

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		Panel B: Bottom decile, one hour after market open					
		Social Media			News Media		
		(1)	(2)	(3)	(4)	(5)	(6)
Asset	Decile	*CSent*	*CAR*	CAR_{-1}	*CSent*	*CAR*	CAR_{-1}
AA.N	Bottom	-6.39	-63.11^{***}	-39.05^{***}	-17.84	-31.28^{**}	-16.68
AAPL.OQ	Bottom	-34.25	-50.36^{***}	10.12^{*}	-43.22	-19.23^{***}	11.19^{**}
AXP.N	Bottom	-3.39	-35.19^{***}	-11.32^{***}	-5.42	-8.01	-6.22^{*}
BA.N	Bottom	-13.32	-22.82^{***}	-13.85^{***}	-34.09	-9.33^{**}	-3.09
BAC.N	Bottom	-31.27	-20.30^{***}	-10.44^{*}	-25.58	18.03	-5.91
CAT.N	Bottom	-6.51	-25.99^{***}	-11.79^{*}	-14.12	4.43	-2.36
CSCO.OQ	Bottom	-23.94	-32.12^{***}	-0.86	-9.80	-35.69^{***}	-7.25
CVX.N	Bottom	-5.44	-15.89	-9.62	-19.31	-17.12^{*}	-4.79
DD.N	Bottom	-2.69	-13.28^{*}	2.30	-1.56	-10.53	-5.41
DIS.N	Bottom	-2.91	3.98	7.69^{*}	-5.15	1.35	-1.23
GE.N	Bottom	-26.82	0.60	5.38	-10.46	-24.69^{***}	-3.34
GS.N	Bottom	-18.98	-15.66^{***}	-2.94^{*}	-42.88	-9.31	-1.87^{*}
HD.N	Bottom	-3.60	-1.30	1.59	-5.64	8.53	5.23
HPQ.N	Bottom	-13.69	-58.76^{***}	-1.77	-21.47	-63.80^{***}	-5.69
IBM.N	Bottom	-10.33	-38.71^{***}	1.09	-12.16	3.72	9.85^{**}
INTC.OQ	Bottom	-10.16	-34.76^{***}	-2.02	-15.52	$-18.78**$	5.78
JNJ.N	Bottom	-3.81	-10.17	-5.24	-7.55	-3.91	-3.35
JPM.N	Bottom	-17.47	-14.62^{**}	3.71	-37.77	$-21.38***$	9.24
KO.N	Bottom	-6.19	-11.30	-1.10	-11.09	-17.97^{***}	-4.69
MCD.N	Bottom	-9.20	-11.21^{**}	3.02	-15.45	-6.20	-0.81
MMM.N	Bottom	-2.71	-3.72	6.01	-6.82	-38.34^{***}	-13.27^{***}
MRK.N	Bottom	-4.29	-27.57^{***}	-13.90^{***}	-8.52	-39.06^{***}	-19.47^{***}
MSFT.OQ	Bottom	-17.66	-27.62^{***}	-10.38^{***}	-10.14	-6.13	-3.25
NKE.N	Bottom	-4.99	-24.94^{***}	-7.66^{**}	-7.00	-5.25	-5.13
PFE.N	Bottom	-6.87	-5.86	8.77^{**}	-13.15	-19.54^{***}	-7.48^{*}
PG.N	Bottom	-3.07	-0.17	8.82^{**}	-6.45	-1.39	-2.50
T.N	Bottom	-8.22	-9.34	-2.49	-12.99	-14.15^{*}	-10.05^{*}
TRV.N	Bottom	-1.24	-14.58^{***}	0.00	-1.22	-9.10	-5.29
UNH.N	Bottom	-1.94	-12.57^{**}	-3.90	-4.29	4.55	4.99
UTX.N	Bottom	-2.84	-12.97^{**}	-3.38	-6.54	-4.32	-0.85
V.N	Bottom	-2.18	-4.16	-6.28	-3.06	15.85^{*}	9.08^{*}
VZ.N	Bottom	-7.68	-7.13	-0.81	-13.36	-20.41^{**}	-7.13
WMT.N	Bottom	-12.82	-12.72^{**}	-0.10	-24.15	-22.87^{***}	-4.17
XOM.N	Bottom	-10.06	-14.43	-1.25	-24.39	-4.16	2.81
Average			-19.08	-2.99		-12.51	-2.74
#Pos/#Neg			2/32	12/22		7/27	8/26
Misclassification Rate			5.9%	35.3%		20.6%	23.5%

Table A.3: Morning Window. This table reports the top (Panel A) and bottom (Panel B) deciles of overnight cumulative sentiment for each sample stock and the corresponding cumulative abnormal returns from market open to the noon. Columns (1) and (4) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01pm the previous day to 9:29am. That is, $\overline{CSent_{i,x}}[16{:}01, 9{:}29]$ as defined in Eq.(5). Columns (2) and (5) are the average cumulative abnormal returns aggregated from 9:30am to 12:00pm measured in basis points (bps) using the 1-minute mid-quote returns in excess of the DJIA returns. That is, $\overline{CAR_{i,x}}[9{:}30, 12{:}00]$ as defined in Eq.(6). Similarly, Columns (3) and (6) are the corresponding average cumulative abnormal returns but aggregated from 9:31am to 12:00pm instead, with the overnight return removed. The $\overline{CAR}$s are conditional on the highest (lowest) sentiment decile, $\mathcal{D}_{i,10}$ ($\mathcal{D}_{i,1}$). The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are constructed from bootstrap simulations of cumulative returns unconditional on sentiment.

