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Does Social Media Sentiment Trump News?

by Baoqing Gan

Thesis submitted in fulfilment of the requirements for the degree of

PhD in Finance

under the supervision of Dr Vitali Alexeev
Dr Christina Nikitopoulos Sklibosios
Dr Danny Yeung

University of Technology Sydney
Faculty of Business

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30 July 2020

Certificate of Original Authorship

I, Baoqing Gan, declare that this thesis, is submitted in fulfilment of the requirements for the award of PhD in Finance, in the Business School at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

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Abstract

The importance of investor sentiment and its influence on financial market has been widely documented. The majority of these studies, however, are either US-centred or focus on a single source of sentiment. In this thesis, I contrast the effects of news and social media sentiment and assess their impacts on markets around the world, using both daily and intraday textual analytics sentiment from Thomson Reuters MarketPsych Indices (TRMI).

In the first chapter, I explore the rapidly changing news and social media landscape and its interplay with market returns and volatility. I find that news media activities (buzz) dominate social media before 2013, while social media has become increasingly important especially after 2016. A similar evolution of lead-lag pattern between news and social media sentiment is also uncovered. Moreover, I discover that market variables exert stronger impact on sentiment than the other way around, and the linkage between volatility and sentiment is more persistent than that between returns and sentiment.

The second chapter examines the role of news and social media sentiment in explaining intraday returns. My analysis of the Dow Jones Industrial Average (DJIA) constituents reveals that sentiment during non-trading hours is a strong yet short-lived predictor of opening returns. Specifically, sentiment from social media induces larger changes than news media. Negative sentiment effects work at higher economic magnitudes than positive sentiment. Nonetheless, these phenomena quickly diminish after the first minute of trading. Robustness tests show that these effects are not driven by corporate earnings announcements. This chapter provides a new set of techniques and develops a novel framework for high-frequency sentiment analysis.

The last chapter applies similar intraday analysis into 14 international markets: Australia, Brazil, Canada, the EU, France, Germany, Hong Kong, India, Japan, Singapore, Spain, Switzerland, the UK and the US. I find that the dominant role of social media in US is not representative of other global markets. News media sentiment expounds a greater impact on stock prices in other major financial markets. Robustness tests show that the aggregation of sentiment up to three hours prior to the market opening helps generate an effective signal for predicting the direction of the opening prices. This chapter underscores the importance of avoiding adopting US evidence naively to other markets.

Overall, this thesis contrasts effects of news sentiment with that of social media sentiment. Applying a novel dataset of high-frequency text analytics, this thesis provides an approach to help shed light on the role social media sentiment plays in the dynamics of stock markets.

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Chapter 1

Introduction

"We think data are objective, but they are actually as interpretable as Shakespeare."

—Mike Potter, the chief technology officer of Qlik.

The finance industry has turned to unconventional and unstructured "alternative data" in recent years. These alternative sources of data include stories, reports, articles, commentaries and posts in news and social media. It is estimated that 80% of the world's data is unstructured, and roughly 2.5 billion GBs of data are created each day.[1] According to the *Digital 2020: Global Digital Yearbook*, there were 3.80 billion social media users in January 2020 worldwide, a more than 9 per cent increase compared with 2019.[2] By employing textual analysis and econometric modelling, financial economists are able to gauge emotions and anticipate market movements.[3] However, the majority of these studies are either US-centred or focus on a single source of sentiment. Seldom have we seen studies that differentiate social media sentiment from news.

In my study, I address the following questions: How has the rapidly evolving social and news media landscape changed in the past decade? How does social and news media sentiment affect stock returns and volatility? What if sentiment is measured for individual stocks rather than the aggregate stock market? Does the market move the sentiment or does investor sentiment influence market? How can the sentiment-and-return feedback loop be disentangled? Is this sentiment effect the same around the world? What similarities and differences do we find in comparison to the US? Taking a unique perspective of contrasting social media with traditional news, I address these questions into the following chapters.

News versus Social Media: the Interplay

Firstly, I look into the dynamic relationships between news and social media activeness and emotions to examine change in the media landscape. Accounting for this variation between the two media sources is important, because the dissemination of information is vital to the efficient functioning of the financial markets. Obtaining insights into this time-varying relationship between different information channels provides a starting point for my subsequent analysis and allows me to discern the relative importance of one media source over the other.

My sentiment data are based on the textual analysis scores of the Thomson Reuters MarketPsych Indices (TRMI), which incorporates an analysis of news and social media in real-time by translating the quantity and emotions of financial economic news and internet messages into manageable information flows. After performing the principal component analysis, I apply the daily TRMI *Buzz* and

[1] "The biggest data challenges that you might not even know you have" by Christie Schneider, 25 May 2016, accessed on 1 May 2020, https://www.ibm.com/blogs/watson/2016/05/biggest-data-challenges-might-not-even-know/.

[2] "Digital 2020: 3.8 billion people use social media", Simon Kemp, 30 Jan 2020, accessed on 4 May https://wearesocial.com/blog/2020/01/digital-2020-3-8-billion-people-use-social-media.

[3] Research such as Antweiler and Frank (2004); Da et al. (2011); Bollen et al. (2011); Mao et al. (2011) have led a trend to quantify qualitative information in 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).

Sentiment scores of Standard & Poor's 500 (S&P500) index from 1 January 2011 to 30 November 2017 to investigate my first research question. Next, I conduct a two-variable rolling-horizon vector autoregression (VAR) analysis to capture the dominance of one media activity over the other. Using the sheer volume of the social and news media activity, commonly known as "buzz", I document three distinct regimes in the first chapter. I find that between 2011 and 2013 the news media coverage stimulates activity in social media. This is followed by a transition period of two-way causality. From 2016, however, changes in the levels of social media activity seem to lead and generate news coverage volume.[4] I uncover a similar evolution of lead-lag patterns between sentiment measures constructed from the tonality contained in the textual data from social and news media posts. These results have been summarised alongside the following daily media sentiment analysis in the recent publication Gan et al. (2019).

Sensitivity to Sentiment: Examination Under the Microscope from Daily to Intraday

Given the above three transition regimes, I further analyse the impact media has on the financial market. Using the same daily TRMI S&P500 *Buzz* and *Sentiment* scores, I analyse the causality between media sentiment and market variables (specifically, return and volatility) under three distinct market information environments. I discover that market variables exert stronger impact on investor sentiment than the other way around. I also find that return responses to social media sentiment almost doubled after a transition period, while return responses to news-based sentiment almost halved to their pre-transition level. The linkage between volatility and sentiment is much more persistent than that between returns and sentiment.

Hitherto, most studies have been concentrating on market-wide sentiment, with only a few exceptions accounting for firm-specific sentiment. The literature examining aggregate market sentiment and broad market indices includes Baker and Wurgler (2006), Baker and Wurgler (2007), Barber et al. (2008), Berkman et al. (2012), Siganos et al. (2014), Stambaugh et al. (2012, 2014) and Sun et al. (2016a), to name a few. The literature investigating firm-specific sentiment and stock returns is only starting to emerge and includes Groß-Klußmann and Hautsch (2011), Sprenger et al. (2014a), Bartov et al. (2018) and Boudoukh et al. (2018).[5] However, what remains missing in the literature is the impact on individual stocks from news and social media sentiment. Moreover, results from the general stock market above show that it is difficult to disentangle the sentiment and stock feedback loop on a daily cycle. Therefore, I continue investigating the sensitivity of stock returns to company-specific

[4] Refer to Figure 2.1 in the Appendix.

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

sentiment based on 1-minute intraday TRMI measures. Specifically, I study whether the build-up of company related sentiment overnight, or during other non-trading hours, helps predict opening prices the next day.

I focus my investigation on the impact of overnight sentiment for several reasons. Firstly, the use of overnight sentiment allows me to have a fixed anchor point for the analysis. Moreover, measuring sentiment in this non-trading period allows me to break the return-and-sentiment loop and thus effectively avoid any endogeneity issue in my analysis. The use of overnight sentiment data also has the benefit of being the highest signal-to-noise measure for what can be a very "noisy" measure. Finally, the majority of firm-specific announcements are scheduled outside of trading hours (Birru, 2018). It stands to reason that the emotions/sentiment generated by these announcements would also be formed and best measured in this non-trading period as well.

How to Break the News-and-Stock Feedback Loop?

The irregularity of sentiment data and its asynchronicity with the returns present a challenge for modelling their causal relation.[6] I combine the sentiment data with the 1-minute stock mid-quotes (average of bid and ask) for all of the Dow Jones Industrial Average (DJIA) constituents' from 2011 to 2017. I focus on the DJIA constituents to mitigate sampling bias from missing observations in the 1-minute sentiment data. Employing an approach akin to an **intraday event study**, I set the market open time (9:30 am EST) as the *event*, and accumulate sentiment data prior to the *event* and check for its correspondence with the cumulative returns after the *event*. I further conduct robustness checks by varying the cumulative sentiment (pre-event) window and opening period (post-event) return windows. To tackle the causality loop between media sentiment and stock trading variations, I perform ordinary least square (OLS) regressions contrasting models of baseline situation and extended control variables for each sampling stocks. Finally, the plots that display every stock's βs along a 45 degree-line provide insightful information to understand each stock's sensitivity to positive or negative news and social media sentiment.

My results reveal that sentiment during non-trading hours is a strong predictor of opening returns. I find that only acute sentiment swings move the market, whereas neutral or mild sentiment fluctuation show little effect. Specifically, the cumulative abnormal returns of DJIA constituent stocks are significantly positively related with the top and bottom decile overnight sentiment from the social and news media. I also find that sentiment from social media induces larger changes in opening prices than news media. Negative sentiment impacts on opening returns at higher economic magnitudes than

[6] Figure 3.1 in the Appendix demonstrates the misalignment between media sentiment and stock market data. More detailed explanation is provided in my job market paper uploaded together.

positive sentiment. Interestingly, these phenomena quickly diminish after the first minute of trading. Robustness tests show that these effects are consistent across multiple event windows and are not driven by corporate earnings announcements. This chapter provides us with a tool that helps shed light on the novel dynamics of the stock market under the current fast changing digital era.

Round-the-Clock Rally: What Is Different Outside the US?

Studies investigating sentiment impact are largely concentrated on the US market and usually employ sentiment measures depending on a single source. To examine similarities and differences between global markets and the US, I use TRMI high-frequency, country-specific equity sentiment data in this chapter. Assisted by the similar intraday event study approach in the previous chapter, I gauge the strength of overnight sentiment and examine how stock markets around the world other than the US react to sentiment from news and social media.

Over the sample period from 1 January 2011 to 30 November 2017, I continue to use 1-minute TRMI sentiment data and match it with Oxford-Man country-specific equity indices data from 14 markets around the globe: Australia, Brazil, Canada, the EU, France, Germany, Hong Kong, India, Japan, Singapore, Spain, Switzerland, the UK and the US. Employing similar methodology as Fraiberger et al. (2018), I evaluate the impact of social (news) media sentiment on the overnight returns of each country. In a series of OLS regressions that control for previous day close-to-close returns, trading volumes, daily average realised volatility and the global "fear" index (VIX), I analyse the differences between social and news media sentiment in each sample market, as well as their asymmetry toward positive and negative sentiment. I find that, in the global markets, the build-up of social media and news sentiment during non-trading episodes leads to changes in the same direction in next day opening returns. I discover that only in the US stock market does social media exert stronger impact on the opening prices, while other global economies display more significant reactions to news media sentiment. Robustness tests demonstrate that the aggregation of sentiment up to three hours before market open generates an effective signal to opening prices. This chapter contributes to the literature of anticipating opening returns in the global stock market using information flow and the investor sentiment contained within.

Contribution

This study contributes to the literature in several ways. Firstly, I emphasise the importance of the time-varying relationship between investor sentiment and the market. Similar to Jiao et al. (2018), I differentiate between two types of media (social and news) and examine the dynamics in the lead-lag relationships between these two channels from both the activeness (*buzz*) side and the emotion (*sentiment*) side conveyed in these data. The results of my analysis of the mutual causality between media sentiment and stock market variables (return and volatility) under different market information environments are consistent with Antweiler and Frank (2004) and Araújo et al. (2018). That is, my results also suggest that the reverse feedback effect from stock variation to media sentiment is stronger than the other way around. Furthermore, my innovative intraday event study approach that takes market open as an "event" effectively breaks up the return-and-sentiment feedback loop and builds an easily understandable benchmark for further analysis. My research based on individual stock-specific sentiment contributes to the literature that investigates overnight investor sentiment and intraday return patterns. I find that stocks quickly revise at the market open, suggesting that overnight information is quickly reflected into opening returns. It also reveals that opinions and investor moods are traveling faster than before with the boom in social media, as stock prices are becoming more sensitive to social media moods. Lastly, the extra evidence of similarities and differences from comparing global markets with the US contributes to a better understanding of sentiment return dynamics. Extending beyond the US market seems to be more intuitive and meaningful than ever before, taking the example of the unprecedented COVID-19 global sentiment rallies. My findings suggest that TRMI social media sentiment presents a significant impact on the US market, whereas in other markets, news media sentiment exhibits stronger effects than social media.

Overall, the results of this study suggest that social media is becoming the dominant media source in the US market. Utilising entity-specific sentiment measures at higher frequencies merits us to better understand the dynamics of stock markets in the current fast-evolving digital era.

Chapter 2

Sensitivity to Sentiment: News vs Social Media

"Public sentiment is everything. With public sentiment, nothing can fail. Without it, nothing can succeed."

—*Abraham Lincoln*

Sensitivity to Sentiment: News vs Social Media

Abstract

We explore the rapidly changing social and news media landscape that is responsible for the dissemination of information vital to the efficient functioning of the financial markets. Using the sheer volume of social and news media activity, commonly known as buzz, we document three distinct regimes. We find that between 2011 and 2013 the news media coverage stimulates activity in social media. This is followed by a transition period of two-way causality. From 2016, however, changes in levels of social media activity seem to lead and generate news coverage volumes. We uncover similar evolution of lead-lag pattern between sentiment measures constructed from the tonality contained in textual data from social and news media posts. We discover that market variables exert stronger impact on investor sentiment than the other way around. We also find that return responses to social media sentiment almost doubled after the transition period, while return responses to news-based sentiment almost halved to its pre-transition level. The linkage between volatility and sentiment is much more persistent than that between returns and sentiment. Overall, our results suggest that social media is becoming the dominant media source.

Keywords: investor sentiment; textual analysis; vector autoregressive (VAR) model; TRMI

2.1 Introduction

The financial sentiment literature has shown that macroeconomic announcements, major geopolitical events, and corporate announcements change investors' sentiment and often influence stock prices. Traditionally, investors receive this information through mainstream financial news reports, official announcements, corporate conference calls, and analysts research reports. Recent advancements in digital and telecommunication technologies facilitated social media platforms such as Twitter and StockTwits in becoming an instant channel for stock information sharing[1], disseminating greater quantities of company related information to the market at faster speeds. The importance of social media in the information dissemination process has been recognized by both regulators and market participants. For example, Bloomberg announced that it would add Twitter accounts to its financial information terminals - a "must-be" tool used by traders on Wall Street.[2] For its part, the US Securities and Exchange Commission (SEC) issued a guidance in 2008 admitting that corporate websites can serve as an effective means for disseminating information to investors, the SEC pointed out in its investigation report toward Netflix that "company communications made through social media channels could constitute selective disclosures and, therefore, require careful Regulation Fair Disclosure (Reg FD) analysis". Then in June 2015, the SEC further announced that "a start-up firm can post Twitter message about its stock or debt offering to gauge interest among potential investors" (Bartov et al., 2018), marking, for the first time, its official acceptance of social media as information dissemination channel.

Classical asset pricing models assume that investors mutually influence each other only through market price mechanisms. This assumption is less realistic since it overlooks the social interactions between investors. In reality, investors communicate and learn information through a combination of news media and social media, making social influence a critical factor of the information dissemination process and asset pricing (Hirshleifer and Teoh, 2009). Social media has been known to create attention-grabbing hot topic that may sway investors' beliefs about company's future outlook, thus forming investor sentiment that ultimately affects stock prices. For example, on 23 April 2013, a fake tweet from official Twitter account of the Associate Press announced that President Obama was injured in two explosions in the White House.[3] According to Washington Post, this hacked tweet was retweeted 4,000 times in less than five minutes with its nearly 2 million followers. Dow Jones Industrial Average

[1]Stafford, P. (2015), 'Traders and investors use Twitter to get ahead of market moves', *FINANCIAL TIMES*, April 29, accessed 12 August 2018, <https://www.google.com.au/amp/s/amp.ft.com/content/c464d944-ee75-11e4-98f9-00144feab7de>.

[2]Alden, W. (2013), 'Twitter arrives on the Wall Street, via Bloomberg', *The New York Times*, April 4, accessed 12 August 2018, <https://dealbook.nytimes.com/2013/04/04/twitter-arrives-on-wall-street-via-bloomberg/>.

[3]Fisher, M. (2013), 'Syrian hackers claim AP hack that tipped stock market by $136 billion. Is it terrorism?' *The Washington Post*, 23 April, accessed 12 August 2018, <https://www.washingtonpost.com/news/worldviews/wp/2013/04/23/syrian-hackers-claim-ap-hack-that-tipped-stock-market-by-136-billion-is-it-terrorism/?utm_term=.5e2044c627e4>.

(DJIA) dropped 143.5 points within 2 minutes, temporarily losing an estimated US$136 billion in value. This incident triggered critiques that the financial industry may have relied too heavily upon trading algorithms that are based on social media content.

In this paper, we explore this rapidly changing social and news media landscape that is responsible for the dissemination of information so vital to the efficient functioning of the financial markets. First, we explore the evolving relationship between social media and news media from 2011 to 2017. Using the sheer volume of social/news media activity, commonly known as buzz, we documented three distinct regimes. We find that between 2011 and 2013 the news media coverage stimulates activity in social media. This is followed by transition period where news and social media activities tend to intertwine. From 2016, however, changes in quantities of social media activity seem to lead and generate news coverage volumes. We find a similar evolving pattern of lead-lag relationship between sentiment measures constructed from the tonality contained in textual data from social and news media posts.

Secondly, given that social media played a more prominent role after 2016 while news media used to be predominant before 2014, we set out to investigate the dynamic in the relationship between media activities and the stock market before and after this transition. In particular, we are interested in how news and social media sentiment affects stock returns and volatility in the periods from 2011 to 2013 and from 2016 to 2017. In dealing with inevitable endogeneity issue in the analysis of this kind, we account for the reverse influence from the stock market on social and news media. Facilitated by restricted bivariate VAR models that contain a media variable and a market variable, we find that the reaction of media sentiment to stock market shocks is more pronounced than the sensitivity of return/volatility to changes from media sentiment. This result is in line with Sprenger et al. (2014c) and Araújo et al. (2018), which find that the market features (return, trading volume and volatility) have stronger effects on media features (bullishness and posting volumes). The analysis of impulse response functions from models in the two separate periods identified above reveals that the speed of reactions for both return and sentiment have accelerated after 2016 compared to the period before 2014. Return responses to social media sentiment almost doubled after the transition period (from 0.03 to 0.07), while return responses to changes in news-based sentiment almost halved to its pre-transition level (from 0.030 to 0.016). These results corroborate our prior findings that social media is more prevalent after 2016. In contrast to return and media sentiment interactions, we find that volatility in both pre-transition and post-transition periods display higher sensitivity to social media sentiment than to news-based sentiment. Stock volatility reactions to shocks from media sentiment are more persistent than return responses. We conclude that the media sentiment does not follow market activity passively, but is actively engaging in shaping the market movements under different information environments.

Our contribution is threefold. Firstly, by separating social and traditional news media, we obtain insights into the time-varying relationship between the two information channels. As a result of the advancement in information and telecommunication technology, as well as the acceptance of the new technology by regulatory authorities, we observe propagation of social media in the later sample periods. Our results suggest that researchers in this topic should and must consider the time-varying nature of the social/news media interplay. To the best of our knowledge, there is no other research that highlights such differences, and details sentiment effects on stock market from different media sources. Secondly, accounting for the bilateral causality between media sentiment and stock market variations, we provide empirical evidence to the expanding literature on investor sentiment and noise trader risk (De Long et al., 1990). Unlike previous work, we use sentiment measures based on textual analysis that synthesizes multiple media channels' information, rather than focusing on a single platform. Lastly, our detailed statistical analysis of the Thomson Reuters MarketPsych Indices (TRMI) data adds value to the validity of textual data in asset pricing applications by shedding light on how information from various media sources is incorporated into stock prices and volatility.

The rest of the paper proceeds as follows: Section 2.2 reviews previous work on investor sentiment, Section 4.2 describes sample data, elucidates the data pre-processing approach, and discusses research methodology, Section 2.4 reports results on the news and social media interplay over time, Section 2.5 analyses causal effects between media sentiment and stock market return/volatility. We conclude in Section 2.6 and propose directions for future research.

2.2 Literature Review

Information have played a central role in investors' choices since the advent of financial markets. Traditionally, the news media played a dominant role. For example, Tetlock (2007) shows that the content of the influential Wall Street Journal, and in particular its tone, can influence the volume of market trading and returns. Stories about a company are so important that the absence of news coverage could impact stock prices. Chan (2003) shows that companies that had no news stories experience reversals in prices in the following month. With the advancement in technology and the rise of social media, the news media is no longer the sole source of information in general and, in particular, for investors. Kwak et al. (2010) examined 106 million tweets and found that 85% of the tweets were news related. In the field of finance, studies have shown that postings on internet message boards (see Wysocki (1998), Antweiler and Frank (2004), Das and Chen (2007), and Chen et al. (2014)), and on other social media platforms such as Twitter and StockTwits (e.g., Sprenger et al. (2014a), Ranco et al. (2015)) can exert influences on stock prices and volatility. The question is whether social media have changed the way that investors consume news.

This is, literally, a billion-dollar question as social media can be subject to manipulation. For example, Lee et al. (2015) found that management use social media to mitigate the negative stock price impact of bad news about a company such as product recall. This strategy is particularly effective because it is not only the content but the tone of the message that can generate sentiment, which can influence the investor reactions to company's announcement.

Investor sentiment is the prevailing attitude of investors as to anticipated price development. It is the accumulation of variety of fundamental factors and technical indicators, such as price history, ratings and reviews, economic news reports, national and world events. According to Baker and Wurgler (2007), investor sentiment is defined as "a belief about future cash flows that is not justified by facts at hand". Broadly, investor sentiment studies can be categorised by the sentiment measure they employ: measures based on fundamental market variables, sentiment extracted from various textual sources, and sentiment scores provided by proprietary vendors such as Thomson Reuters MarketPsych and RavenPack.[4]

Investor Sentiment and Stock Market

Early research on investor sentiment and stock market movements are generally based on sentiment created from market fundamental variables (Baker and Wurgler, 2006, 2007). These sentiment proxies allowed to test behavioural finance theories such as security market under- and overreactions.[5] Empirical research on this topic makes three assumptions. First, two groups of investors play together in the market: irrational noise traders and rational arbitragers. Second: noise traders' sentiment-driven characteristics create risks to their counterparts to bet against them, which demotivate the arbitragers' trading behaviour during high sentiment periods (De Long et al., 1990). Third: there are costs to arbitrage, e.g. limit to short-sale and capital constraint (Shleifer and Vishny, 1997).

Market microstructure literature assists in tying investor sentiment to market volatility by dissecting the trading frictions, or bid-ask spread, into different components. Depending on which component is dominant, there are two mechanisms prescribing the relationship between sentiment and market volatility. First, investor sentiment negatively impacts on bid-ask spread and trading price volatility. Glosten and Milgrom (1985) proposes that adverse selection costs, as part of the bid-ask spread, are negatively correlated with sentiment-driven noise trading. In strong emotional periods, more noise trading results in narrower bid-ask spread, which concerns trading costs and risks, and price

[4]There are categories of studies that we omit here for brevity, but nevertheless, presenting interesting directions, namely studies based on internet search behaviour, and studies relying on non-economic factors, such as weather and health conditions affecting investors' risk aversion and trading behaviour.

[5]Such "behaviour augmented" models usually consider various investor heuristic bias, for example, overconfidence and self-attribution bias (Daniel et al., 1998), conservatism and representativeness (Barberis et al., 1998), and confirmation bias (Rabin and Schrag, 1999)). Other behavioural models that focus on investor attention (Odean, 1999; Barber and Odean, 2007; Karlsson et al., 2009) or account for the interactions between different types of investors (Hong and Stein, 1999) have also been widely applied.

volatility. Second, investor sentiment positively influences bid-ask spread and price volatility. Order processing costs and inventory costs, taking a larger component of bid-ask spread than the adverse selection component (Huang and Stoll, 1997), are proved to be positively related to price risks and the opportunity cost of holding securities (Amihud and Mendelson, 1986). Such risk is shown to be positively linked with investor sentiment as it is harder to evaluate the misvaluations during high sentiment periods (De Long et al., 1990).

Empirical studies applying fundamental variable based sentiment index to examine stock price movement include: De Bondt and Thaler (1985), Brown and Cliff (2004), Baker and Wurgler (2006), Baker and Wurgler (2007), Barber and Odean (2007), Karlsson et al. (2009), Canbaş and Kandır (2009), Stambaugh et al. (2012), and Sayim and Rahman (2015). Findings from these studies, however, are mixed. For example, Brown and Cliff (2004) and Oliveira et al. (2013) find little or no predictability to short-term stock returns from investor sentiment, while others reveal evidence supporting the short-term price deviations as demonstrated by behavioural models.

If such short-term deviations exist, fundamental variable based sentiment indices, constructed at most monthly, may be too aggregated. More granular sentiment data at higher frequencies can be derived from other sources, providing a more detailed account of short-term fluctuations.

Investor Sentiment Based on Textual Analysis

In recent decades, advancements in textual analysis and machine learning techniques had shifted the focus of investor sentiment literature to the analysis of the relationship between stock market and information quantity, as well as sentiment conveyed within textual data (see Tetlock, 2007; Tetlock et al., 2008; Loughran and McDonald, 2011b). Empirical research relying on scanning and scoring texts from filed documents and press releases is abundant and still expanding. There are four main information sources examined by research: **corporate filings** (e.g., Loughran and McDonald, 2011a; Jegadeesh and Wu, 2013), **professional financial news releases** (e.g., Antweiler and Frank, 2006; Engelberg, 2008; Fang and Peress, 2009; Engelberg et al., 2012; Garcia, 2013), **internet message boards** such as *Yahoo!Finance*, *RatingBull* and *SeekingAlpha* (see Wysocki, 1998; Antweiler and Frank, 2004; Das and Chen, 2007; Chen et al., 2014), and **social media platforms** such as *Twitter* and *StockTwits* (e.g., Sprenger et al., 2014c; Ranco et al., 2015), *Google* search volume (e.g., Da et al., 2011) and *Facebook's* Gross National Happiness index (Siganos et al., 2014).[6]

Most of the empirical work focuses on either the volume (e.g., coverage) or the sentiment (positive vs negative emotions or tonality) conveyed in textual data, research that considers both is rarely observed. In fact, as pointed out by Liu and McConnell (2013), both the level of media attention and

[6]Our review of empirical research that utilize various textual data sources in this field is far from exhaustive. For comprehensive survey, refer to Kearney and Liu (2014) and Brzeszczyński et al. (2015).

the tones within press articles are significantly associated with the various types of corporate events, which ultimately impact stock prices and volatility. We adhere to this view and conduct our analysis accounting for both the level of coverage and the sentiment tonality expressed by media outlets.

Due to the limited computational power at early stages of textual analysis and the requirement of manually-handled "training" process for algorithms such as Naive Bayesian Classification, sample sizes in some of the earlier works are relatively small. One could only focus on either a small group of representative companies, or constrain the sampling period to a short time frame, but not both.[7] This small sample problem is better dealt with in Leung and Ton (2015) and Renault (2017). Covering more than 2,000 public firms in Australia from 2003 to 2008, Leung and Ton (2015) examines over 2.5 million stock related messages posted on *HotCopper* forum, and finds that small, high growth, and hard-to-valuation stocks tend to be easily affected by internet message board. Renault (2017) abstracts textual sentiment from 750,000 StockTwits at intra-day level between September 2014 and April 2015 and finds that sentiment changes in the first-half trading hour manifest market return predictability to the last half-hour.

Investor Sentiment Based on MarketPsych Indices

To break the confinements of data availability from small number of assets, short observation period, and single type of media source, several studies reap the reward of unique data set from professional financial data vendors such as Thomson Reuters and Dow Jones. This type of data takes advantage of combining more comprehensive content for certain categories of information (news or social media), rather than focusing on a standalone platform. For instance, using sentiment indicators from Thomson Reuters News Scope (TRNS) and texts data from Thomson Reuters News Archive (TRNA), Heston and Sinha (2017) validates the effectiveness of textual sentiment data to predict stock returns. They provide evidence that daily textual sentiment only predict return at short-term (one or two days) horizon, whereas weekly sentiment indices contains predictability up to a quarter.

Different from News Analytic data, Thomson Reuters MarketPsych Indices (TRMI), the dataset employed in this paper, contains synthesized quantities and emotional measures from a wide range of traditional news channels as well as social media platforms.[8] We contrast sentiment captured by TRMI from social and news media to the Baker & Wurgler index (BW) commonly used in investor sentiment analysis.[9] The correlations between social and news media TRMIs and the BW index are 0.54 and

[7]For example, Ranco et al. (2015) uses Twitter API to analyse 30 Dow Jones companies involving 151 events and covering the period from June 2013 to September 2014, while Das and Chen (2007) examines 24 high-tech companies in the two-months period from July to August 2011.

[8]While description of the sub-sample employed in this paper is presented in Section 4.2, the detailed summary of the full dataset is provided in the supplementary appendix.

[9]We are grateful to Jeffrey Wurgler for making their monthly investor sentiment data publicly available on his website at NYU Stern. Assessed on 8 February 2019, <http://people.stern.nyu.edu/jwurgler/>.

0.44 respectively, demonstrating a degree of commonality between TRMI sentiment indicators and the *BW* index.[10] Yet, the magnitudes of correlation coefficients are indicative of divergence of these two measures, suggesting that the TRMI sentiment indices capture different investor sentiment from BW. 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 allowing us to study the dynamics in temporal displacement within sentiment scores (news vs social) and between sentiment and market variables (sentiment vs returns and/or volatility).

Recent studies have already shown the effectiveness and validity of this dataset in measuring media-related investor sentiment. For example, Michaelides et al. (2015) (see Table 5 therein) matches the manually collected sovereign downgrade news events with TRMI metrics, and confirms the consistency and validity of TRMI variables. A further research conducted by Michaelides et al. (2018) uses TRMI and manually constructed FX currency related news to control for media based public information, confirming consistency between these two groups of measures. Investigating the market dynamics between TRMI sentiment index and Brazil stock index (IBovespa), Araújo et al. (2018) finds strong reverse causation from market movements to media sentiment.

Our paper is complimentary to Sun et al. (2016a), Nooijen and Broda (2016), and Jiao et al. (2016) in that we focus on the aggregate US equity market. Concentrating on intraday (half-hour) data from TRMI, Sun et al. (2016a) explores the within day return predictability for the Index. They substantiate that changes of TRMI sentiment in the first half trading hour are helpful to forecast the last two trading hours' stock index returns, which is different from within day momentum effect. They point out that this predictability enables to create economic value when evaluated with market-timing strategy. Examining the MSCI US Equity Sector Indices from TRMI, Nooijen and Broda (2016) finds higher predictability for stock volatility than for return. They highlight the significance of distinguishing different market environments, for example, calm or volatile periods. Contrasting social media with news using TRMI media quantity measures, Jiao et al. (2016) develops a generalised asset pricing model that accommodates various behavioural biases. They use this model to examine social and news media effects on volatility and volume of 2,613 US stocks from 2009 to 2014. They document evidence that higher social media sentiment leads to higher volatility and trading volume in the next months. In contrast, improvements in news sentiment result in decreased volatility and volume in the coming month.

This paper contributes to the literature in several ways. Firstly, similar to Jiao et al. (2016), we discriminate two different types of media, social vs news, and examine the dynamics in the lead-lag relationships between these two channels from both the activeness (*Buzz*) and the emotions (*Sentiment*) conveyed in data from these two channels. But, in contrast to Jiao et al. (2016), we address the impor-

[10] See supplementary appendix for details.

tant question: had the media landscape changed from 2011 to 2017, and how social and news media had interacted with each other over this period. Secondly, as pointed out by Baker and Wurgler (2007) and Nooijen and Broda (2016), we emphasise the importance of time-varying relationship between investor sentiment and the market. That is, we analyse the mutual causality between media sentiment and stock market variables (return and volatility) under different market information environments: (i) period of conventional news media dominance, (ii) transitory period with no clear lead effect of one information channel over the other, and (iii) period of increasing dominance of social media. Extending the strand of literature that uses MarketPsych Indices investor sentiment, our exploration and results reveal new facts about the role of information in asset pricing in the social media era.

2.3 Data and Methodology

Our dataset is comprised of two sources: sentiment data and stock market data. Our sentiment data is based on Thomson Reuters MarketPsych Indices (TRMI) textual analysis scores for the company group. Our stock market data are obtained from Datastream and Wharton Research Data Services. Details on each dataset and data pre-processing methods are provided below.

2.3.1 Sentiment Data

In contrast to the definition in Baker and Wurgler (2006), we refer to investor or market sentiment as the overall attitude of investors toward a single security or financial market. It is the tone of an asset or a market, its crowd psychology. Thomson Reuters MarketPsych Indices (TRMI) incorporates analysis of news and social media in real-time by translating the quantity and emotions of financial economic news and internet messages into manageable information flows.[11] TRMI provides three content categories: **news**, **social** and **combined**, based on English language articles and posts dating back to 1998. TRMI covers more than 2,000 news sources, including leading professional financial news presses such as *The Wall Street Journal, The Financial Times, and The New York Times*, as well as other less influential news content synthesised by Thomson Reuters News Feed Direct, Factiva News, *Yahoo!* and Google News. TRMI also claw and scrape the top 30% of over 2 million blogs, stock message boards and social media sites minute-by-minute, including StockTwits, *Yahoo!Finance*, and *SeekingAlpha*. Term weighting and scoring approach of TRMI is based on the Loughran and McDonald (2011b) dictionary scheme, which is proved to be more suitable to financial contexts rather than the psycho-social dictionary scheme of the Harvard General Inquirer (GI) used in Tetlock (2007). These

[11]The data are provided by Thomson Reuters Financial and Risk Team as part of TRMI product. TRMI covers a plethora of securities and markets, including: more than 12,000 companies, 36 commodities and energy subjects, 187 countries, 62 sovereign markets, 45 currencies, and, since 2009, more than 150 cryptocurrencies. For more details, see *Thomson Reuters MarketPsych Indices 2.2 User Guide, 23 March 2016, Document Version 1.0.*

data allow us to study and contrast the difference in sentiment effects from social and news media.

TRMI offers three types of sentiment indicators for a specific company or company group: 1) **Emotional** indicators including *Sentiment*, *Anger*, and *Fear*; 2) **Fundamental** perceptions such as *Long vs Short*, *Earnings Forecast*, and *Interest Rate Forecast*; and 3) **Buzz** metric, a measure indicative of how much activity market-moving topics, such as *Litigation*, *Mergers*, and *Volatility* are being generated and discussed. After the social media posts or news articles are published in the TRMI content sources, a linguistic software abstracts the new content feed, parses and scores the content and attributes the score to global indices, companies, bonds, countries, commodities, currencies, and cryptocurrencies. In fact, TRMI offers a total of 35 emotional scores. We decide to focus on *Sentiment* after performing Principal Component Analysis (PCA) and checking variance decomposition of the first two principal components.[12] However, *Buzz* metric is conceptually different from the emotional and fundamental scores. It measures the volume of information flow and, therefore, is not incorporated in the PCA analysis with other scores. Yet, *Buzz* metric is crucial in our analysis of social vs traditional news media dominance throughout the sample period.