Panel A: Top decile, one hour after market open

		Social Media			News Media		
Asset	Decile	(1) *CSent*	(2) *CAR*	(3) CAR_{-1}	(4) *CSent*	(5) *CAR*	(6) CAR_{-1}
AA.N	Top	6.72	32.15***	−7.22	10.84	29.31**	−3.68
AAPL.OQ	Top	46.34	60.56***	1.05	62.32	46.95***	−2.65
AXP.N	Top	4.03	−1.89	−5.33	10.31	6.26	−2.99
BA.N	Top	10.11	23.33***	13.40*	26.51	3.71	0.76
BAC.N	Top	9.01	39.02***	8.49	13.91	9.52	−2.84
CAT.N	Top	5.61	9.01	−12.83*	10.88	−12.51	−0.52
CSCO.OQ	Top	9.49	34.50***	2.69	25.59	20.02**	1.63
CVX.N	Top	5.28	−5.94	3.58	11.51	−2.43	−6.10
DD.N	Top	2.33	17.54***	3.65	2.15	−0.35	0.94
DIS.N	Top	5.62	14.31*	10.50**	6.79	−6.99	−1.00
GE.N	Top	7.74	8.17*	−4.41	25.34	16.97***	5.10
GS.N	Top	8.68	5.45	11.21	20.31	9.45	11.62
HD.N	Top	9.62	27.78***	−1.54	19.32	11.35	7.86
HPQ.N	Top	8.77	28.23**	9.66	19.70	27.85**	6.17
IBM.N	Top	11.05	18.93***	9.34	31.32	−4.24	3.99
INTC.OQ	Top	15.13	23.87***	15.53**	29.58	14.38**	18.88***
JNJ.N	Top	7.02	6.23**	−1.81	12.51	2.84	−2.80
JPM.N	Top	8.28	16.74*	−0.35	19.48	−11.68*	−9.05*
KO.N	Top	6.49	0.00	−0.06	15.41	20.17***	12.54***
MCD.N	Top	6.44	23.75***	6.24	11.04	3.52	5.73
MMM.N	Top	4.68	14.57**	11.36**	10.25	17.65***	13.85**
MRK.N	Top	6.27	31.71***	6.74*	11.63	44.24***	21.89***
MSFT.OQ	Top	24.92	6.48	−5.51	49.02	7.14	−6.23
NKE.N	Top	9.68	48.88***	6.09	9.32	19.51**	6.50
PFE.N	Top	6.81	12.28	2.82	13.26	15.91**	2.36
PG.N	Top	4.94	7.77	8.28	9.35	0.98	5.32
T.N	Top	11.62	2.87	−0.05	17.58	−2.25	−1.93
TRV.N	Top	1.39	12.65**	−1.06	1.76	2.32	−1.79
UNH.N	Top	4.31	20.49***	6.55	8.29	4.56	−0.84
UTX.N	Top	3.52	−1.57	−5.89	6.89	16.74***	5.71
V.N	Top	5.72	27.04***	5.20	6.65	8.46	5.96
VZ.N	Top	9.92	0.27	−7.41	18.71	7.61	3.15
WMT.N	Top	10.90	28.22***	12.78***	19.27	18.57***	6.49
XOM.N	Top	6.34	5.19*	−2.76	14.75	−15.71	−4.26
Average			17.60	2.91		9.70	2.93
#Neg/#Pos			4/30	14/30		8/26	14/20
Misclassification Rate			11.8%	41.2%		23.5%	41.2%