Several studies have verified the validity of the textual sentiment measures provided by TRMI e.g., Michaelides et al. (2015), Sun et al. (2016a), Nooijen and Broda (2016), and Michaelides et al. (2018). In our analysis we employ daily observations from 2011 to 2017 for the *MPTRXUS500* company group index that aggregates sentiment and tone of the largest 500 companies in the US, and aims at capturing the index sentiment. The data are updated each day at 3:30pm US Eastern time, including weekends and other non-trading days.[13] According to Heston and Sinha (2017), daily textual sentiment possesses short-term return predictability. Table 2.1 presents descriptive statistics for the sentiment indices and the media activity measure, *Buzz*, based on social media and news respectively. Sentiment scores are buzz-weighted, averaging any positive references net of negative references in the last 24 hours. Upon examination of the descriptive statistics, we observe the following facts: first, *Buzz*, a sheer media coverage volume metric for both social and news media, has a much larger absolute value than sentiment (average *Buzz* value of 116,484.46 for social media and 202,401.31 for news, while sentiment mean values are close to zero). Social media *Buzz* is highly positively skewed with the third moment equals to 1.37, and contains several large outliers.The kurtosis of 6.32 indicates a leptokurtic distribution. In contrast, news media buzz is more symmetric and contains less outliers than social media, with skewness equal to -0.01 and kurtosis 3.91 - slightly higher than 3. Lastly, all of the TRMI indices are significantly autocorrelated with potential long memories.[14]

[12]Results of our PCA analysis are detailed in the supplementary appendix.
[13]Further details on the TRMI data can be found in the MarketPsych white paper by Peterson (2013).
[14]In the unreported tables, we conduct Durbin-Watson (DW) test and Ljung-Box test with up to 5 lags (LB-5). Evidence of autocorrelation with potential long memories for all available social and news emotional indices are available upon request.

2.3.2 Stock Market Data

The sample period for the stock market data is consistent with the availability of our TRMI data and sampled daily from January 1, 2011 November 30, 2017. Fortunately, this period avoids the turmoil of the global financial crisis (GFC) episodes from 2008 to 2010 and escapes potential influence of change in data sources last reported by TRMI in 2009. At the same time, this sample period covers a phase of rapid development of social media, allowing us to compare and contrast social and news based sentiment directly. Following Antweiler and Frank (2004), and Sprenger et al. (2014c), we employ stock return and volatility as our main stock market variables, with descriptive statistics summarised in Table 2.1:[15]

Table 2.1: Descriptive Statistics for the company group over the period 2011/01/01-2017/11/30. *Sentiment*, obtained from TRMI, is bounded on [-1,1]. Negative and positive values denote negative and positive sentiment, zero denotes neutral score. *Buzz*, representing the volume of information flow, differs from *Sentiment* index, and is only bounded from below at 0. *Sentiment* and *Buzz* indices are obtained from TRMI under asset group code MPTRXUS500 which aggregates information on the top 500 US-based companies and resembles Index. *Returns* are calculated as $r_t = log(P_t/P_{t-1})$, where P_t is the daily close price for the index obtained from Datastream. Reported return figures are annualized by multiplying the daily return values by 252. *VIX* data is acquired from WRDS CBOE volatility index futures closing prices. The unreported Durbin-Watson test and Ljung-Box 5 lags test for all indices show presence of autocorrelation for all series.

	Mean	Std	Max	Min	Skew	Kurt	25th	Median	75th	IQR
					Social media:					
Sentiment	-0.020	0.030	0.082	-0.127	-0.32	2.80	-0.040	-0.016	0.001	0.042
Buzz	116,484	35,769	311,543	14,179	1.37	6.32	94,587	110,860	130,317	35,730
					News media:					
Sentiment	-0.017	0.037	0.126	-0.173	-0.29	3.22	-0.042	-0.015	0.009	0.051
Buzz	202,401	47,847	387,635	1,468	-0.01	3.91	172,081	202,994	231,451	59,369
					Market:					
Return	0.09	1.99	10.42	-15.52	-0.54	8.78	-0.68	0.06	1.07	1.75
VIX	16.34	5.58	48	9.14	2.07	8.34	12.85	14.89	17.96	5.11

We believe that the implied volatility of stock index futures (VIX) is more suitable to our analysis than the traditional realised volatility measures since investor sentiment is tied to a forward looking perspective, as defined by Baker and Wurgler (2007). On the contrary, realised volatility such as standard deviation or squared terms of prior period returns, takes a backward looking view, and thus is less relevant to our investigation. This is in line with Han and Park (2013) who compares realised volatility and VIX and proves the appropriateness of VIX for out-of-sample and forward-looking research.

Our econometric frameworks requires that variables are covariance stationary, with their first two moments finite and time-invariant. Our results from unit root tests indicate that all variables are covariance stationary.[16]

[15] A full list of all data sources and acronyms is available in Table A.3 in the appendix.

[16] Augmented Dickey-Fuller and Phillips-Perron unit test results for models with a (i) constant, (ii) drift, and (iii) drift and time trend are presented in Section A.1.2 of the appendix.

2.3.3 Data Aggregation Process

In order to familiarise the reader with the properties of our two main TRMI indices, *Buzz* and *Sentiment*, we plot the raw series, autocorrelation functions (ACF) and partial autocorrelation functions (PACF) up to 40 lags in Appendix Figures A.1 and A.3 (pages 130 and 131). We observe large outliers and strong weekly seasonality in *Buzz* series for both social and news media. Winsorizing *Buzz* metrics at the 99 percentile (right tail only) mitigates the effects of extreme outliers.[17]

To deal with weekly effects in *Buzz* and *Sentiment* series, we regress *Sentiment* and winsorized *Buzz* on day-of-the-week dummy variables, retaining fitted residuals as our seasonally adjusted data. Figure A.2 in the appendix plots the winsorized and seasonality adjusted *Buzz* series. Lastly, we align seasonality adjusted TRMI indices with market variables for trading days only. The values for sentiment indices during non-trading days are averaged with the sentiment index value on the first trading day immediately after a weekend or public holiday. For example, sentiment indices on Monday represent average values based on Saturday, Sunday and Monday sentiment scores. Figure A.4 in the appendix depicts the seasonality adjusted and non-trading day merged *Sentiment* series. After combining with stock market data, our sample size reduces from 2,526 observations to 1,803 for each time-series. A comparison of Figures A.2 and A.4 shows that we have successfully removed the weekly seasonality from both the buzz and sentiment series. This concludes our data pre-processing, with both series, *Buzz* and *Sentiment*, exhibiting stationary, strong autocorrelation and long memory, allowing us to pinpoint the best econometric framework for this type of series.

2.3.4 Econometric Framework

To capture interdependence between news and social media while avoiding explicit exogeneity assumptions, we adopt the vector autoregressive (VAR) framework.[18] VAR provides a simple framework systematically capturing rich dynamics in multiple time-series. We rely on a rolling-window VAR approach to investigate our main research questions, respectively: (1) How social and news media interact with each other over time? (2) What are the dynamic relationships between media activities and stock market activities?

To identify a group of simultaneous equation models, one has to make assumptions about endogeneity of the variables considered: which variables are deemed endogenous while others are purely exogenous? These decisions are often criticized as being too subjective (Gujarati, 2009). VAR overcome this shortcoming since it does not assign any prior distinction between endogenous and exogenous variables, i.e. all variables in VAR are endogenous. Thus, to investigate how social and news media

[17]We perform asymmetric winsorizing since *Buzz*, describing media activity quantities, is bounded on $[0, \infty)$.

[18]Sims (1980) advocated VAR models as providing a theory-free method to estimate linear interdependence among time-series and to avoid the "incredible identification restrictions".

activeness (*Buzz*) and emotions (*Sentiment*) intertwine with each other over time, and further to probe how media sentiment and stock market associate with each other, we adopt a general VAR framework setup shown as follow:[19]

General Setup: Let $\mathbf{x}_t$ be a multivariate time series, a VAR process of order 1, or VAR(1) for short, follows the model:

$$\mathbf{x}_t = \phi_0 + \mathbf{\Phi} \cdot \mathbf{x}_{t-1} + \epsilon_t$$

where ϕ_0 is a k-dimensional vector, $\mathbf{\Phi}$ is a $k \times k$ matrix, and $\{\epsilon_t\}$ is a sequence of serially uncorrelated random vectors with mean zero and covariance matrix Ω.[20] For instance, $\mathbf{x}_t$ could consist of any number of the following variables:

- market data (e.g., *return*, *volume*, and/or *volatility*);
- TRMI social indices (e.g., *buzz*, *sentiment* and/or *fear*);
- TRMI news indices (e.g., *buzz*, *sentiment*, *gloom*, etc.);

$\mathbf{x}_t$ can be generalized to VAR(p), where p is the number of lags considered. To choose the appropriate lag length, p, we use the Akaike Information Criterion (AIC) and Schwartz's Bayesian Information Criterion (BIC).[21] BIC generally penalizes free parameters more strongly than AIC, allowing for more parsimonious models.[22]

2.4 News vs Social Media: Dominating Causality Pattern

We investigate the question: how financial news media landscape changed in the past decade by examining the dynamic relations between $Buzz_S$ and $Buzz_N$ from estimating a VAR(1) model using S&P500 TRMI company group data. *Buzz* metric is conceptually different from the emotional and fundamental scores.[23] It measures the volume of information flow and, in fact, is used in calculating the emotional and fundamental scores. We choose it because it is the most representative stock index in the US market, comprising of the most liquid large-cap companies representing approximately 80% of the US equity market capitalization. By restricting the analysis to the S&P500 group, we ensure that the companies in our aggregate sample are sufficiently large to receive regular media coverage. To help with the interpretation of the results, we rewrite the general VAR model in scalar form, where we set $k = 2, \mathbf{x}_t = (Buzz_S, Buzz_N)'$:

$$\begin{aligned} Buzz_{S,t} &= \phi_{S,0} + \Phi_{11} Buzz_{S,t-1} + \Phi_{12} Buzz_{N,t-1} + \epsilon_{1,t}, \\ Buzz_{N,t} &= \phi_{N,0} + \Phi_{21} Buzz_{S,t-1} + \Phi_{22} Buzz_{N,t-1} + \epsilon_{2,t}. \end{aligned} \tag{2.1}$$

[19]A full list of variables, the notations and definitions of them used in this study is available in Table A.3.
[20]$\{\epsilon_t\}$ is also called impulse, or innovations (Tsay, 2005).
[21]For notation and definition details, refer to Table A.3 in the appendix.
[22]We conduct formal hypothesis test using the likelihood ratio statistic. Our results are reported in Section B.2.3.
[23]See supplementary appendix for details on these definitions in Section B.3.

Here, $\Phi_{1,2}$ denotes the linear dependence of $Buzz_{S,t}$ on $Buzz_{N,t-1}$ with lagged dependent variable $Buzz_{S,t-1}$ also as a regressor, so $\Phi_{1,2}$ captures the conditional effect of $Buzz_{N,t-1}$ to $Buzz_{S,t}$ given $Buzz_{S,t-1}$. Analogous interpretation for $\Phi_{2,1}$ applies. Gujarati (2009) distinguishes four cases for such VAR system:

1. Unidirectional causality from $Buzz_N$ to $Buzz_S$ if $\Phi_{1,2}$ is significantly different from zero while $\Phi_{2,1}$ is **NOT** significantly different from zero;
2. Inverse unidirectional causality from $Buzz_S$ to $Buzz_N$ if $\Phi_{2,1}$ is significantly different from zero while $\Phi_{1,2}$ is **NOT** significantly different from zero;
3. Feedback, or bilateral causality, when **both** $\Phi_{1,2}$ and $\Phi_{2,1}$ are significantly different from zero;
4. Independence, when **neither** $\Phi_{1,2}$ nor $\Phi_{2,1}$ are significantly different from zero.

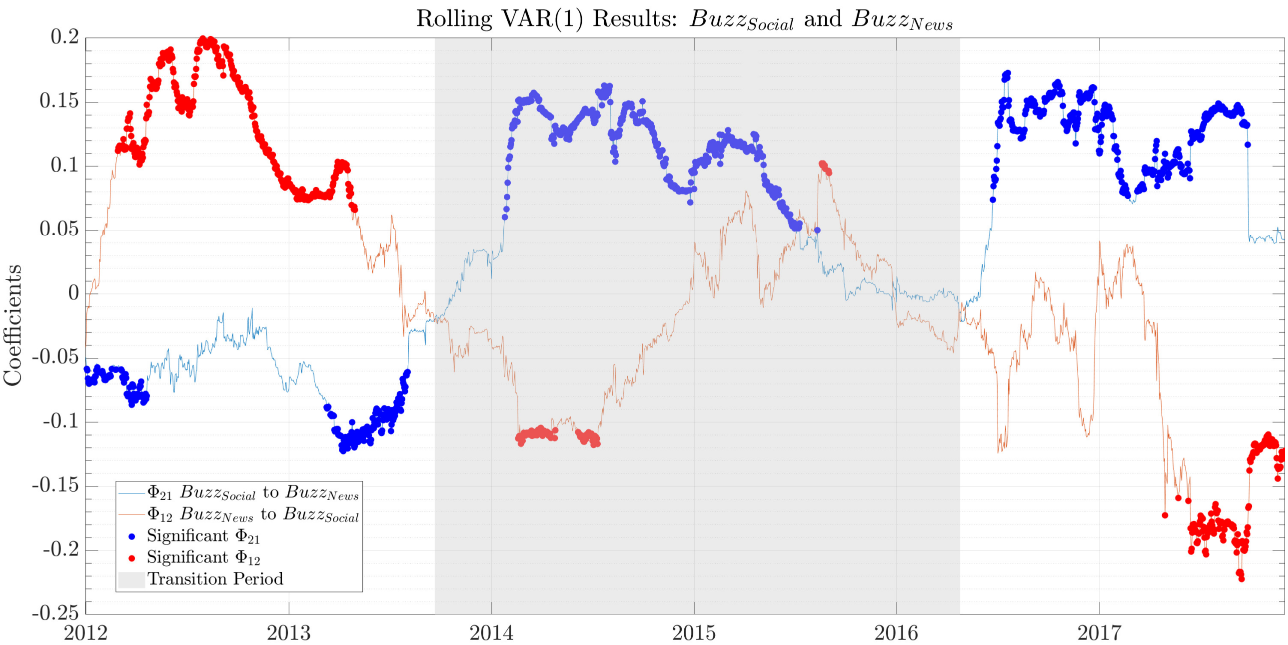
Our interest lies in the off-diagonal regression coefficients because the level and significance of VAR off-diagonal coefficients characterize causal relationships, while diagonal elements only show autocorrelation effects.

To perform a rolling-window analysis, we use the past 365 days (i.e. the prior one-year period) as an estimation window. We obtain off-diagonal elements of slope coefficients (Φ_{12} and Φ_{21}) and test their significance. We repeat this analysis on each day for the reminder of the sample to capture the dynamics and evolution of the causal relationship over time. Figure 2.1 presents the results of this procedure. Each vertical pair of observations represents the off-diagonal slope coefficients of a VAR(1) model. Statistically significant results are emphasised with bold points.[24] Following DeMiguel et al. (2014), we define "dominating" or "leading" series as follow: in an off-diagonal coefficients plot of a two-variable rolling-horizon VAR system, if one coefficient is significant, the other coefficient is insignificant, then the significant series "leads" or "dominates" the insignificant series. If both coefficients are significant, then the higher magnitude coefficient "leads" or "dominates" the lower magnitudes series.

From Figure 2.1, we observe that the blue and red coefficients crossed in October 2013. Prior to this "transition" point, the magnitude of red line (Φ_{12}) is above blue line (Φ_{21}), with more numbers of Φ_{12} coefficients being significant than the Φ_{21} coefficients. For example, in Table 2.2 Panel A left side, we report one of the VAR(1) results based on equation (1) in the pre-transition period. ϕ_{12}, the impact from $Buzz_N$ to $Buzz_S$, is 0.1927 and significant at 1% level. By contrast, ϕ_{21}, the impact from $Buzz_S$ to $Buzz_N$, is -0.0329 and not statistically significant. This phenomenon reveals the fact that news media activity dominates social media activities before October 2013. After this "flip-point", we

[24]Based on our analysis, a VAR model with 7 lags is optimal according to BIC criterion. Detailed AIC and BIC results are available in our supplementary appendix (Table B.2 Panel A on page 146). However, we report VAR(1) as it is a parsimonious form of VAR(7) based on the model specification test shown in Table B.3 on page 147 of the appendix. According to Table B.3, most of the intermediate lags' coefficients in VAR(7) model are insignificant, and only the coefficients of the seventh-lag and the coefficients of the first lag are significant, suggesting that the optimal lags determined by the information criteria might be due to the remaining weekly seasonality, which could not be modelled. Similar rolling window VAR(1) approach was used in DeMiguel et al. (2014) in investigating the cross-correlations between size portfolios over time. The results of our VAR(7) model are available upon request.

Figure 2.1: Rolling Window VAR(1) Off-Diagonal Elements - daily *Buzz*. This plot depicts the inter-relationships between $Buzz_S$ and $Buzz_N$ series from 2011/01/01 to 2017/11/30. Sample contains 2,526 observations for each series, with the first 365 observations used as pre-estimation window. The red line represents the leading effect from news media to social media, Φ_{12} in equation system 2.1, and the blue line indicates the leading effect from social media to news, Φ_{21} in equation system 2.1. Coefficients that are significant at the 90% level are shown with bold dots. The shaded area indicates a transition period. We rely on the crossings of the two lines: estimated effect of previous $Buzz_S$ on current $Buzz_N$ (blue line) and estimated effect of previous $Buzz_N$ on current $Buzz_S$ (red line). In the beginning of our sample, as we roll the estimation window, the two lines converge. Towards the end of our sample, the two lines begin to diverge. We used the first and the last crossing points as the dates for the beginning and the end of the transition period, respectively.



observe that the values of blue coefficients exceed the red coefficients. From 2014 to 2016, there are periods that both blue and red coefficients are significant, indicating news and social media mutually Granger cause each other. We interpret this period as a transition period (the grey shaded period). We find that the "flip-point" date identified from our data coincidences with the SEC's permission to new format media announcements as mentioned in Section 4.1. Lastly, we find that after mid-2016, Φ_{21} (the blue line, social to news) trends further upward, remaining significant, while Φ_{12} (the red line, news to social) fluctuates and tend to trend downward, indicating a prominent influence of social media on conventional news. Meanwhile, as shown in the right side of Panel A Table 2.2, ϕ_{21}, the coefficient from $Buzz_S$ to $Buzz_N$, equals to 0.1101 and is significant at 1% level, while a lower level ϕ_{12}, the coefficient from $Buzz_N$ to $Buzz_S$, is not statistically significant. This result confirms the dominant effect of social media over news after January 2016. Overall, our results shows that there has been a change in the information landscape and market conditions with the distinct propagation of social media is playing a predominant role in the flow of information.