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Panel B: Bottom decile, one hour after market open							
		Social Media			News Media		
		(1)	(2)	(3)	(4)	(5)	(6)
Asset	Decile	*CSent*	*CAR*	CAR_{-1}	*CSent*	*CAR*	CAR_{-1}
AA.N	Bottom	-6.39	−60.86***	−36.79***	−17.84	−45.87***	−31.26**
AAPL.OQ	Bottom	-34.25	−49.91***	10.58	−43.22	−16.46***	13.96**
AXP.N	Bottom	-3.39	−34.44***	−10.57**	−5.42	−1.82	−0.03
BA.N	Bottom	-13.32	−18.02***	−9.05**	−34.09	−5.90	0.33
BAC.N	Bottom	-31.27	−28.59***	−18.73**	−25.58	22.93	−1.01
CAT.N	Bottom	-6.51	−14.29	−0.09	−14.12	8.59	1.80
CSCO.OQ	Bottom	-23.94	−40.44***	−9.18**	−9.80	−39.44***	−11.00***
CVX.N	Bottom	-5.44	−13.23	−6.97	−19.31	−18.19*	−5.85
DD.N	Bottom	-2.69	−17.83**	−2.25	−1.56	−14.83*	−9.71*
DIS.N	Bottom	-2.91	4.68	8.39*	−5.15	1.43	−1.16
GE.N	Bottom	-26.82	−0.45	4.34	−10.46	−36.91***	−15.57***
GS.N	Bottom	-18.98	−20.19***	−7.47**	−42.88	−17.71**	−10.26***
HD.N	Bottom	-3.60	−2.64	0.26	−5.64	9.84	6.54
HPQ.N	Bottom	-13.69	−51.33***	5.67	−21.47	−63.20***	−5.09
IBM.N	Bottom	-10.33	−37.16***	2.63	−12.16	2.54	8.68
INTC.OQ	Bottom	-10.16	−32.45***	0.29	−15.52	−24.02***	0.53
JNJ.N	Bottom	-3.81	−10.24	−5.31	−7.55	−2.73	−2.17
JPM.N	Bottom	-17.47	−9.57	8.76	−37.77	−12.73*	17.90***
KO.N	Bottom	-6.19	−7.14	3.07	−11.09	−12.64*	0.63
MCD.N	Bottom	-9.20	−14.21***	0.02	−15.45	−1.58	3.81
MMM.N	Bottom	-2.71	−6.33	3.40	−6.82	−43.16***	−18.09***
MRK.N	Bottom	-4.29	−26.47***	−12.80**	−8.52	−37.77***	−18.18***
MSFT.OQ	Bottom	-17.66	−29.73***	−12.50***	−10.14	−4.58	−1.70
NKE.N	Bottom	-4.99	−17.50**	−0.22	−7.00	−3.62	−3.51
PFE.N	Bottom	-6.87	−19.14***	−4.51	−13.15	−12.98**	−0.92
PG.N	Bottom	-3.07	−3.10	5.89	−6.45	−1.09	−2.21
T.N	Bottom	-8.22	−6.32	0.53	−12.99	−10.37	−6.26
TRV.N	Bottom	-1.24	−11.31*	3.27	−1.22	−3.54	0.28
UNH.N	Bottom	-1.94	−16.44***	−7.77*	−4.29	2.44	2.88
UTX.N	Bottom	-2.84	−9.34	0.26	−6.54	−7.14	−3.67
V.N	Bottom	-2.18	4.98	2.85	−3.06	12.76	6.00
VZ.N	Bottom	-7.68	−6.89	−0.57	−13.36	−19.21**	−5.93
WMT.N	Bottom	-12.82	−14.77**	−2.15	−24.15	−24.58***	−5.88
XOM.N	Bottom	-10.06	−12.93	0.25	−24.39	−1.36	5.61
Average			−18.63	−2.54		−12.44	−2.66
#Pos/#Neg			2/32	17/17		7/27	13/21
Misclassification Rate			5.9%	50.0%		20.6%	38.2%

Figure A.1: Sentiment effect asymmetry. The figure contrasts the magnitudes of stock returns in response to social and news media sentiment. Coordinates represent absolute values of average CARs (in bps) conditional on the highest (top) and lowest (bottom) sentiment days. A symmetry in return response to sentiment is achieved along the 45-degree line provided as a reference. The linear fit (grey-colored line) is based on the values from Tables 3 and 4.

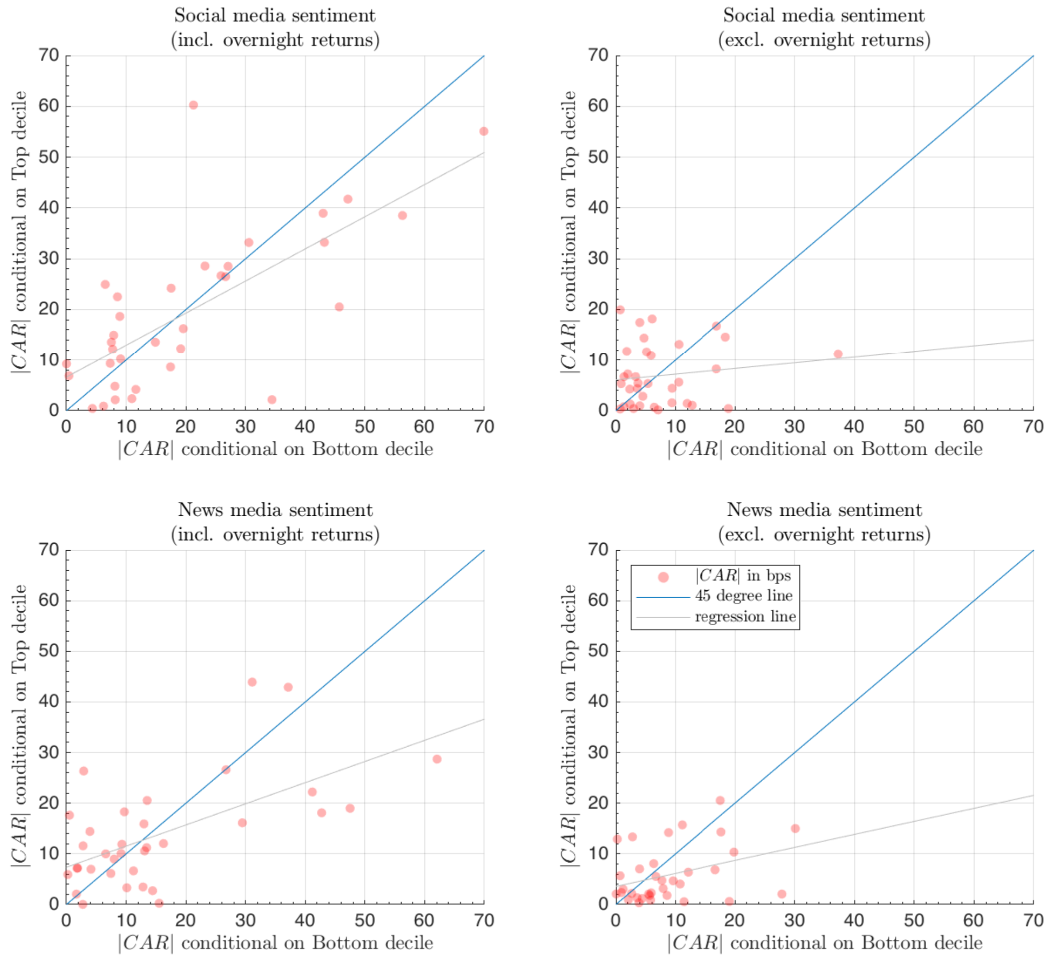
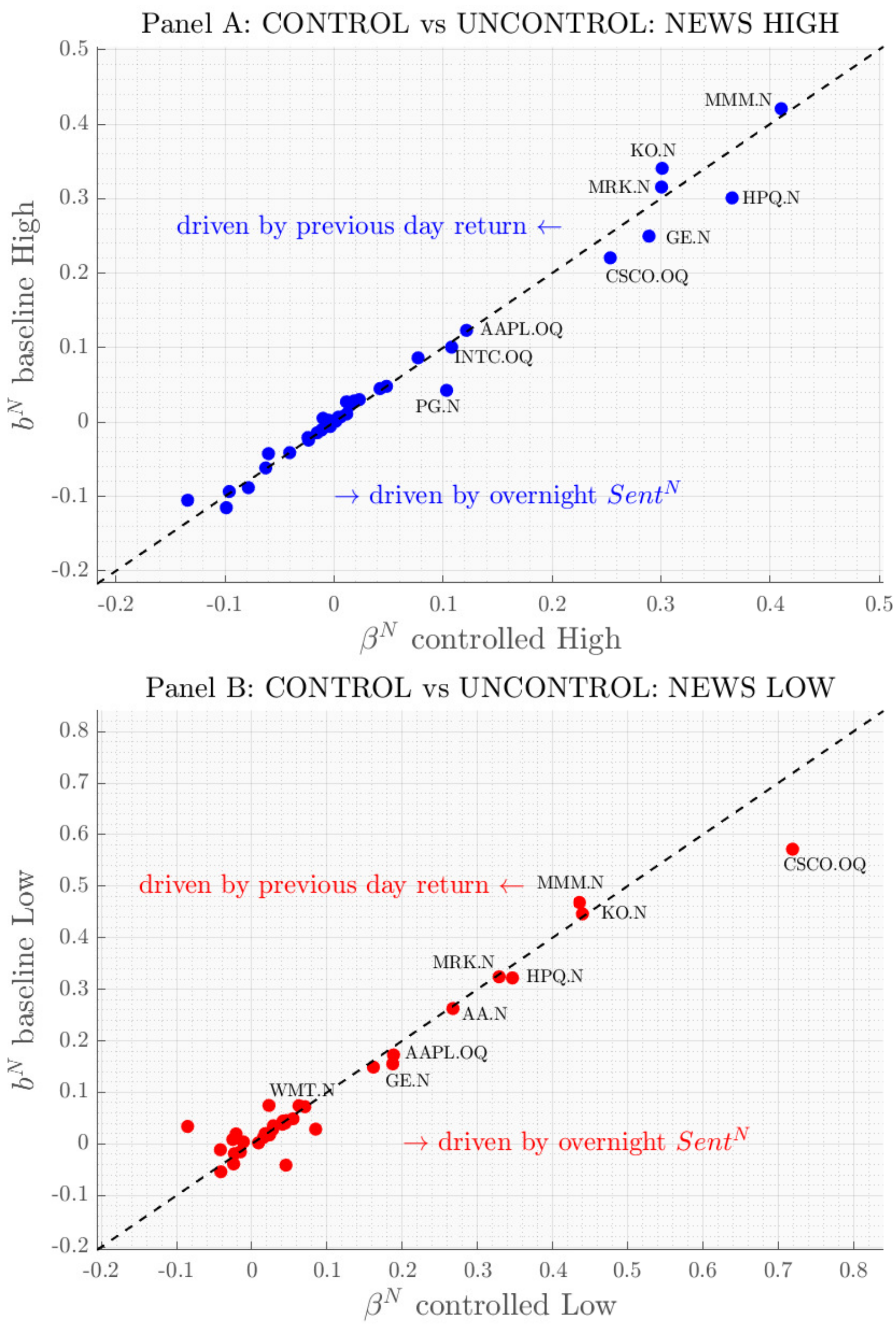