Table 2.2: Before vs After Transition Period VAR Slope Coefficients: Social vs News. Panel A reports the estimated VAR(1) slope coefficients for system equations 2.1:

$$Buzz_{S,t} = \phi_{S,0} + \Phi_{11} Buzz_{S,t-1} + \Phi_{12} Buzz_{N,t-1} + \epsilon_{1,t}$$
$$Buzz_{N,t} = \phi_{N,0} + \Phi_{21} Buzz_{S,t-1} + \Phi_{22} Buzz_{N,t-1} + \epsilon_{2,t}$$

Panel B presents the estimated VAR(1) slope coefficients for system equations 2.2:

$$Sent_{S,t} = \phi_{S,0} + \Phi_{11} Sent_{S,t-1} + \Phi_{12} Sent_{N,t-1} + \epsilon_{1,t}$$
$$Sent_{N,t} = \phi_{N,0} + \Phi_{21} Sent_{S,t-1} + \Phi_{22} Sent_{N,t-1} + \epsilon_{2,t}$$

p-values below 0.1, 0.05, and 0.01 are denoted as *, **, and *** respectively. In Panel A, ϕ_{12} represents the effects from news media volume to social media activeness, while ϕ_{21} shows the impacts from social media activity to news article volume. ϕ_{11} and ϕ_{22} in Panel A are the autocorrelations for $Buzz_S$ and $Buzz_N$ respectively. In Panel B, ϕ_{12} and ϕ_{21} coefficients represent the effects from net sentiment on news media to social media based sentiment, while ϕ_{21} shows the impacts from social media sentiment to news-based sentiment. ϕ_{11} and ϕ_{22} in Panel B are the autocorrelations for $sent_S$ and $Sent_N$ respectively.

Panel A: $Buzz_S$ vs $Buzz_N$

	Pre-transition Period					Post-transition Period			
	Coef.	*s.e.*	*t*-stat	*p*-value		Coef.	*s.e.*	*t*-stat	*p*-value
ϕ_{11}	0.8719	0.0418	20.86***	0.00***	ϕ_{11}	0.5199	0.0684	7.60***	0.00***
ϕ_{12}	0.1927	0.0388	4.96***	0.00***	ϕ_{12}	0.0416	0.0998	0.42	0.68
ϕ_{21}	-0.0329	0.0547	-0.60	0.55	ϕ_{21}	0.1101	0.0435	2.53***	0.01***
ϕ_{22}	0.5577	0.0508	10.97***	0.00***	ϕ_{22}	0.7021	0.0634	11.07***	0.00***

Panel B: $Sent_S$ vs $Sent_N$

	Pre-transition Period					Post-transition Period			
	Coef.	*s.e.*	*t*-stat	*p*-value		Coef.	*s.e.*	*t*-stat	*p*-value
ϕ_{11}	0.6421	0.0465	13.81***	0.00***	ϕ_{11}	0.6807	0.0435	15.65***	0.00***
ϕ_{12}	0.2325	0.0601	3.87***	0.00***	ϕ_{12}	0.0166	0.0481	0.34	0.73
ϕ_{21}	-0.0089	0.0390	-0.23	0.82	ϕ_{21}	-0.1589	0.0470	-3.38***	0.00***
ϕ_{22}	0.4503	0.0504	8.94***	0.00***	ϕ_{22}	0.3907	0.0520	7.51***	0.00***

Next, we examine how the emotions expressed in news and social media intertwine with each other across time. Following the same methodology, we represent $k = 2, \mathbf{x}_t = (Sent_S, Sent_N)'$ in the General

Setup of VAR(1)[25] In Figure 2.2, we observe a sharp difference in the magnitudes of VAR coefficients (between Φ_{12} and Φ_{21}) prior to the shaded transition period. Specifically, the one-day lead effect from news sentiment to social (red, Φ_{12}) is significantly higher than the effect from social sentiment to news (blue, Φ_{21}). For example, in the left side of Panel B in Table 2.2, one of the VAR regression results in the "Pre-transition Period" shows that the coefficient of news to social sentiment effect (ϕ_{12}) is 0.2325 with t-statistics and p-value significant at 1% level. In contrast, the coefficient of social to news sentiment effect (ϕ_{21}) is -0.0089, a much lower level compared with ϕ_{12}, 0.2325, with insignificant p-value (0.82). Continuing our investigation of Figure 2.2, we find that, in spite of some fluctuations in the transition period when news and social mutually influence each other, the impact of social media sentiment effect dominates in the final part of our sample period, which is similar to the buzz analysis pattern. We also observe that most of the red (Φ_{12}) coefficients are not significant in this post-transition episodes, while more blue (Φ_{21}) coefficients are significant and at higher magnitudes. For instance, the right side of Panel B in Table 2.2 indicates that one of the "Post-transition Period" VAR has social to news effect (ϕ_{21}) of -0.1589, which is significant at 1% level. But influences from news to social media sentiment (ϕ_{12}) become insignificant (p-value of 0.73) at a lower level of 0.0166. This result is consistent with the pattern we identified in Figure 2.1. In both figures, news media impacts are leading social media effects before the transition period, however, after the transition period, this pattern is reversed.[26]

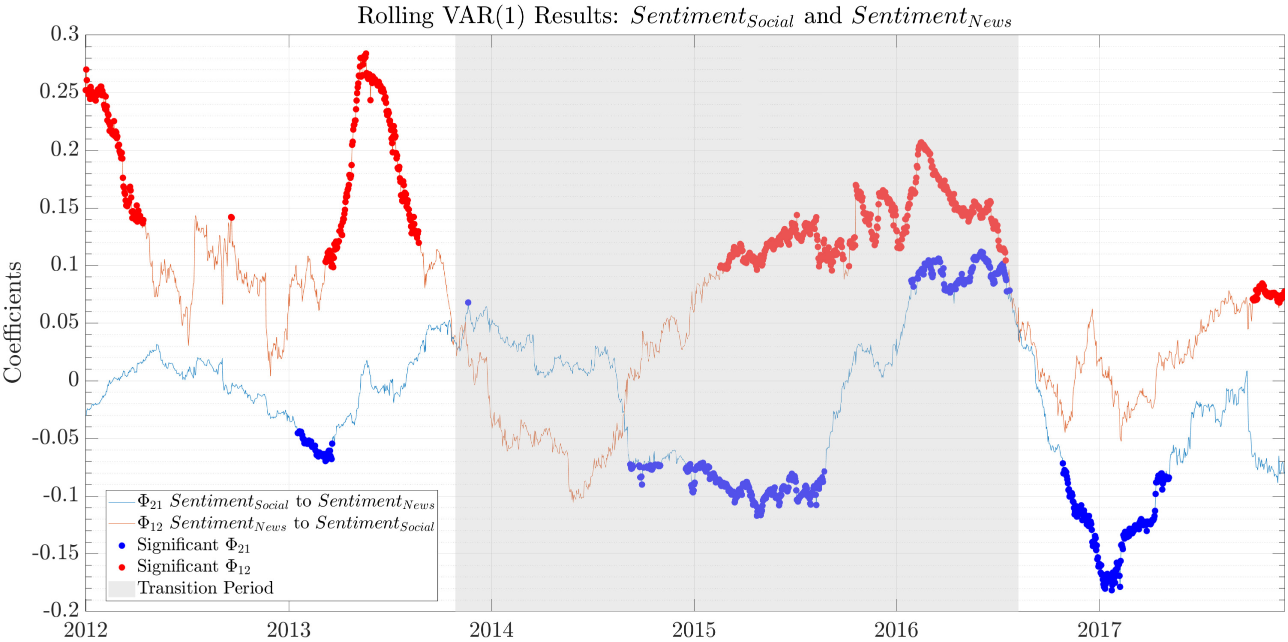
[25]Table B.3 Panel B in the Appendix provides evidence substantiating that VAR(1) is a parsimonious model of VAR(7) by listing coefficient estimates for intermediate lags and their significance levels, and rewrite the model as equation system (2):

$$\begin{aligned} Sent_{S,t} &= \phi_{S,0} + \Phi_{11} Sent_{S,t-1} + \Phi_{12} Sent_{N,t-1} + \epsilon_{1,t} \\ Sent_{N,t} &= \phi_{N,0} + \Phi_{21} Sent_{S,t-1} + \Phi_{22} Sent_{N,t-1} + \epsilon_{2,t} \end{aligned} \tag{2.2}$$

The rolling-window results from equation system (2) are plotted in Figure 2.2.

[26]Changes in TRMI data source does not appear to be the cause of this time-varying relationship. As shown in Figure B.5 on page 158, the major change in social media sources used by MarketPsych was in 2009, when Thomson Reuters added Moreover Technology into the aggregated news feed, while news media source had its last revamp in 2005. The data provided to us by Thomson Reuters for this research begins in 2011, which is not interfered by the change of data source from TRMI.

Figure 2.2: Rolling Window VAR(1) Off-Diagonal Elements - daily *Sentiment*. This plot depicts the inter-relationships between $Sent_S$ and $Sent_N$ series from 2011/01/01 to 2017/11/30. Sample contains 2,526 observations for each series, with the first 365 observations used as pre-estimation window. The shaded area indicates a transition period. The red line represents the leading effect from news media to social media, Φ_{12} in equation system 2.2, and the blue line indicates the leading effect from social to news, Φ_{21} in equation system 2.2. Coefficients that are significant at the 90% level are shown with bold dots.



2.5 Media vs Market: Sub-sampling Period Comparison

Now that we have established that there is a transition period, we turn our attention to the question of how sentiment impacts on the stock market during the two periods: the pre-2014 and post-2016 sessions. Accordingly, we merge and synchronise the seasonality adjusted social and news *Sentiment* series with stock variables by averaging *Sentiment* values on non-trading days. Next, to deal with the scale difference problem, we standardise all series to have zero mean and unit standard deviation prior to estimation. As identified in the previous section, we separate our sample period into three sub-periods: the pre-transition period (from Jan 2011 to Dec 2013), the transition period (from Jan 2014 to Dec 2015), and the post-transition period (from Jan 2016 to Nov 2017).

2.5.1 Sentiment vs Return

To examine the relationship between returns and sentiment, we estimate the following two systems by replacing $k = 2$, $x = (Sent_S, r)'$ and $x = (Sent_N, r)'$ respectively in the General Setup of VAR(1):

$$\begin{aligned} Sent_{S,t} &= \phi_{S,0} + \Phi_{11} Sent_{S,t-1} + \Phi_{12} r_{t-1} + \epsilon_{1,t} \\ r_t &= \phi_{N,0} + \Phi_{21} Sent_{S,t-1} + \Phi_{22} r_{t-1} + \epsilon_{2,t} \end{aligned} \tag{2.3}$$

$$\begin{aligned} Sent_{N,t} &= \phi_{S,0} + \Phi_{11} Sent_{N,t-1} + \Phi_{12} r_{t-1} + \epsilon_{1,t} \\ r_t &= \phi_{N,0} + \Phi_{21} Sent_{N,t-1} + \Phi_{22} r_{t-1} + \epsilon_{2,t} \end{aligned} \tag{2.4}$$

This VAR setup allows us to account for the mutual impacts between return and media sentiment. We focus on the pre-2014 and after-2016 episodes, omitting the transition period because the dominating pattern during the transition period is less obvious.[27].

Panels A and B in Table 2.3 summarise the results for VAR systems in (3) and (4) respectively over pre- and post-transition periods. The coefficients estimated are the initial sensitivities of the dependent variable to lagged independent variables. For example, ϕ_{12} from both pre- and post-transition periods in Panels A and B are positive and significant at 5% level: 0.0995 in the pre-transition period, and 0.1929 in the post-transition period for the social media sentiment VAR system in Panel A; 0.1060 in the pre-transition period and 0.2171 in the post-transition period for the news sentiment regression in Panel B. These results indicate that returns have positive and significant impacts on both social and news sentiment. In contrast, initial sensitivities of returns to sentiment, the ϕ_{21} coefficients in Panels A and B, are insignificant for all four estimators. This result is consistent with the extant literature. For example, Sprenger et al. (2014a) also finds that the feedback effect from stock market to social media variables prevails. To get a better understanding of these results, and to contrast news and social media effects, we generate Impulse Response Functions (IRFs) for the leading 20 working days (equivalent to approximately one month) in Figure 2.3.

[27]As is shown in Table B.2 in the Appendix, VAR(5) is optimal for these two systems according to BIC. However, we report VAR(1) results in Table 2.3 due to parsimony of VAR(1) model combined with the fact that intermediate lags, that is lags 2, 3, and 4, are insignificant. The lag 5 (trading days only data) corresponds to remaining weekly seasonality, which could not be modelled. This is consistent with our analysis in Section 2.4, where we analysed sentiment indices and observed significance at lag 7 (calendar day weekly seasonality)

Table 2.3: Before vs After Transition Period VAR Slope Coefficients: Sentiment Vs Market. Panel A reports the estimated VAR(1) slope coefficients for:

$$Sent_{S,t} = \phi_{S,0} + \Phi_{11}Sent_{S,t-1} + \Phi_{12}r_{t-1} + \epsilon_{1,t}$$
$$r_t = \phi_{N,0} + \Phi_{21}Sent_{S,t-1} + \Phi_{22}r_{t-1} + \epsilon_{2,t}$$

Panel B reports the estimated VAR(1) slope coefficients for:

$$Sent_{N,t} = \phi_{S,0} + \Phi_{11}Sent_{N,t-1} + \Phi_{12}r_{t-1} + \epsilon_{1,t}$$
$$r_t = \phi_{N,0} + \Phi_{21}Sent_{N,t-1} + \Phi_{22}r_{t-1} + \epsilon_{2,t}$$

Panel C reports the estimated VAR(1) slope coefficients for:

$$Sent^2_{S,t} = \phi_{S,0} + \Phi_{11}Sent^2_{S,t-1} + \Phi_{12}V_{t-1} + \epsilon_{1,t}$$
$$V_t = \phi_{N,0} + \Phi_{21}Sent^2_{S,t-1} + \Phi_{22}V_{t-1} + \epsilon_{2,t}$$

Panel D reports the estimated VAR(1) slope coefficients for:

$$Sent^2_{N,t} = \phi_{S,0} + \Phi_{11}Sent^2_{N,t-1} + \Phi_{12}V_{t-1} + \epsilon_{1,t}$$
$$V_t = \phi_{N,0} + \Phi_{21}Sent^2_{N,t-1} + \Phi_{22}V_{t-1} + \epsilon_{2,t}$$

p-values below 0.1, 0.05, and 0.01 are denoted as *, **, and *** respectively. In Panel A, ϕ_{12} represents the effects from return shocks to social media sentiment, while ϕ_{21} shows the impacts from social media sentiment to return. ϕ_{12} and ϕ_{21} coefficients in Panel B represent the same lead-lag relations as shown in Panel A, but for news-based sentiment. ϕ_{11} and ϕ_{22} are the autocorrelation for *Sentiment* and *Return* in Panels A and B. Likewise, in Panel C, ϕ_{12} represents the effects from volatility (VIX) to social media sentiment, while ϕ_{21} shows the impacts from social media sentiment to stock volatility. ϕ_{12} and ϕ_{21} coefficients in Panel D represent the same lead-lag relations as shown in Panel C, but for news-based sentiment. *Sentiment* is measured as the squared term of the seasonality adjusted and non-trading day averaged *Sentiment* series in Panels C and D, and ϕ_{11} and ϕ_{22} are the autocorrelation for $Sent^2$ and VIX in these two panels.

Panel A: $Sent_S$ **vs** *Return*

	Pre-transition Period					Post-transition Period			
	Coef.	*s.e.*	t-stat	p-value		Coef.	*s.e.*	t-stat	p-value
ϕ_{11}	0.3957	0.0581	6.81***	0.00***	ϕ_{11}	0.6041	0.0503	12.02***	0.00***
ϕ_{12}	0.0995	0.0455	2.19**	0.03**	ϕ_{12}	0.1929	0.1040	1.85*	0.06*
ϕ_{21}	-0.0345	0.0807	-0.43	0.67	ϕ_{21}	-0.0130	0.0301	-0.43	0.67
ϕ_{22}	-0.0925	0.0632	-1.46	0.14	ϕ_{22}	-0.1256	0.0624	-2.01**	0.04**

Panel B: $Sent_N$ **vs** *Return*

	Pre-transition Period					Post-transition Period			
ϕ_{11}	0.4469	0.0561	7.97***	0.00***	ϕ_{11}	0.4007	0.0572	7.00***	0.00***
ϕ_{12}	0.1060	0.0567	1.87*	0.06*	ϕ_{12}	0.2171	0.0949	2.29**	0.02**
ϕ_{21}	0.0849	0.0620	1.37	0.17	ϕ_{21}	0.0555	0.0374	1.48	0.14
ϕ_{22}	-0.0896	0.0626	-1.43	0.15	ϕ_{22}	-0.1257	0.0621	-2.02**	0.04**

Panel C: $Sent^2_S$ **vs** V_t

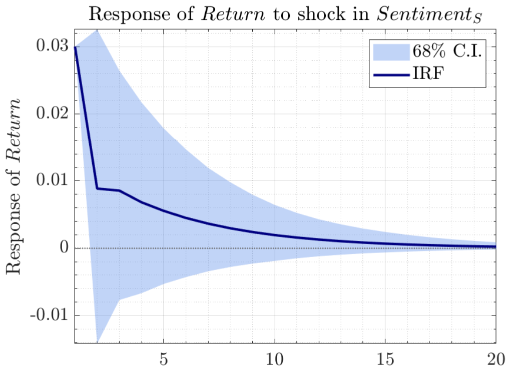
	Pre-transition Period					Post-transition Period			
ϕ_{11}	0.1520	0.0627	2.43**	0.02**	ϕ_{11}	0.5932	0.0508	11.67***	0.00***
ϕ_{12}	-0.0035	0.0677	-0.05	0.96	ϕ_{12}	-0.0386	0.1827	-0.21	0.83
ϕ_{21}	0.0270	0.0326	0.83	0.41	ϕ_{21}	-0.0027	0.0100	-0.27	0.79
ϕ_{22}	0.8327	0.0353	23.61***	0.00***	ϕ_{22}	0.8214	0.0358	22.95***	0.00***

Panel D: $Sent^2_N$ **vs** V_t

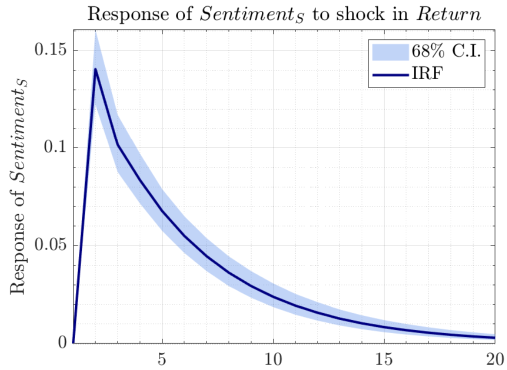
	Pre-transition Period					Post-transition Period			
ϕ_{11}	0.0385	0.0629	0.61	0.54	ϕ_{11}	0.3080	0.0607	5.07***	0.00***
ϕ_{12}	0.1889	0.1256	1.50	0.13	ϕ_{12}	0.6468	0.2877	2.25**	0.02**
ϕ_{21}	0.0089	0.0177	0.50	0.62	ϕ_{21}	0.0135	0.0078	1.74*	0.08*
ϕ_{22}	0.8287	0.0353	23.50***	0.00***	ϕ_{22}	0.8052	0.0368	21.90***	0.00***

Figure 2.3: *Sentiment* vs *Return* Sub-sample Comparison. Panel (a) to (d) are IRFs of $x_t = (Sent_S, r_t)'$; panel (e) to (h) are IRFs of $x_t = (Sent_N, r_t)'$. "Pre" denotes Pre-transition period: 2011/01/01-2013/12/31; "Post" denotes Post-transition period: 2016/01/01-2017/11/30. Horizontal axis represent lagged days of IRFs. All time-series are standardized to have zero mean and unit variance. Error bands are constructed at the 68% interval following Sims and Zha (1999).

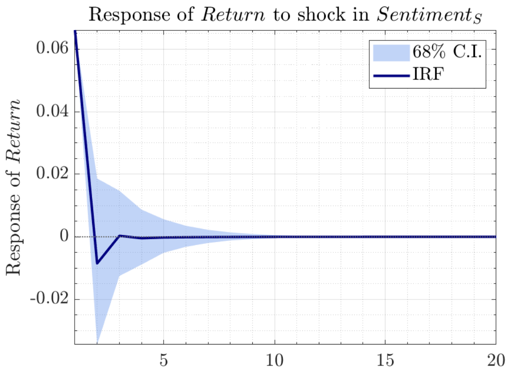
(a) Pre: r_t response to $Sent_S$ shocks



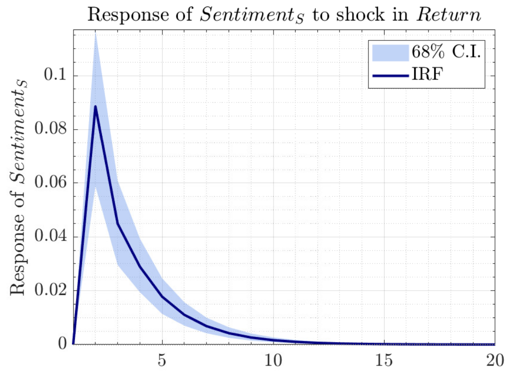
(b) Pre: $Sent_S$ response to r_t shocks



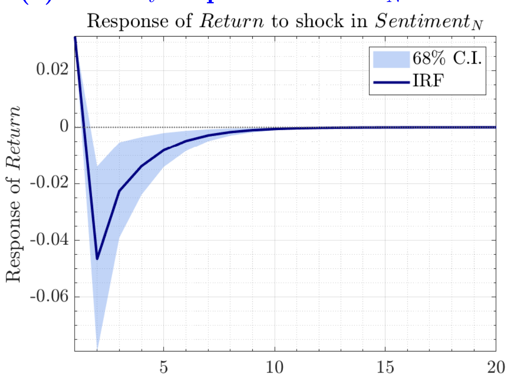
(c) Post: r_t response to $Sent_S$ shocks



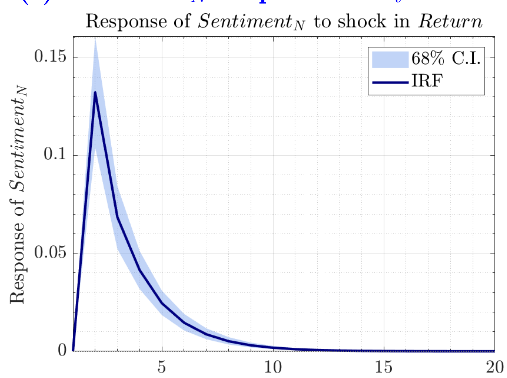
(d) Post: $Sent_S$ response to r_t shocks



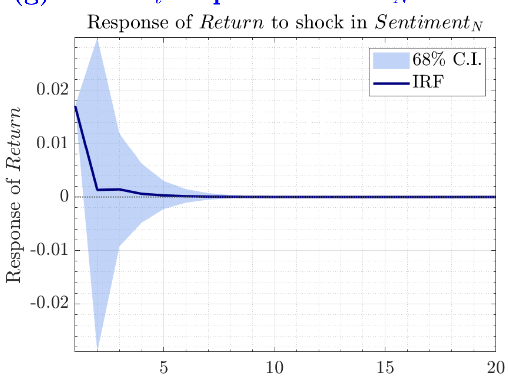
(e) Pre: r_t response to $Sent_N$ shocks



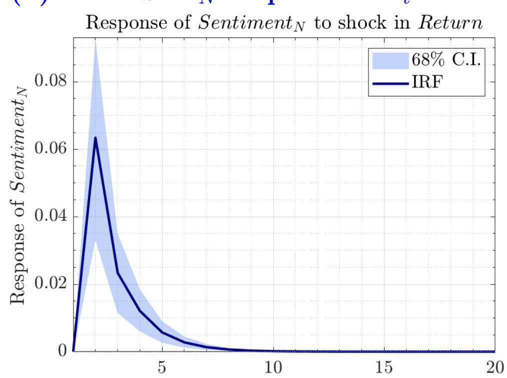
(f) Pre: $Sent_N$ response to r_t shocks



(g) Post: r_t response to $Sent_N$ shocks



(h) Post: $Sent_N$ response to r_t shocks



Plots on the left of Figure 2.3 represent IRFs that capture return responses to social or news media sentiment shocks. Panels (a) and (c) represent responses of return to **social** meida sentiment shocks in the pre- and post-transition period respectively, whereas Panels (e) and (g) are return responses to **news** sentiment shocks in the two sub-sampling periods respectively. All four left-hand side IRFs show that the initial impacts on return from sentiment (both social and news) are positive, and reverting back to zero gradually with deviations at different speeds. This finding is consistent with the overreaction hypothesis, which proposes that sudden surges in investor sentiment lead to temporarily spikes in stock prices that will retreat shortly.

A comparison of Panels (a) and (c) of Figure 2.3 reveals two interesting findings. First, the influence of social media sentiment on return increased after the transition period. In particular, the magnitude of IRFs expands from 0.03 before 2014 to 0.07 after 2016 - the sensitivity almost doubled the level after the transition. Second, the speed of revision for the temporary mispricing induced by social media sentiment has accelerated after 2016, comparing with that before 2014. In the pre-transition period, return reverts back to its original level in approximately 3 weeks (15 working days), while in the post-transition period, return shocks dissipate in only 2-3 days. Interestingly, the pattern of news media is just the opposite. The magnitude of initial impacts drops down from the pre-transition level of 0.030 (Panel (e)) to 0.016 in the post-transition period (Panel (g)) - approximately halved in value. Similar to the social media effects, the speed of reversion from news media influences also expedited in the post-transition period: return reverts back to its original level in about 8 to 9 working days in the pre-transition period (Panel (e)), but it only takes approximately 5 working days to revert in the post-transition period (Panel (g)).

Comparing Panels (a) and (e) in Figure 2.3, we find that, in the pre-transition period, returns are more sensitive to news sentiment impact than to social media sentiment. Panel (e) shows that with respect to a unit of shocks from news sentiment, returns over-correct to a negative level with a relatively narrower (more statistically significant) error band. In Panel (a), however, return gradually retreat with a wider error band with respect to shocks from social media sentiment. In contrast, a comparison between Panels (c) and (g) reveals that, in the post-transition period, returns exhibit strikingly higher sensitivity to social media sentiment impact than to news sentiment, as manifested by the higher initial reaction level (0.07 in Panel (c) vs 0.016 in Panel (g)) with a much narrower, thus more significant, error band in Panel (c) compared to Panel (g).

Panels of the IRFs on the right-hand side of Figure 2.3 indicate the reverse causalities of each of its respective left-hand side IRFs. All four panels (Panels (b), (d), (f) and (h)) exhibit similar patterns: a unit of shocks from stock return causes positive and significant increases in both social media based and news based sentiment the next day (observe spikes at lag 1 in the IRFs), and the increased sentiment revert back to zero exponentially at different speeds and in varied magnitudes. Similar to the results of the return responses, we find that the speed of sentiment reactions has also accelerated in the post-transition period. It takes about 20 working days for social media sentiment to correct itself before 2014 (Panel (b)), while it only takes approximately 12 working days to correct itself after 2016 (Panel (d)). Responses of news sentiment expedited, too. A unit of return shocks gives rise to rises in news sentiment that disappears in about 11 working days in the pre-transition period (Panel (f)), while this effect dies out in only approximately 7 working days in the post-transition sessions (Panel (h)).

Focusing on the magnitudes of sentiment responses (Panels (b), (d), (f) and (h) in Figure 2.3), we observe that both social media and news sentiment become less sensitive to returns at the post-transition period. For instance, a unit of return shocks results in 0.14 unit of heightened social media sentiment in the pre-transition period (Panel (b)), but this impact reduces to 0.09 unit in the post-transition period (Panel (d)). A unit of return shocks brings about 0.13 unit of news sentiment surges in the pre-transition session (Panel (f)), but this response contracts to a lower level of 0.065 at the post-transition stage (Panel (h)). It seems to be counter-intuitive to observe a reduced sensitivity to return in both social media and news sentiment (comparing Panels (b) with (d), and comparing (f) with (h)), but in fact it is not. One possible explanation to this phenomenon could be attributed to the scarcity of investor attention nowadays. The abundance of communication platforms and information channels facilitates information exchanges among noise traders, but at the same time, it also dilutes individual tone or sentiment. As a result, a single opinion would be less influential under the increased information flow, leading to a lowered level of media sensitivity to stock return. Another feasible explanation for this decreased sensitivity might come from the stricter requirements from the censorship authority and regulatory bodies, as documented and exemplified in Section 4.1.

In sum, the findings of interaction between return and sentiment in this subsection validate and extend the media induced transition pattern identified in Section 2.4: social media effects become stronger after 2016, whereas news media plays the predominant role before 2014. For both return and sentiment series, the speeds of correction in IRFs with regard to unexpected shocks have accelerated in the post-transition period compared with the pre-transition period, irrespective of the types of media used in sentiment measure. Relative to the pre-transition period, the magnitude of return responses to social media sentiment have elevated in the post-transition period, while such magnitude dwindled with respect to news-based sentiment post-transition. Albeit stronger than the causal effects from sentiment to returns, feedback effects of returns on social on news media based sentiment have both depreciated in the post-transition period compared to the pre-transition levels.

2.5.2 Sentiment vs Volatility

Applying the same methodology in investigating the return-sentiment effects, we continue to explore the dynamic relationships between media sentiment and stock volatility at the pre- and post-transition periods. We estimate the following system equations, by representing $k = 2$, $x = (Sent_S^2, VIX)'$ and $x = (Sent_N^2, VIX)$ respectively into the General Setup.

$$\begin{aligned} Sent_{S,t}^2 &= \phi_{S,0} + \Phi_{11} Sent_{S,t-1}^2 + \Phi_{12} V_{t-1} + \epsilon_{1,t} \\ V_t &= \phi_{N,0} + \Phi_{21} Sent_{S,t-1}^2 + \Phi_{22} V_{t-1} + \epsilon_{2,t} \end{aligned} \tag{2.5}$$

$$\begin{aligned} Sent_{N,t}^2 &= \phi_{S,0} + \Phi_{11} Sent_{N,t-1}^2 + \Phi_{12} V_{t-1} + \epsilon_{1,t} \\ V_t &= \phi_{N,0} + \Phi_{21} Sent_{N,t-1}^2 + \Phi_{22} V_{t-1} + \epsilon_{2,t} \end{aligned} \tag{2.6}$$

We choose VIX (V_t) as a measure of volatility in the above two systems because investor sentiment affects asset prices by shaping investors' beliefs about the future. In contrast, traditional realized volatility measures (RV), such as standard deviation or squared term of prior returns, are backward-looking. Therefore, we believe that an implied, forward-looking volatility measure is more closely related to investor beliefs and more appropriate to this research. A detailed comparison between historical volatility and VIX is provided by Han and Park (2013). In order to assess whether VIX is associated with both positive and negative sentiment, we take the squared term of sentiment ($Sent_S^2$ and $Sent_N^2$) as a measure of the high sentiment period with strong emotions.[28] The benefit of using squared term of sentiment lies in its incorporation of the disagreement of opinions expressed in social and news media. Since our sentiment scores are volume-weighted[29] net values of positive and negative emotions conveyed in the parsed texts, the higher the $Sent^2$, the more likely that the grouped investors are driven by a similar kind of emotion. For example, when $Sent_S^2$ takes a value close to 1, most investors posting in social media are extremely optimistic, or are uniformly angry. Therefore, higher values of $Sent^2$ indicate less disagreement among investors' opinions. On the other hand, we interpret lower values of $Sent^2$ as containing more disagreement among investors' opinions, since a lower value of $Sent^2$ might result from: i) weak emotions expressed in media; and ii) strong positive and negative emotions expressed at the same time, but these parsed texts' scores cancelling with each other. We do not worry

[28] The choice of $Sent^2$ is rooted in the fact that the relationship between volatility and sentiment is nonlinear. Only extreme values of sentiment show relationship with VIX, and both high negative and high positive sentiment resulted in high VIX values. The transformation is consistent with the choice of absolute value of sentiment, $|Sentiment|$, in Brown (1999, p.84, Hypothesis 1) when analysing correlation between sentiment and volatility. Berger and Turtle (2015, p.65, Eq.1) document quadratic relationship between sentiment and volatility of portfolio returns. Using maximum likelihood estimation of the Box-Cox power transformation parameter, λ, in a linear model of the form $Sent^\lambda = \alpha + \beta \times VIX$, we confirm our choice to square *Sentiment* variable at the 95% confidence level. Results of this estimation are provided in Figure A.5 in the appendix on page 132.

[29] Thomson Reuters MarketPsych Indices 2.2 User Guide, 23 March 2016, Document Version 1.0, Chapter 13, page 32: *'all emotional measures are "buzz-weighted" indices.'*

about this difference because both case indicate a higher level of disagreement of opinions. Similar to the return-sentiment mutual impacts analysed in prior subsection, we match TRMI sentiment data with VIX by averaging the non-trading days' sentiment indices, and standardise each variable to contain zero mean and unit standard deviation before importing each series to the VAR systems.

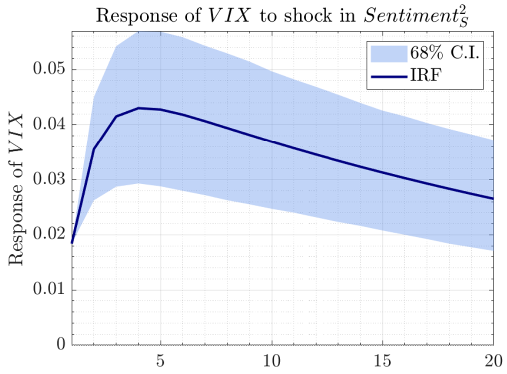
Panels C and D in Table 2.3 display the coefficients estimated and their level of significance for system equations (5) and (6) in the pre- and post-transition periods, respectively. These results suggest that the autocorrelation effect is more salient than the cross-impacts between sentiment and volatility. However, these values only indicate the initial responses, which do not help trace out the dynamics of responses for the dependent variable over time. Therefore, we put more emphasis on the impulse response functions (IRFs) rather than examining details of the VAR coefficients.

Left-hand side panels in Figure 2.4 (Panels (a), (c), (e) and (g)) depict the Impulse Response Functions (IRFs) of VIX responses to shocks from social media sentiment or news-based sentiment in both the pre- and post-transition periods. And the responses of media sentiment to shocks from VIX associated with the corresponding left panels, i.e. the feedback or reverse causality, are displayed in the right-hand side IRFs (Panels (b), (d), (f), and (h)). The top two panels in both sides (Panels (a), (b), (c), and (d)) are IRFs of the VIX and **social** media sentiment VAR system, while the bottom two panels in both sides (Panels (e), (f), (g) and (h)) are IRFs of the VIX and **news** media VAR system.

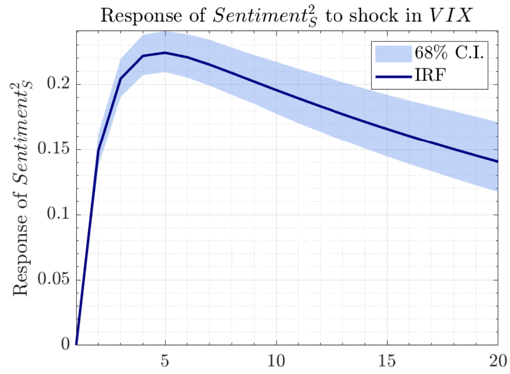
In both Panel (a) and (c) of Figure 2.4, we find that the extrema of VIX occur in 4 to 5 working days (about a week) following one unit of unexpected rise in social media sentiment, in the pre- and post-transition period respectively, and this process gradually corrects itself toward the original level. Error bands of these two IRFs do not cross zero, suggesting that volatility (VIX) responses are statistically different from zero over the IRFs forecasting window. In contrast to return responses (left side IRFs in Figure 2.3) that all revert back to zero within our IRFs observation window, the reaction of volatility (left side IRFs in Figure 2.4) dissipates after at least 20 working days (about a month), implying a more persistent effect compared to returns. In addition, we observe that in the pre-transition period, stock volatility is positively related to heightened social media sentiment (Panel (a)) - strong sentiment generates high VIX, while in the post-transition period (Panel (c)), volatility is negatively associated with the rising social media sentiment. VIX responses to news sentiment shocks (Panels (e) and (g)), however, exhibit totally different patterns from that of social media. Comparing Panels (e) and (g), we find that initial VIX response to news sentiment shocks in the pre- and post-transition periods contain similar values (about 0.006 to 0.007). Interestingly, in Panel (e), the IRFs coefficients over-correct in 4 working days, whereas in Panel (g), the IRFs gradually dilute over the observation window. Consistent with the social media effects shown in Panels (a) and (c), estimated IRFs do not revert back to zero at the 20 working-day observation window. The broader error bands in Panels (e) and (g), which cross zero at lagged 1 to 2 days after the shock, indicate that volatility is less sensitive to news sentiment

Figure 2.4: $Sentiment^2$ **VS** $\boldsymbol{VIX}$ **Sub-sample Comparison.** Panels (a) to (d) are IRFs of $x_t = (Sent^2_S, V_t)'$; Panels (e) to (h) are IRFs of $x_t = (Sent^2_N, V_t)'$. "Pre" denotes Pre-transition Period: 2011/01/01-2013/12/31; "Post" denotes Post-transition Period: 2016/01/01-2017/11/30. Horizontal axis represents lagged days of IRFs (20 days). All time-series are standardized to have 0 mean and variance equal to 1. Error bands are constructed at the 68% interval following Sims and Zha (1999).