Figure A.2: Contrasting estimated of controlled and uncontrolled models: The case of News Media. The figure contrasts regression estimates from the baseline (uncontrolled) and the controlled models in Eqs.(8) and (9), respectively, for the case of news media sentiment. It complements the results shown in Figure 7. Each scatter point represents an intersection of the two slope coefficients from Eq.(8) on the y-axis and Eq.(9) on the x-axis. For example, the scatter points for CSCO.OQ are constructed based on the regression output reported in Table 8. The scatter points are labelled with stock tickers if at least one of the coefficients is significant at the 10% level. Panel A considers the effect of controlling for the previous day return CAR_{t-1} when news media sentiment is high ($\mathcal{D}_{i,10}$), while Panel B shows the effect when sentiment is low ($\mathcal{D}_{i,1}$).

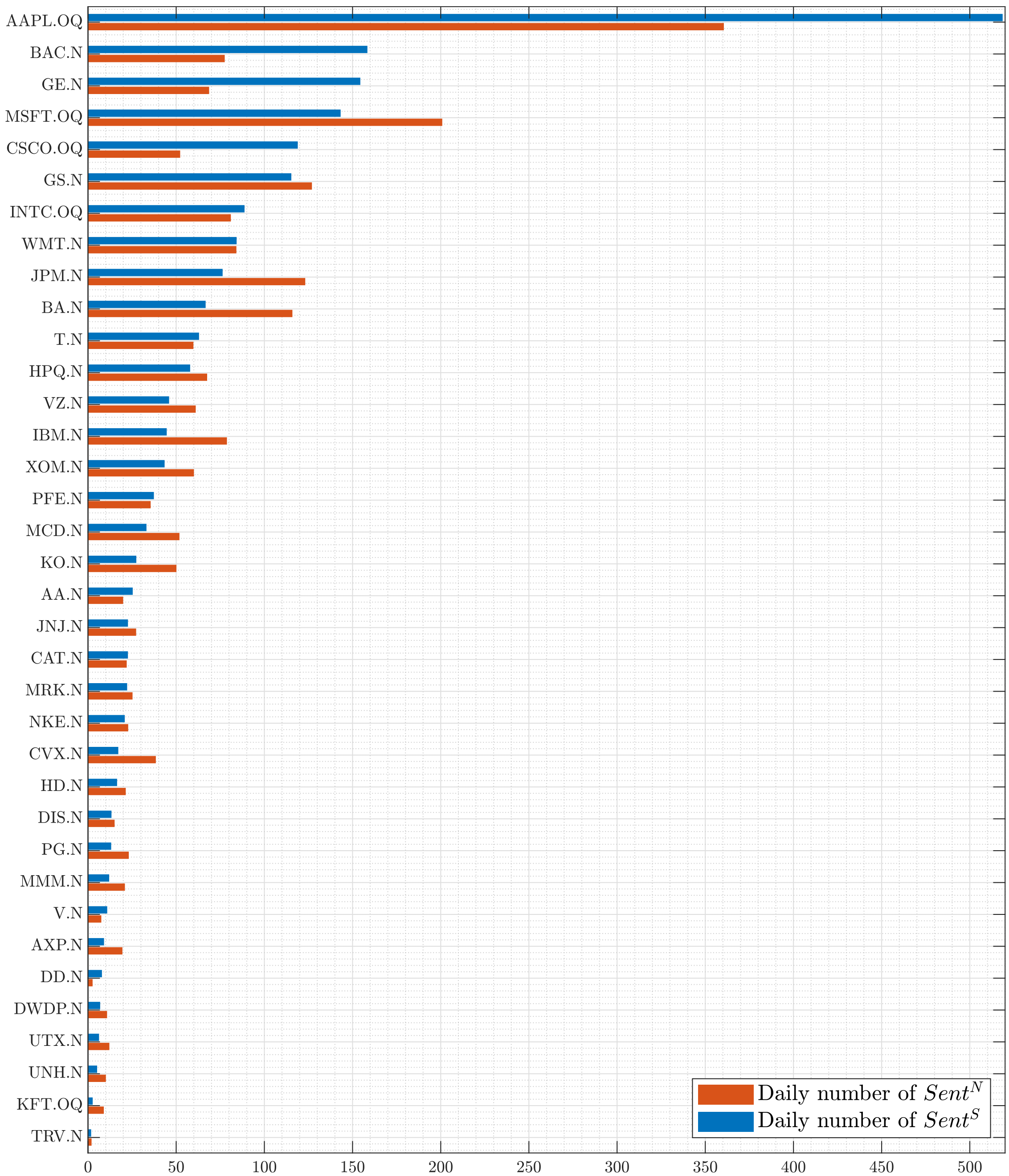


A.2 Number of Observations: Raw TRMI Data

Table A.4: Thomson Reuters MarketPsych Indices — Data Availability of Raw Sentiment Scores. The table tallies the number of observations available for the period from 1 January 2011 to 30 November 2017 for each DJIA constituents as well as the overall Dow Jones company group from Thomson Reuters MarketPsych Indices (TRMI). $Buzz^S$ and $Buzz^N$ capture the volumes of the social or news media activities. $Sent^S$ and $Sent^N$ are the net positive and negative emotion scores for each entity from the social and news media, respectively. The number of *Sent* observations for a given asset and media type is less than the corresponding number of *Buzz* observations as sentiment analysis of some messages may not be always performed. Generally, the discrepancy is greater for social media than for news.

RIC	$Buzz^S$	$Buzz^N$	$Sent^S$	$Sent^N$
AA.N	77,541	54,850	64,063	50,369
AAPL.OQ	1,476,678	983,446	1,310,025	910,719
AXP.N	28,943	57,471	22,970	49,300
BA.N	196,935	331,032	168,487	292,763
BAC.N	463,226	227,393	400,181	195,850
CAT.N	68,265	61,293	57,194	55,463
CSCO.OQ	340,545	149,162	300,459	132,024
CVX.N	53,402	112,879	43,411	97,178
DD.N	23,156	7,857	19,965	6,592
DIS.N	41,484	43,998	33,652	38,117
GE.N	445,679	202,292	390,059	173,480
GS.N	337,229	368,779	291,235	320,741
HD.N	51,712	60,676	41,674	54,084
HPQ.N	169,747	192,543	146,304	170,659
IBM.N	138,948	223,869	112,768	198,993
INTC.OQ	263,700	232,588	224,186	204,624
JNJ.N	71,096	79,074	57,250	68,966