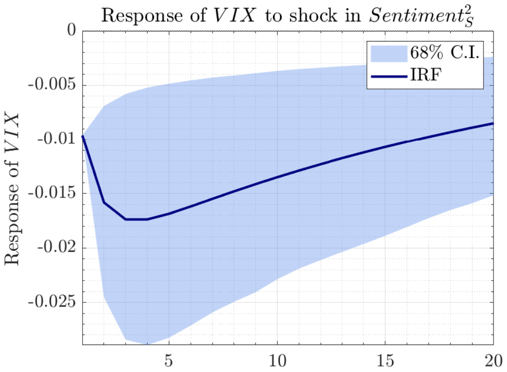
(a) Pre: VIX **response to** $Sent^2_S$ **shocks**



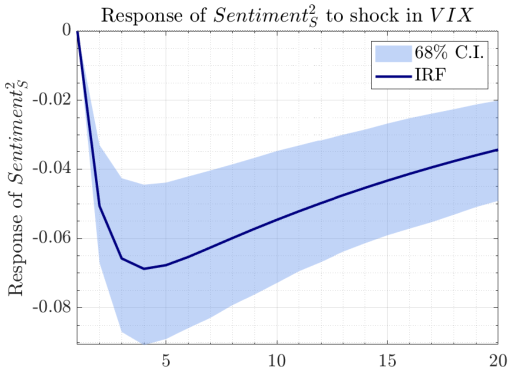
(b) Pre: $Sent^2_S$ **response to** VIX **shocks**



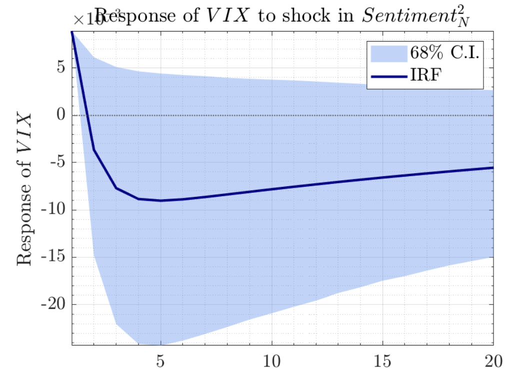
(c) Post: VIX **response to** $Sent^2_S$ **shocks**



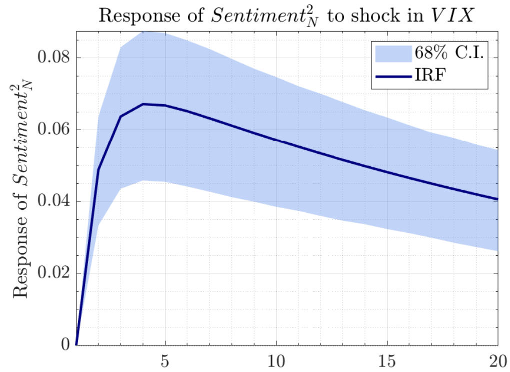
(d) Post: $Sent^2_S$ **response to** VIX **shocks**



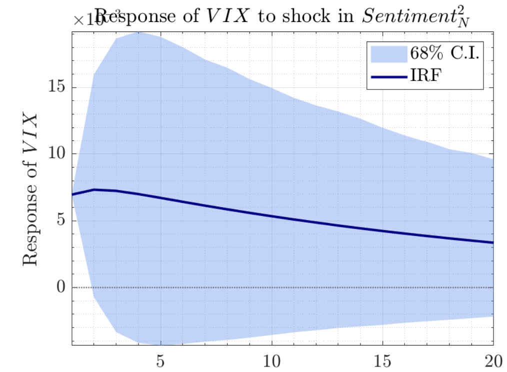
(e) Pre: VIX **response to** $Sent^2_N$ **shocks**



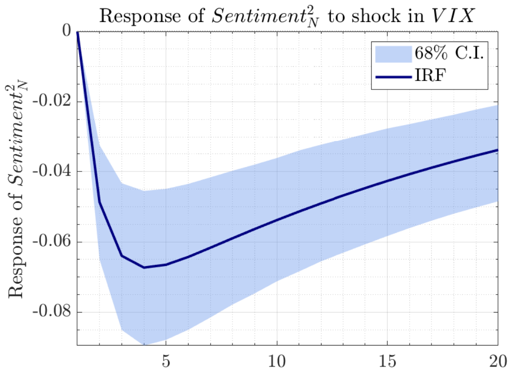
(f) Pre: $Sent^2_N$ **response to** VIX **shocks**



(g) Post: VIX **response to** $Sent^2_N$ **shocks**



(h) Post: $Sent^2_N$ **response to** VIX **shocks**



shocks than to social media sentiment shocks.

A comparison between the magnitudes of all four left-hand side panels with the right-hand side panels in Figure 2.4 reflects the fact that feedback effects from VIX to social media or news-based sentiment are stronger than the causal effects from media sentiment to VIX: the error bands of all four plots in the right side are significantly different from zero, and they are all narrower: statistically more significant than their left-hand side counterparts. In the pre-transition period, the positive IRFs in Panels (b) and (f) show that both social media and news-based sentiment spike higher following shocks from VIX, meaning the media formulates less disagreement with strong emotions after VIX surges higher. In the post-transition period, however, the upward concaved IRFs in Panels (d) and (h) illustrate that sentiment in social and news media with heightened VIX, regardless of the media type, becomes more neutral or contains more disagreement of opinion: both IFRs plots touch the troughs (approximately -0.07) after approximately 4 working days. In contrast to the fully correction situation in right side IRFs of Figure 2.3, none of the four right-hand side figures in Figure 2.4 displays fully correction after about 20 working days (one month), suggesting that VIX has a more persistent feedback effect on the media sentiment than return does.

To summarise the results in this section, although market volatility and media sentiment mutually cause each other, we find evidence that the feedback effects from market volatility on media sentiment prevail. This is consistent with Antweiler and Frank (2004), in their analysis of stock message boards, that stock messages help predict market volatility, however, the reverse feedback is stronger. Using TRMI data for the Brazilian market, Araújo et al. (2018) finds similar results, that is the reverse causal effects from VIX to social media or news-based sentiment are stronger than the causal effects from media sentiment to volatility. In addition to the aforementioned studies, we also find that VIX is more sensitive to social media sentiment than to news-based sentiment in terms of both reaction magnitudes and significance level. Comparing the pre- and post-transition periods, we observe that before 2014, high VIX level and strong emotions (or less disagreement) mutually cause each other, irrespective of the media type. After 2016, the heightened VIX is associated with neutral emotions (or more disagreement) for both social media and news. A comparison across the analysis performed for return in prior subsection (Figure 2.3) with analysis for volatility conducted in this subsection (Figure 2.4) reflects that, the mutual effects between media sentiment and volatility present a more persistent pattern than the inter-linkages between sentiment and return.

2.6 Conclusion

In this paper, we examine the dynamic relationships between social and news media activity, and the impact media has on the financial market. This paper contributes to the literature in several ways.

Firstly, we examine the relationship between two different types of media, traditional news media and the rapidly growing social media. Our results show that the influence of news media in terms of generating activity and imparting sentiment have waned in the period between 2011 and 2017. By 2016, social media had become the dominant information source in generating media activity and sentiment. Next, we examine whether the rising influence of social media have permeated through the financial markets by examining the time-varying relationship between investor sentiment and the market. That is, we analyse causality between media sentiment and market variables (specifically, return and volatility) under different market information environments: (i) period of conventional news media dominance at the beginning of our sample, and (ii) period of increasing dominance of social media at the end of our sample. Our findings indicate that social media is becoming dominant. This should be of great interests (and possibly, concern) to regulators as social media is vulnerable to manipulation and misinformation.

We also discover that, generally, market variables exert stronger impact on investor sentiment than the other way around. That is, the reaction of media sentiment to stock market changes is more pronounced than the sensitivity of return and volatility to changes in media sentiment. However, when we contrast the two types of media at the pre- and post-transition periods, we find that return responses to social media sentiment almost doubled after the transition period, while the return responses to news-based sentiment almost halved to its pre-transition level. We observe that volatility in both pre- and post-transition periods display higher sensitivity to social media sentiment than to news-based sentiment. In addition, we find that the linkage between volatility and sentiment is much more persistent than that between returns and sentiment. These results corroborate our prior findings that social media is becoming the dominant media source. Overall, our exploration and results reveal new facts about the role of information in the social media era. An interesting extension in future work could focus on individual companies at a more granular frequencies to assess the timeliness of the two media types.

Chapter 3

Investor Sentiment under the Microscope

"In the 21st century, it is the flow of attention, not information (which we already have too much of), that matters."

—MIT Technology Review

Investor Sentiment Under the Microscope

Abstract

Market-wide investor sentiment is known to exert influence on stock prices. Fewer studies have explored the impact of firm-specific investor sentiment on stock prices. Using the most granular intraday sentiment measures available, the minute-to-minute Thomson Reuters MarketPsych Indices (TRMI), we examine how the overnight build-up of investors' mood in news and social media affects opening stock returns. Our analysis reveals that sentiment formed during non-trading hours is a strong predictor of opening returns. Moreover, the sentiment generated by increasingly popular social media exerts a greater impact on opening prices than the sentiment found in traditional news media. Our results show that the impact of sentiment is asymmetric, with negative sentiment having a preeminent impact on opening returns. We find that the influence of sentiment quickly diminishes after the first minute of trading. These findings are consistent across a number of different models and specifications, providing further evidence against non-behavioral theories in this fast-paced digital era.

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

3.1 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 stories, reports, articles, comments, and posts in news and social media. Employing textual analysis and econometric modelling, financial economists are able to gauge the emotions to help anticipate price movement.[1] One example of the success of using investor sentiment to predict future returns is demonstrated by the recent episode of COVID-19. The sentiment indices compiled by RavenPack that applied textual analysis to glean emotion from media postings display an uncanny ability to predict returns even in the wildly fluctuating markets.[2] In spite of this impressive display, a survey of the literature reveals that the forecasting ability of sentiment is highly contentious.[3] Even less is known about what drives stock price changes following substantive sentiment swings.

Hitherto, most studies concentrated on market-wide sentiment, with only a few exceptions accounting for firm-specific sentiment. The literature examining aggregate market sentiment and broad market indices includes Baker and Wurgler (2006), Baker and Wurgler (2007), Barber et al. (2008), Berkman et al. (2012), Siganos et al. (2014), Stambaugh et al. (2012, 2014) and Sun et al. (2016a), to name a few. The literature investigating firm-specific sentiment and stock returns is now only starting to emerge and includes Groß-Klußmann and Hautsch (2011), Sprenger et al. (2014a), Bartov et al. (2018) and Boudoukh et al. (2018).[4] In this paper, we investigate whether the build-up of company-related sentiment overnight, or during other non-trading hours, helps predict opening prices the next day. Our analysis is performed on a granular 1-minute intraday sentiment level offered by Thomson Reuters MarketPysch Indices (TRMI). TRMI is the industry standard for machine-learning sentiment analysis that parses as many as 55,000 news sites and 4.5 million social media sites, blogs and tweets.[5] In spite of the availability of 1-minute intraday data, we focus our investigation on the impact of overnight sentiment for several reasons. Firstly, the use of overnight sentiment allows us to have a fixed anchor point for our analysis. Moreover, measuring sentiment in this non-trading period allows us to break

[1]Research such as Antweiler and Frank (2004); Da et al. (2011); Bollen et al. (2011); Mao et al. (2011) have led a trend to quantify qualitative information in 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]More details on the ability of these indices to predict stock returns during the COVID-19 crisis can be found at the following website (`https://coronavirus.ravenpack.com/`).

[3]For instance, Azar and Lo (2016a) 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. (2016a) 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.

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

[5]'Tracking social media: The Mood of the Market', 28 Jun 2012, *The Economist*, accessed on 10 Nov 2019, `https://www.economist.com/graphic-detail/2012/06/28/the-mood-of-the-market`.

the return-and-sentiment loop and thus effectively avoid any endogeneity issue in our analysis. The use of overnight sentiment data also has the benefit of being the highest signal-to-noise measure for what can be a very "noisy" measure. Finally the majority of firm-specific announcements are scheduled outside of trading hours (Birru, 2018). It stands to reason that the emotions/sentiment generated by these announcements would also be formed and best measured in this non-trading period as well.[6]

Next, we combine the sentiment data with the 1-minute stock mid-quotes (average of bid and ask) for all of the Dow Jones Industrial Average (DJIA) constituents from 2011 to 2017. 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 (9:30 am EST) as the *event*, we accumulate sentiment data prior to the *event* and check for its correspondence with the cumulative returns after the *event*. We find that only the top and bottom deciles of the cumulative sentiment exhibit predictive power, while moderate changes in the sentiment tonality are inconsistent in predicting the returns.

Our study offers novel insights into the influence of news and social media sentiment on stock returns. We find that both social and news media sentiment can predict the opening stock returns. The results indicate that overnight sentiment and returns on the following day are strongly positively correlated, 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 their corresponding cumulative abnormal returns (CARs) is as high as 0.79, while similarly, for the **news** sentiment it is only 0.57. Both correlation coefficients are significant at the 1% level. In order to avoid the influence from overnight returns, which is usually captured in the first minute of trading, we also conduct comparative analysis by controlling for the first minute of trading. Upon excluding the first minute and aggregating returns from 9:31 am instead of 9:30 am, the correlation between social (news) media sentiment and CARs plunges to 0.44 (0.17), and the news sentiment group is now not significant at the 10% level. Moreover, we find that strong overnight investor sentiment (top and bottom deciles) signals potential outperforming strategies. The average profits across our sample of stocks when longing high and shorting low **social media** sentiment ranges from 36.24 to 39.00 basis points (bps), depending on the length of the event windows. Similar long-short portfolios based on **news media** sentiment ranges from 21.84 to 22.16 bps, providing additional evidence of the weaker effect of the news media when compared with social media. These mispricing opportunities, however, are short-lived and diminish quickly when returns are aggregated from 9:31 am rather than 9:30 am, effectively excluding the opening price. We provide consistent results by showing qualitatively similar evidence across the first half hour, first hour and morning windows, along with the overall next trading

[6] Jiang et al. (2012) reveals that over 95% of their sample announcements are outside of 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.

day's reaction. 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.

One benefit of having access to 1-minute data is that it allows us to examine the behaviour of media sentiment 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. These differences in their daily movements highlights the benefit of using intraday data to investigate the varying impact of social and news media sentiment on returns. Importantly, our results indicate that sentiment in the three hours immediately prior to the stock market opening have the greatest predictability on stock returns. Viewed alongside the previous result that social media sentiment is demonstrated to be the most influential on opening returns, these findings highlight the need to employ more granular data to capture the impact of sentiment on the stock market.

Finally, 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 it has also permeated through to the asset markets. A recent study by Gan et al. (2019) documents how the transition of the influence has taken place. Where 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 unsurprising considering that 3.80 billion people are using social media on mobile devices in January 2020, with a growth of 321 million new users—a year-on-year increase of more than 9 per cent (Global Digital Reports 2020). In this study, we show that overnight sentiment in social media has a greater impact on the opening stock returns compared to the influence of news media. This result still holds even after controlling for the potential endogeneity between stock returns and sentiment.

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 the issue that messages in the media might just rehash events in the market, and find that investor sentiment after market closure is significantly positively related to the stock's trading hour performance. The correlation between stock returns and after-hours social media sentiment on the top/bottom decile days is 0.4012; the same correlation with regard to the news media is 0.4080. Our bootstrap simulation results show that these correlation coefficients are both statistically significant at the 1% level. To resolve this endogeneity concern, we control for the previous day return performance. We conduct robustness checks by performing a group of comparative baseline and controlled OLS regressions. We find that the predictability from overnight social and news media sentiment still persists when 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 'events' in our sample overlap with earnings announcement days.

Finally, we show that our results holds for a number of varied window lengths between fifteen minutes and six hours. We demonstrate that our results are consistent when the pre-event window is varied. Yet, the return predictability does diverge depending on different window lengths. As a consequence of this exercise, we are able to assess the predictive accuracy of sentiment cumulated over periods of various lengths. Our findings suggest that using sentiment data from two to three hours prior to market opening results in the most accurate predictions of opening price directions and the highest average profits. 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 also dampens the accuracy of opening price prediction.

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, for example, Groß-Klußmann and Hautsch (2011), Chouliaras (2015), Sun et al. (2016a), Renault (2017), Boudoukh et al. (2018) and Behrendt and Schmidt (2018). Using 20-second frequency Reuters NewsScope Sentiment data (an early version of TRNA), Groß-Klußmann and Hautsch (2011) shows that "relevance" news sentiment indicators have predictability for future LSE stock price trends. Chouliaras (2015) examines 13,145 intraday news articles and finds strong negative sentiment return predictability in the European and international stock markets, in 5-minute and 30-minute time frame. Sun et al. (2016a) and Renault (2017) uncover half-hour sentiment predictability in the U.S. stock index exchange-traded fund (ETF) returns that is similar to but different from the intraday momentum effect. Our results are in line with these studies. Our paper is also closely related to Boudoukh et al. (2018) which separates the overnight and intraday sessions and isolates different types of news information. Yet, we focus on the opening return rather than volatility as did Boudoukh et al. (2018). A seemingly contradicting paper is provided by Behrendt and Schmidt (2018) that uses 5-minute Twitter sentiment of DJIA constituent stocks and shows that the relationship between Twitter moods and a stock's absolute returns is economically negligible. However, by taking the absolute values of returns, their study focuses on the stock return volatility instead of the return itself, which is the main subject of our paper. Moreover, O'Hara (2014) points out that one reason why nowadays high-frequency traders (HFTs) are so successful is that they use 'big data' and natural language processing (NLP) to make decisions. Our paper offers low-frequency traders (LFTs) a framework to better understand the market dynamics to help level the playing field with high-frequency traders.

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., 2014a, among others).[7] 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 S&P 500 tweets, Sprenger et al. (2014a) finds that negative news inducing price reaction is 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 categorical, in other words, either positive or negative. In contrast, assisted by the quantile percentile technique, we are able to quantify a more precise level of emotional scores that can be exploited to generate signals.

Last, we add to the literature that measures the informational aspect of market efficiency. Engelberg et al. (2018) summarises three explanations to stock predictability: risk, mispricing, and data-mining. Under the microscope of intraday data, our study helps shed light on how information is propagated and incorporated into the market during trading and non-trading episodes. Prior studies in this realm include Morck et al. (2000), Dang et al. (2015), Boudoukh et al. (2018), Lou et al. (2019) and Jiang et al. (2019), to name a few. Perhaps Boudoukh et al. (2018) and Jiang et al. (2019), among others, are most closely linked to our study in that we all use textual analysis sentiment to capture the impact of news arrival and break down overnight, weekends and normal trading hours. The substance of our research, however, is quite different. 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. They also demonstrate 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

[7] 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.

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. We distinguish ourselves in two ways. First, the prior two studies applied **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 a missing part by comparing effects from social media with news. Second, our analysis of media sentiment along various non-trading hour windows generates exciting new insights into how the abnormal stock returns and the overnight media coverage mutually influence each other, which is quite rare in the existing literature.

The rest of this paper proceeds as follows. Section 3.2 describes in detail our sample data and methodology. The main results are provided in Section 3.3. In Section 3.4, we proceed with robustness tests and discussions about what drives our main findings. Section 3.5 concludes the paper.

3.2 Data and Methodology

3.2.1 Sentiment Data

Our company-specific investor sentiment data are sourced from Thomson Reuters MarketPsych Indices (TRMI), a proprietary dataset that scrapes and scores texts from various news press and social media via textual analysis algorithms and generates both quantities and emotion scores.[8] To contrast the impact from different media outlets, we use 1-minute firm-specific sentiment scores based on *social* media and *news* media respectively—the most granular data available from TRMI. Our sample period spans from 1 January 2011 to 30 November 2017, which covers a period of swift social media development.

We focus on the Dow Jones Industrial Average (DJIA) constituents to mitigate sampling bias from missing observations in the 1-minute sentiment data. Our choice 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.

Table A.4 summarises sentiment data availability and reports the total number of non-missing

[8] These data are provided by the Thomson Reuters Financial and Risk Team (re-structured as Refinitiv from 2019) as part of a TRMI product. 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.

observations and average daily counts for social and news media for the Dow Jones Index and each of its constituents. Stocks delisted from the DJIA during the sample period are included. Reflecting on the saliency of each stock based on these figures, 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, Travelers.[9]

3.2.2 Stock Price Data

The Dow Jones Industrial Average (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 31 November 2017 to match 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 and is indexed by $j = 0, ..., J$. Assets are indexed by i where $i = 0$ represents a broad market index benchmark, while $i = 1, ..., N$ denotes a stock. The continuously compounded return, $r_{i,t,j}$, is calculated as

$$r_{i,t,j} = \begin{cases} \ln\left(\frac{P_{i,t,j}}{P_{i,t,j-1}}\right) & \text{for } j = 1, ..., J \\ \ln\left(\frac{P_{i,t,0}}{P_{i,t-1,J}}\right) & \text{for } j = 0 \end{cases}$$

where $P_{i,t,j}$ is a mid-quote price.[10] We use the previous available observation to fill in missing values in the price series. Outlying return observations based on bid and ask quotes and prices are replaced with the preceding data points.[11]

3.2.3 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 high-frequency sentiment and stock return data to help identify

[9] 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 Travelers are 81 and 2, respectively.

[10] 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.

[11] 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. We identified a single outlier for Apple Inc in our entire sample corresponding to the stock split on a 7-for-1 basis on 9 June 2014.

patterns and irregularities in our dataset. In Figure 3.1 (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 12:00 am to 11:59 pm with 1,440 minutes in total and the vertical axis covers the entirety of our sample period totalling 2,526 days.[12] Each pixel representing 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 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 3.1 indicates vividly that it is nontrivial to aggregate sentiment observations due to the irregularity of the data, especially in light of the asynchronicity with the returns.[13]

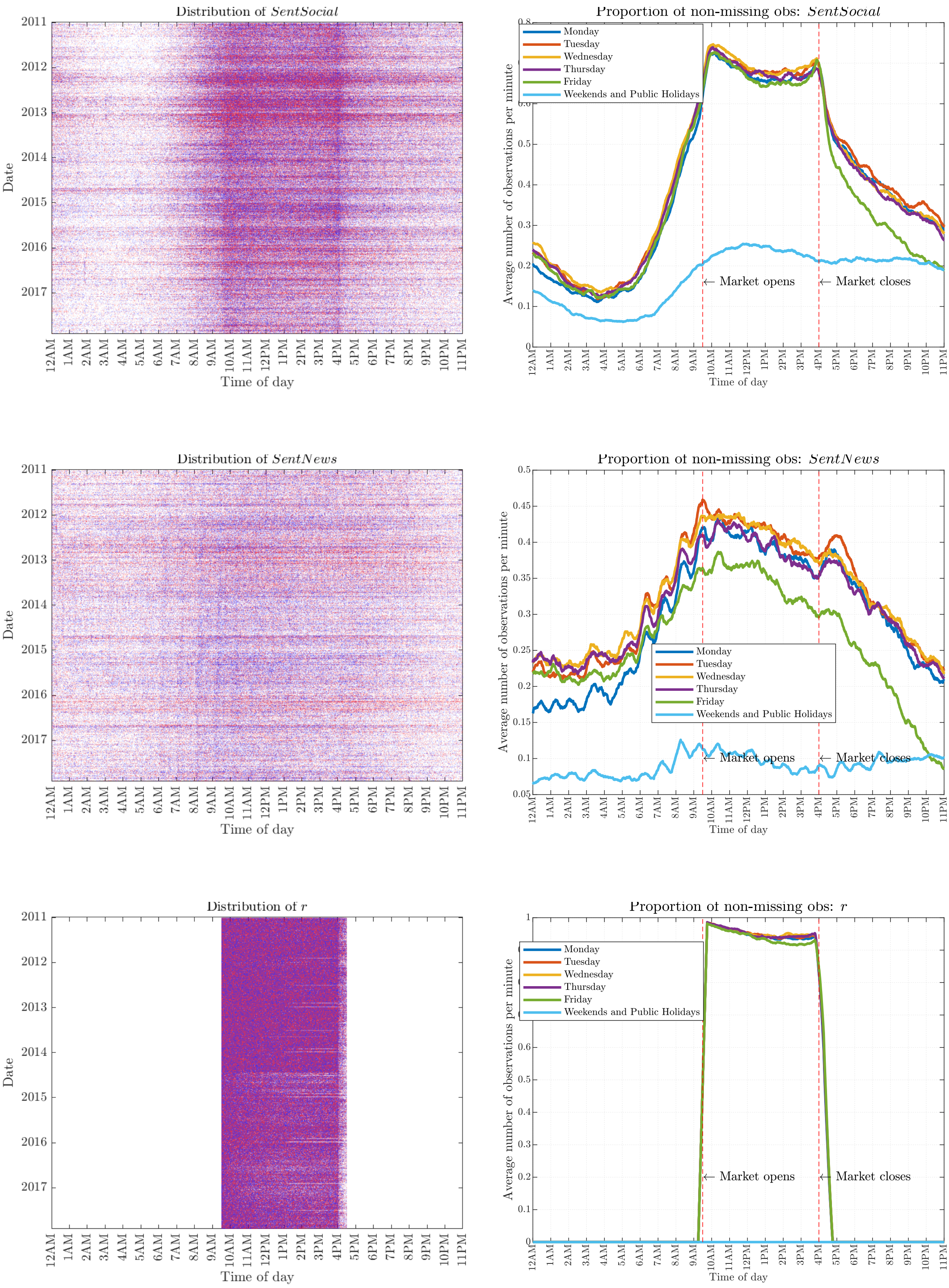
The irregularity of sentiment data and its asynchronicity with the returns present a challenge for modelling their causal relation. A solution proposed in this paper benefits from the availability of of 1-minute intraday data and focuses on the impact of accumulated overnight sentiment just before the market opens. Market opening and closing times offer logical anchors and allow unambiguous temporal separation of investor 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 intertwined and the results are convoluted. 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 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 (9:30 am EST) as the *event*, we

[12] Box plots in Figure B.13 in the Supplementary Online Appendix offer a closer look at the distributions of social versus news media sentiment.

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

Figure 3.1: 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), as well as an asset's **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 are shown in blue, missing data appear as a white colour in the heatmaps. Right-hand side panels display proportions of non-missing observations corresponding to variables on the left-hand side and capture intraday and day-of-the-week patterns.



accumulate sentiment data prior to the *event* and check for its correspondence with the cumulative returns after the *event*.[14] We find that only the top and bottom deciles of cumulative sentiment exhibit predictive power, while moderate changes in sentiment tonality are inconsistent in predicting the returns. We define the abnormal return of stock i on day t at time j as:

$$AR_{i,t,j} = r_{i,t,j} - r_{0,t,j}, \tag{3.1}$$

where $r_{0,t,j}$ is the index return on day t at intraday interval j. The cumulative abnormal return on stock i on day t at time j is:

$$CAR_{i,t}\left[\tau_1, \tau_2\right] = \sum_{j=\tau_1}^{\tau_2} AR_{i,t,j}, \tag{3.2}$$

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

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

$$CSent_{i,t}\left[\tau_{-1}, \tau_0\right] = \sum_{j=\tau_{-1}}^{\tau_0} Sent_{i,t,j}, \tag{3.3}$$

where, in defining the pre-event window, we set $\tau_0 = 9{:}29$ on day t and $\tau_{-1} = 16{:}01$ on the day prior. This allows us to focus on the sentiment accumulated from the market closing on the previous day to just before the market open 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). 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.[15] We conduct several robustness checks by varying pre-event window lengths, which is described in later sections.

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

[14] 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.

[15] For convenience, Table A.3 in the Appendix lists all variable definitions, data sources and acronyms. Variables based on social or news media are denoted with (S) or (N) superscripts, respectively. Thus, $Sent^{(S)}$ and $Sent^{(N)}$ represent sentiment data from (S)ocial and (N)ews media, respectively.

sentiment periods (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 hypothesise that such sentiment may be better positioned to exhibit predictive power, while moderate changes in sentiment tonality may be inconsistent in predicting the returns. 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:

$$\mathcal{D}_{i,x} = \{t : d_{i,x-1} < CSent_{i,t}\,[\tau_{-1}, \tau_0] \leq d_{i,x}\}. \tag{3.4}$$

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%. The average cumulative sentiment in each decile x is, therefore,

$$\overline{CSent_{i,x}}\,[\tau_{-1}, \tau_0] = \frac{1}{|\mathcal{D}_{i,x}|} \sum_{t \in \mathcal{D}_{i,x}} CSent_{i,t}\,[\tau_{-1}, \tau_0]. \tag{3.5}$$

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:

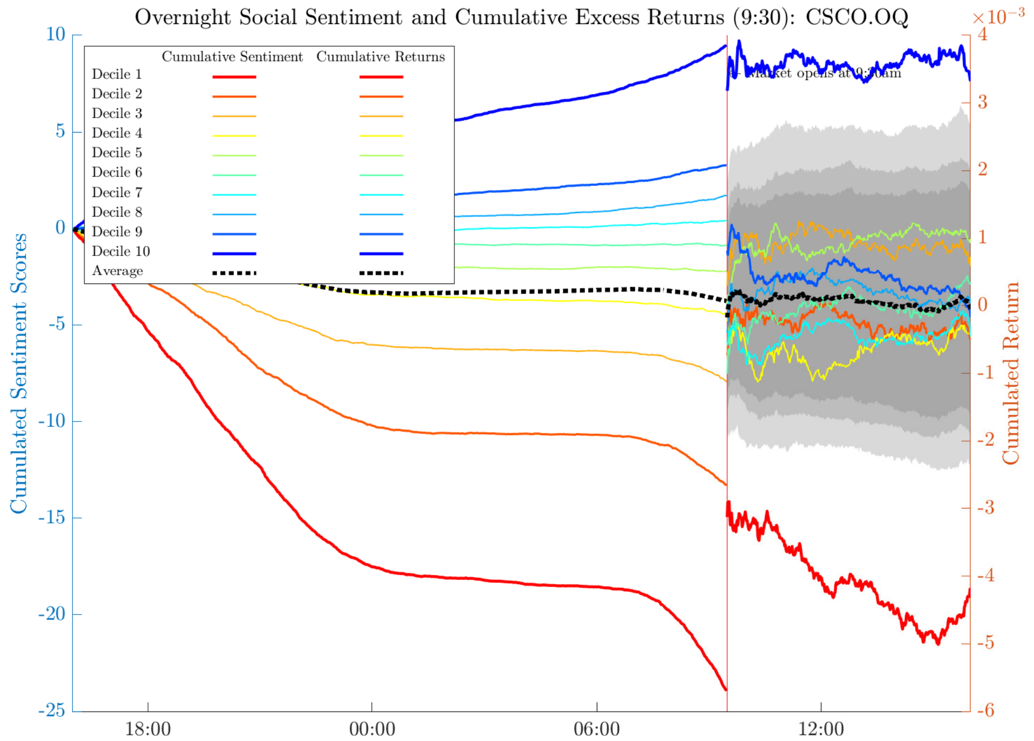
$$\overline{CAR_{i,x}}\,[\tau_1, \tau_2] = \sum_{t \in \mathcal{D}_x} CAR_{i,t}\,[\tau_1, \tau_2]. \tag{3.6}$$

In the discussion of our findings 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 but when the overnight returns are excluded, namely $\overline{CAR_{i,1}}\,[9{:}31, 16{:}00]$ and $\overline{CAR_{i,10}}\,[9{:}31, 16{:}00]$.

3.3 Findings

In this section, we set out to explore whether sentiment formed during non-trading hours can act as a strong predictor of opening returns. We take the reader on a journey through model specifications and methodology by demonstrating our approach using a single stock as an example. We apply this framework to all the stocks in our sample and summarise 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 impact on opening returns and discuss the longevity of sentiment estimates in predicting stock returns.

Figure 3.2: Social Media: Overnight Sentiment and Opening Returns (CSCO.OQ) Sentiment and returns 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 4:01 pm to 9:29 am). 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 9:30 am, while in the bottom panel, it starts from 9:31 am, skipping 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 $M = 2,000$.



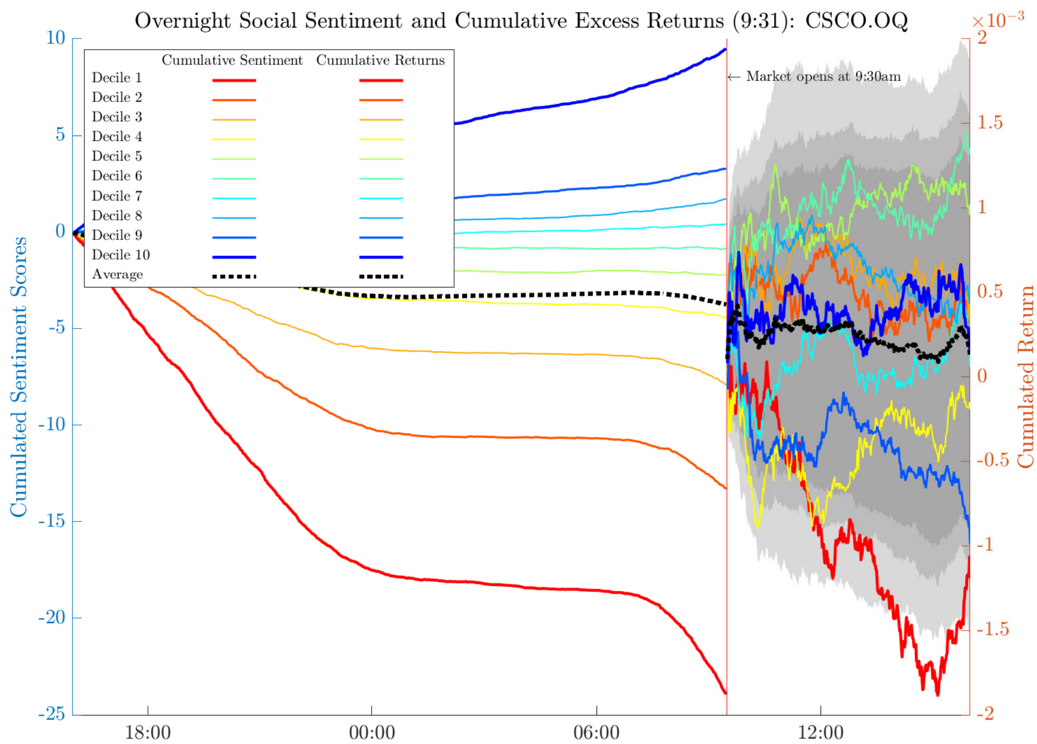
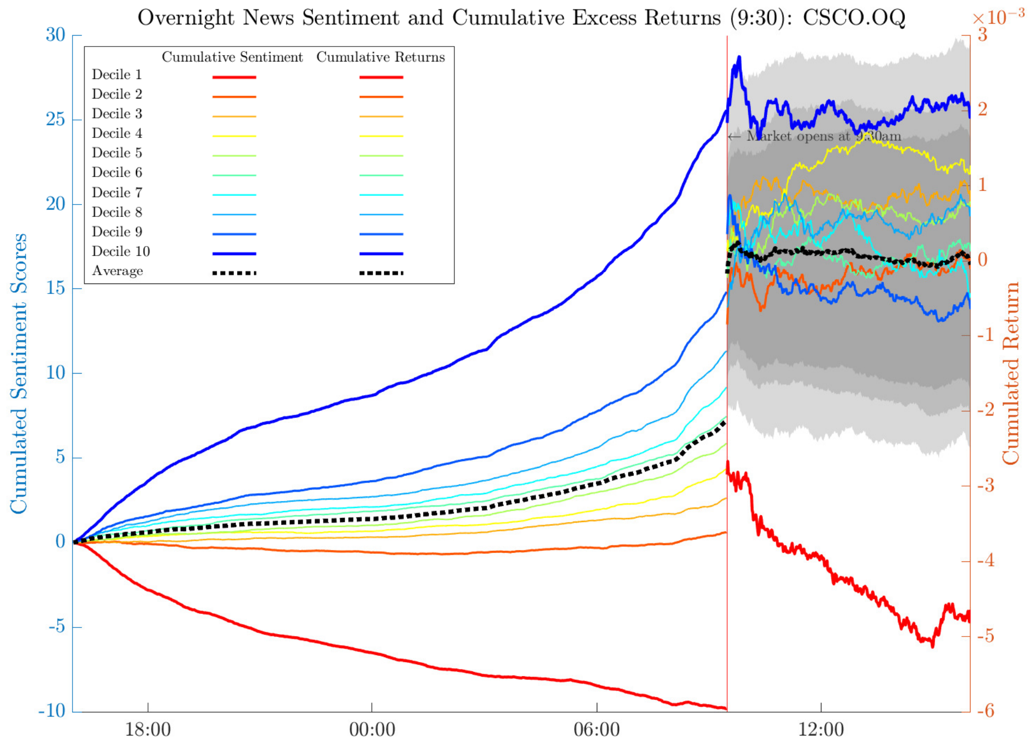
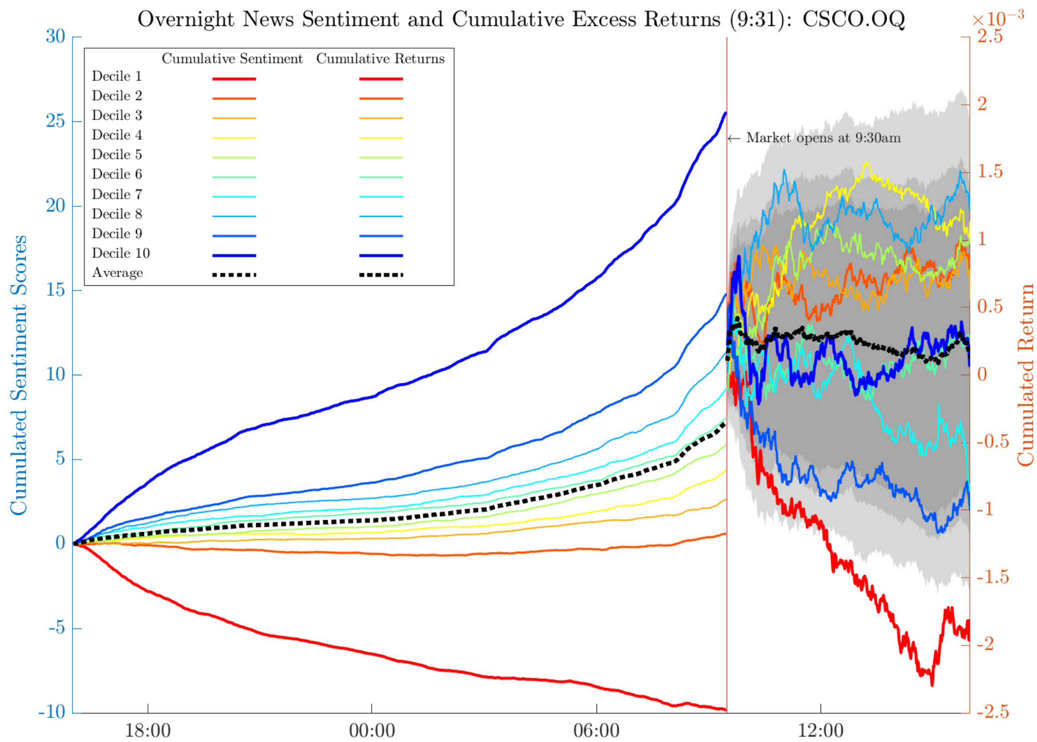