JPM.N	72,096	359,119	192,823	311,167
KFT.OQ	9,103	26,750	6,726	22,658
KO.N	85,066	141,893	69,217	126,629
MCD.N	101,715	145,284	83,752	130,989
MMM.N	38,514	60,766	30,326	52,848
MRK.N	69,885	73,191	56,075	63,800
MSFT.OQ	429,844	564,742	361,855	507,409
NKE.N	65,722	64,843	52,647	57,582
PFE.N	113,727	103,159	94,373	89,748
PG.N	39,585	64,748	33,208	58,429
T.N	190,843	178,099	159,040	151,011
TRV.N	6,290	5,761	4,520	5,107
UNH.N	16,843	30,028	13,058	25,630
UTX.N	20,132	35,870	15,836	30,595
V.N	35,036	21,529	27,532	19,075
VZ.N	145,293	183,045	116,153	154,311
WMT.N	250,033	237,907	212,873	212,538
XOM.N	131,756	172,538	109,729	151,723
.DJI	2,753,603	2,536,911	2,593,029	2,449,177

Figure A.3: Sentiment Data Availability: News vs Social media. The figure compares the average daily counts of non-missing observations from social (in blue) and news (in red) media. The calculations are based on *Sentiment* scores at 1-minute frequency sourced from Thomson Reuters MarketPsych Indices (TRMI). The sample period is from 1 January 2011 to 30 November 2017, totaling 2,526 days. The constituents of DJIA presented in the figure are sorted by the average daily counts of sentiment scores from social media.



A.3 Data pre-processing and Distribution of Event-days

We focus on the *sentiment* measure rather than the measure of coverage quantity (*buzz*) or other 34 emotion scores provided by TRMI (such as *joy*, *fear* or *gloom*). Firstly, *sentiment* synthesises all emotion indices for an entity (i.e., a stock or an index) providing more observations than any individual emotion score.[37] Secondly, we find that the salience in *sentiment* series is consistent with *buzz* series. Interested readers are referred to Table A.4 and Figure A.3 for the availability of these data. Moreover, observations in *priceForecast*, *dividends*, *managementChange*, *laborDispute*, *layoffs* and *cyberCrime* — some of the least populated emotion scores — are too sparse over our time period and sample of stocks. Therefore, our primary variables of interest are *sentiment* scores from news and social media, which we refer to as $Sent^N$ and $Sent^S$, respectively. These variables offer a combined measure of both the quantity of coverage and the attitudes expressed in articles or posts. For convenience, Table 1 lists all the variable definitions, data sources and acronyms. Variables based on social or news media are denoted with (S) or (N) superscripts, respectively.

The data pre-processing and operations with high-dimensional high-frequency data are computationally demanding even for modern computing power. After pre-filling missing observations and aligning the sentiment series with the returns, we obtain a set of contiguous 1-minute non-missing equidistant series for each stock i and the indices: $Sent^S_{i,t,j}$, $Sent^N_{i,t,j}$ and $r_{i,t,j}$. Our sample of 35 securities and the index covers the period from 1 January 2011 to 30 November 2017, totalling 3 variables × 36 assets × 2,526 days × 24 hours × 60 minutes = 392,843,520 observations. In the context of our intraday event study, the computational speed can be greatly improved if the three series for each asset i are reshaped into $2,526 \times 1,440$ matrices using the days-by-row and minutes-by-column mesh:

$$\underbrace{\mathbf{Sent}_i^S}_{(2{,}526\times1{,}440)}, \quad \underbrace{\mathbf{Sent}_i^N}_{(2{,}526\times1{,}440)} \quad \text{and} \quad \underbrace{\mathbf{r}_i}_{(2{,}526\times1{,}440)}$$

The result of this reshaping can be visualised in Figure 1 in the heatmaps representing all available 1-minute sentiment and return data. The data are arranged by time-of-day (horizontal axis totaling 1,440 minutes) on each day of the sample (vertical axis totaling 2,526 days) with each pixel on the heatmap representing a single 1-minute observation.

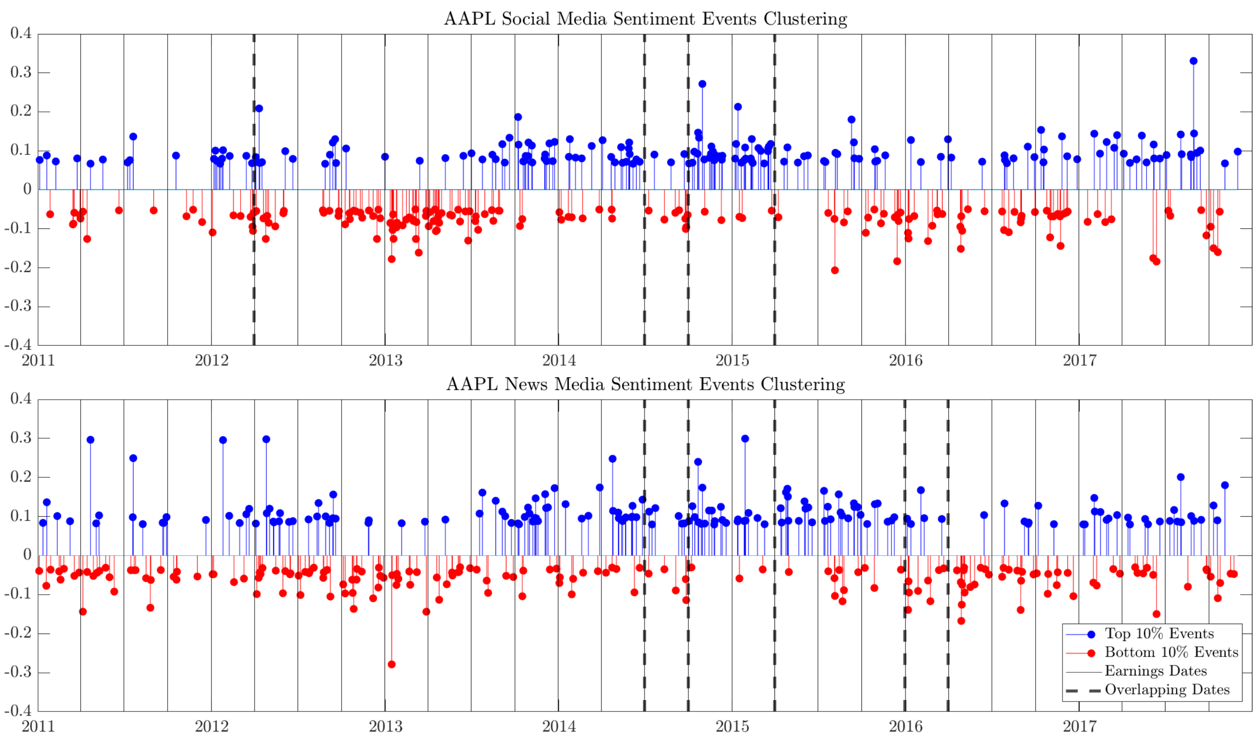
We remove days that contain more than 95% of zero 1-minute asset returns. That is, to be included in the analysis, the day must contain at least 72 (=1,400×0.05) observations of mid-quotes or prices to be included as a day-event. This step eliminates weekends, holidays and days with thin trading, allowing us to focus on a sample of records to be useful for the study. On average, a typical stock in the sample contains 1,741 event-days. For each stock, cumulative sentiment was calculated daily at a chosen intraday window length, and the distribution o these sentiment values analysed. Most stocks in our sample have evenly dispersed cumulative overnight sentiment across the 1,741 event-days. A few stocks (e.g., TRV.N and UNH.N) exhibited an uneven distribution of 'events' across sentiment deciles due to either highly polarized emotion days or a particularly large number of days with thin trading (at least at the 1-minute frequency). Considering the sparsity of the 'event-day' data, a decision to remove Kraft-Heinz (formerly Kraft Foods) from our sample was made as the number of events was deficient for a meaningful modeling. A particularly interesting

[37] See Thomson Reuters MarketPsych Indices 2.2 User Guide, 23 March 2016. According to the user guide, *sentiment* is a volume-weighted net score of all the positive and negative emotions in the media.

observation is that the number of event-days in mid-deciles of overnight sentiment for KFT, TRV, UNH, UTX, AXP, DD and DIS is lower than at the extreme deciles. The reason for this is that we removed some of the event-days for these assets due to an unusually low number of bid/ask quotes on days with neutral overnight sentiment — days with unusually low number of bid/ask quotes typically corresponded to the 5th and 6th sentiment deciles. This provides further evidence in support of our hypothesis that overnight sentiment influences the markets.

A.4 Excessive Sentiment and Earnings Announcements

Figure A.4: Excessive Sentiment Event Clustering and Earnings Announcements Overlap. By way of example, we illustrate our approach using AAPL.OQ. The blue and red pins highlight the dates (horizontal axis) and magnitudes (vertical axis) of the most positive and negative overnight sentiment, respectively. Earnings announcement dates are represented by vertical black solid lines. When a strong sentiment day coincides with an earnings announcement date, the occurrence is depicted with a dashed black line. Data on quarterly earnings announcement dates are obtained from Compustat. Both earnings days and earnings reporting days have been considered, resulting in immaterial differences.



It is reasonable to argue that days with excessive sentiment from social or news media are the days where important announcements could have taken place. We analyse the concurrence of earnings announcement release dates with the collection of days with the most positive and negative cumulative overnight sentiment (i.e., the top and bottom deciles).

To illustrate how we compute the overlapping rate, we demonstrate our method in Figure A.4 using Apple Inc (AAPL.OQ) as an example. We choose AAPL.OQ due to its high media coverage, allowing a more conservative illustration due to the increased probability of coincidental overlap with earnings announcements. The upper (lower) panel in Figure A.4 shows strong social (news) media sentiment days for the period from 1 January 2011 to 30

November 2017. While the cumulative sentiment data are available daily, the blue and red pins highlight the dates (horizontal axis) and magnitudes (vertical axis) of the most positive and negative overnight sentiment, respectively. In fact, these are the top and bottom 10% sentiment event-days used in our main analysis — the days with the most pronounced sentiment. We observe no obvious clustering in days with strong sentiment. Earnings announcement dates are represented by the vertical black solid lines. If a strong positive or negative sentiment day coincides with an earnings announcement date, we highlight this occurrence with a dashed black line. For example, we find four overlapping days out of 174 sentiment event-days based on the social media (top panel) and five overlapping days based on the news media (bottom panel), representing 2.29% and 2.87% overlap. We find similar results for other stocks in the sample.

A.5 Tried-and-true vs Bold-and-New: on commonality between Baker & Wurgler and Thomson Reuters MarketPsych Indices

Thomson Reuters MarketPsych Indices (TRMI) contain synthesized quantities and emotional measures from a wide range of traditional news channels as well as social media platforms. We contrast sentiment captured by TRMI from social and news media to the "tried-and-true" Baker & Wurgler index (BW) commonly used in investor sentiment analysis in the past decade. To create comparable series, we aggregate the TRMI social media and news sentiment scores (denoted as $Sent^{(S)}$ and $Sent^{(N)}$ respectively) into monthly frequency and report the correlations between TRMI and the BW sentiment indices in Table A.5. The results in Table A.5 demonstrate commonalities between TRMI sentiment indicators and the BW index, yet, the magnitude of correlation coefficients are indicative of divergence in these two measures, suggesting the TRMI sentiment indices capture different investor sentiment from BW's. Thus, on one hand, strong positive correlation provides merit for using TRMI as it captures commonality in general trend of these two indicators. On the other hand, TRMI provides sentiment scores at a much higher frequencies (up to 1-min) allowing us to study the dynamics in temporal displacement within sentiment scores (news vs social) and between sentiment and returns.

Table A.5: Correlation Between BW and TRMI Sentiment Indices. Sample period is from Jan 2011 to Nov 2017. TRMI sentiment indices are aggregated into monthly frequency to match the BW index. BW sentiment data are obtained from personal website of Jeffrey Wurgler at NYU Stern at http://people.stern.nyu.edu/jwurgler/data/. BW and BW_O denote the investor sentiment index and the orthogonalised sentiment index based on Equations (2) and (3) in Baker and Wurgler (2006). ***, **, and * indicate significance levels of 1%, 5%, and 10% respectively.

	$Sent^{(S)}$	$Sent^{(N)}$	BW	BW_O
$Sent^{(S)}$	1.000			
$Sent^{(N)}$	0.784***	1.000		
BW	**0.543*** **	**0.440*** **	1.000	
BW_O	**-0.358*** **	**-0.318** **	0.339***	1.000