Figure 3.3: News Media: Overnight Sentiment and Opening Returns (CSCO.OQ) Sentiment and returns data are at 1-minute frequency from 1 January 2011 to 30 November 2017. Overnight sentiment is cumulated daily from previous day close to current day open (i.e., from 4:01 pm to 9:29 am). Cumulative sentiment 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 9:30 am, while in the bottom panel, it starts from 9:31 am, skipping 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 $M = 2,000$.





3.3.1 Opening Return Patterns

We demonstrate our main analytical approach and findings in Figures 3.2 and 3.3 using CSCO.OQ as an example. The left-hand side series of curves depict the decile-sorted cumulative *social* media sentiment (Figure 3.2) and cumulative *news* media sentiment (Figure 3.3), respectively.

We obtain cumulative overnight sentiment by aggregating 1-minute sentiment scores from the previous day market close to the current day open. Specifically, on each trading day, we trace out sentiment trends originating from the first minute past the market closure on the previous day and leading up to market open on the current day. The overnight cumulative sentiment series are then sorted and fragmented into deciles. The days with the most positive and negative overnight sentiment are represented by $\mathcal{D}_1$ and $\mathcal{D}_{10}$, respectively. In Figures 3.2 and 3.3, the average cumulative sentiment series conditional on $\mathcal{D}_x$ are presented by a set of curves on the left-hand side, where x is a decile. The curves are in descending order, by construction, with the most positive (conditional on the $\mathcal{D}_{10}$ decile) and negative (conditional on the $\mathcal{D}_1$ decile) sentiment represented by blue and red curves, respectively. On the right-hand side of the panels in Figures 3.2 and 3.3, we present the corresponding cumulative abnormal returns. Each sentiment decile is followed by its corresponding conditional CAR mapped with the same colour.

The top panels in Figures 3.2 and 3.3 illustrate the evolution of the cumulative abnormal returns accruing from 9:30 am, that is, inclusive of the first minute return. In contrast, the bottom panels reveal the dynamics of the average conditional CARs when the first minute return is excluded. The grey-shaded bands are the 99%, 95% and 90% confidence intervals based on the average CARs of 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 $\mathcal{D}_x$) and the number of simulations is set to $M = 2,000$.[16] The dashed black curves show the average sentiment and CARs across all T days.

The top panels in Figure 3.2 and 3.3 expose strikingly similar patterns from social and news sentiment: average CARs on days with the most positive (blue) and negative (red) overnight sentiment are considerably different from average CARs not conditioned on sentiment. Spanning outside of the most conservative confidence band, the $\mathcal{D}_1$- and $\mathcal{D}_{10}$-associated CARs are statistically significant at 99% level. The impact is asymmetric with the difference between positive and negative emotions 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.

Observing the top panels in Figures 3.2 and 3.3, we find a compelling distinction in overnight

[16] Refer to Table B.8 in Supplementary Online Appendix for the decile sizes of each stock.

sentiment dynamics between social and news media. First, the overnight social media sentiment exhibits a time-sensitive effect with varying persistence. From 4:01 pm to midnight, the sentiment accrues quickly, showing steeper slopes and waning down from midnight to early morning at around 6:00 am-7:00 am. 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 7:00 am suggests that negative overnight emotions continue to intensify before the market open. This timeline is consistent with most social media users' daily routines.[17] Second, the news media tend to be more positive compared with the social media. Figure 3.3 shows that both the average cumulative sentiment (black-dashed line) and most of the overnight news media sentiment deciles (except for the red line representing $\mathcal{D}_1$) are trending upward, accruing to positive sentiment values. The speed of such positive sentimental drift is accelerated after 6:00 am and is strongest in $\mathcal{D}_{10}$ (the blue line). For the case of CSCO.OQ, the cumulative overnight news media sentiment scores bottom out at -10 and are capped at +25, with the mean at about +7. However, for the social media, the range is between -24 to +9 with an average score of approximately -5. This is rather intuitive, since social media users, in general, are more prone to post extremely negative comments and discussions than news article reporters, whose opinions need to be based on facts and are moderated.

The difference between overnight and intraday returns is of considerable interest to us as it may bring to light the issues in finance concerning the efficient markets 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) suggest 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 which subsequently decline in the first hour of trading. Similarly, for broad-based index exchange-traded funds, Kelly and Clark (2011) find the overnight returns are on average larger than the intraday returns. In contrast, we find that on days with the most negative sentiment overnight, the overnight return is significantly lower than on any other days.

To test how far into the day does overnight sentiment carry predictive power, Figures 3.2 and 3.3 contrast conditional CARs inclusive and exclusive of the first minute of trading as shown in the top and bottom panels, respectively. We observe that the significant predictability of heightened overnight sentiment disappeared when the first minute is excluded from CARs. Interestingly, this effect is

[17] 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.

asymmetric: only days with the most negative overnight sentiment continue to exhibit significantly negative CARs after the first minute is removed. Positive-sentiment-induced CARs, however, becomes insignificant and scrawling within the 90% confidence band. This phenomenon happens in both the social media and news media sentiment groups. The effect can be observed by contrasting the top and bottom panels in Figures 3.2 and 3.3 focusing on the bold red lines that show cumulative sentiment on the left-hand side for $\mathcal{D}_1$ and the corresponding average CAR (in matched colour) extending outside of the 99% confidence bands. Past literature have shown that the speed of adjustment varies across different assets for overnight returns to arrive at the efficient level. The sample of DJIA stocks used in this research consists of the most liquid stocks traded, therefore greatly mitigate the problem of sluggishness in price discovery of the overnight returns. However, even if this sluggishness exists for our sample, it does not interfere with our results because the same conditions apply to both groups inclusive or exclusive of the first minute. That is, the sluggishness in price discovery of the overnight returns would have exerted the same effect on the upper and lower panels of Figures 3.2 and 3.3, if the sluggishness exists.

We find that most of the daily CARs identified in the top panels are driven by the first minute of trading. This result is more prominent on the negative side. The evidence of economic significance of the overnight return is striking but in line with Cooper et al. (2008) and Lou et al. (2019).[18]

We conduct the same analysis for all the stocks in our sample and summarise the results in Table 3.1. We find no discernible pattern between the intermediate overnight sentiment deciles and the associated CARs. Accordingly, in Table 3.1, we report the results of the two extreme sentiment deciles only and their corresponding CARs. Columns (1) and (6) are average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01 pm the previous day to 9:29 am. That is, $\overline{CSent_{i,x}}\,[16{:}01, 9{:}29]$ as defined in Eq.(3.5). It should be noted that $\overline{CSent}$ values are comparable across deciles for a specific asset but are not comparable across assets. This is due to the relative sparsity of sentiment data even among DJIA constituents. As reported in Table A.4, 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 between AAPL and DD (Table 3.1, social media, -34.25 and -2.69) *does not* imply a more negative tonality for AAPL. For a given asset, however, comparison among deciles may reveal long-term sentiment trends. For example, for AAPL, the difference between the most positive and negative social media sentiment (46.34-34.25) reveals an overall positive tonality over the entire period, while for DD, the sentiment tonality appears to be negatively skewed (2.33-2.69). The correlation between Columns (1) and (2) is 0.7908, and that between Columns (6) and (7) is 0.5749. After eliminating the

[18]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.

overnight return from $\overline{CAR}$s, the correlations are reduced substantially to 0.4367 between Columns (1) and (4) and to 0.1667 between Columns (6) and (9).

Columns (2) and (7) are the average cumulative abnormal returns aggregated from 9:30 am to 4:00 pm 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.(3.6). Similarly, Columns (4) and (9) are the corresponding average cumulative abnormal returns but, instead, aggregated from 9:31 am to 16:00 pm, with the overnight return removed.[19] The $\overline{CAR}$s are conditional on sentiment deciles, $\mathcal{D}_{i,10}$ (highest sentiment) and $\mathcal{D}_{i,1}$ (lowest sentiment).

In columns denoted Top-Bottom (T-B) in Table 3.1 we report the returns, in bps, on a long-short strategy intended to exploit the difference in price behavior conditional on the heightened sentiment tonality that is accumulated overnight, just before the start of a trading day.[20] Specifically, Columns (3) and (8) consider CARs inclusive of the overnight return and contrast the viability of the long-short strategy for social media- and news media-based sentiment. In 25 out of 34 stocks in our sample, an investment strategy conditional on social media sentiment results in higher returns.[21] The investment strategy based on social media sentiment shows remarkable consistency: the returns on the strategy are positive for all 34 stocks without exception (refer to Column 3), while the strategy returns based on news media exhibit 7 negative values out of 34 (Column 8). The bottom row reinforces the conclusion that social media based strategies, on average, result in higher gains (30 bps vs 22.156 bps). Similarly, Columns (5) and (10) consider CARs but with the overnight return excluded. While the social media based strategy, on average, remains more prominent (8.21 bps vs 5.62 bps), the gains are at magnitudes lower when compared to CARs inclusive of the overnight return. Moreover, the returns on a long-short strategy for individual securities are inconsistent, with 10 and 11 stocks showing negative strategy gains for social and news media, respectively.

Table 3.1 reveals several compelling insights. First, the highest and lowest overnight sentiment is positively associated with cumulative excess return the next day. This relation is stronger for social media than for news media sentiment. The correlation coefficient between social media based-series in Columns (1) and (2) is 0.7908, while the correlation coefficient between news media-based series

[19] We performed robustness checks of our results by conducting analysis under a number of different CAR aggregation windows lengths, τ_2, as defined in Eq.(3.6). We report the results for the CARs over the first half-hour (up to 10:00 am) in Table 3.2, the first hour (up to 10:30 am) in Table 3.3, and the morning session (up to 12:00 pm) in Table 3.4. The results are qualitatively similar and do not affect our conclusion.

[20] To implement this strategy, one do not need to submit orders on top of the limit order book and close out almost immediately. The rise of electronic communications networks (ECNs) has facilitated the pre-opening and after-hours trading. Several studies have document the impact of pre-opening/after-hour trading on opening returns, for instance, Barclay and Hendershott (2003), Barclay and Hendershott (2008) and Moshirian et al. (2012). The ECNs allows market participants to place orders and trade with each other directly and anonymously. According to Barclay and Hendershott (2008), trades can occur at any time of the day or night as long as the ECN system is turned on. In fact, our robustness tests show that as long as the first minute is included in the next day's holding period, sentiment's predictability can be realized. We thank one of the examiners to point out this issue.

[21] Exceptions include CVX, GE, GS, KO, MMM, MRK, T, UTX and VZ.

in Columns (6) and (7) is 0.5749. When the overnight return is excluded from CAR, the correlation coefficients between social media- and news media-based series drop to 0.4367 and 0.1667, respectively, (i.e., correlation between Columns (1) and (4), and between (6) and (9)), with the latter coefficient becoming not statistically significant.[22] This evidence clearly suggests that overnight investor 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.

Next, we identify the asymmetry between the positive and negative sentiment effects. By contrasting the CARs conditional on the top and bottom sentiment from Columns (2) and (7) in Table 3.1 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, in Column (2) of Table 3.1, an average CAR of -43.19 bps is generated when conditioned on days with the most negative social media sentiment. On days with the most positive social media sentiment, an equivalent 33.23 bps CAR is attained, which is 9.96 bps lower than on the negative side. Therefore, the short leg in the long-short strategies from Columns (3), (5), (8) and (10) appears to be the driving force in sentiment-based strategies. This finding is consistent with Stambaugh et al. (2012) and Stambaugh et al. (2014) in that the short lag of long-short anomaly strategies is more profitable. When the overnight return is omitted from conditional CARs, the long-short strategies continue to generate positive returns, although their magnitudes are substantially lower. That is, on average, across all stocks, 8.21 bps versus 39 bps for long-short strategies based on social media sentiment and 5.62 bps versus 22.16 for news media.

Third, the information contained in overnight sentiment is quickly reflected in the opening price, pointing to the efficiency of the market. Therefore, in assessing CARs aggregated from 9:31 am instead of 9:30 am, in Columns (4) and (9) 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 bps and -11.93 bps depending on whether the overnight return is included or excluded. 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 (7) and (9) in Table 3.1 display similar patterns for news media sentiment. Average CARs on days with negative news sentiment are -47.50 bps and -19.07 bps and on positive sentiment days these figures reach 18.99 bps 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

[22]Similar patterns are observed in Tables 3.2, 3.3 and 3.4 where, in assessing the robustness of our results, we consider conditional CARs aggregated to the first half-hour of a trading day, the first full hour and until noon (that is the morning trading session only), respectively.

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 the discussion of our findings from Table 3.1, we present Figure 3.4 where the contrast between unconditional returns and returns conditional on sentiment is readily apparent. Additionally, by contrasting the top and bottom panels of Figure 3.4, the importance of the opening return is conspicuous.

[23]In Figure B.11 of the Supplementary Online Appendix, we compute the average daily counts of buzz and sentiment scores from the social and news media and rank the stocks in our sample with respect to their 'saliency'.

Table 3.1: Daily CARs conditional on the top and bottom overnight sentiment. This table reports the top and bottom deciles of overnight cumulative sentiment for each sample stock and the corresponding cumulative abnormal returns the next day. Columns (1) and (6) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01 pm the previous day to 9:29 am. That is, $\overline{CSent_{i,x}}[16{:}01, 9{:}29]$ as defined in Eq.(3.5). Columns (2) and (7) are the average cumulative abnormal returns aggregated from 9:30 am to 4:00 pm 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.(3.6). Similarly, Columns (4) and (9) are the corresponding average cumulative abnormal returns but aggregated from 9:31 am to 4:00 pm instead, with the overnight return removed. The $\overline{CAR}$s are conditional on sentiment deciles, $\mathcal{D}_{i,10}$ (highest sentiment) and $\mathcal{D}_{i,1}$ (lowest sentiment). In Column (3) and (8), T-B are the returns, in bps, on a long-short strategy intended to exploit this difference. The last row 'Average' indicates the average return on the strategy across all stocks. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are based on confidence bands constructed from bootstrap simulations of the unconditional cumulative returns.

		Social Media					News Media				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stock i	Cond.decile	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B
AA.N	Top	6.72	38.95***	81.93	−0.42	18.49	10.84	26.61**	53.35	−6.38	5.75
	Bottom	−6.39	−42.98***		−18.91		−17.84	−26.73*		−12.13	
AAPL.OQ	Top	46.34	55.09***	124.99	−4.42	5.00	62.32	43.92***	75.03	−5.68	-4.98
	Bottom	−34.25	−69.91***		−9.42		−43.22	−31.11***		−0.69***	
AXP.N	Top	4.03	−2.17	32.25	−5.61	4.94	10.31	7.18	9.03	−2.07	-2.02
	Bottom	−3.39	−34.42***		−10.54*		−5.42	−1.85		−0.05	
BA.N	Top	10.11	26.67***	52.56	16.74**	33.66	26.51	3.30	13.41	0.34	4.22
	Bottom	−13.32	−25.89***		−16.92***		−34.09	−10.11*		−3.87	
BAC.N	Top	9.01	41.74***	88.88	11.21*	48.49	13.91	14.42	18.34	2.06	29.93
	Bottom	−31.27	−47.14***		−37.27***		−25.58	−3.93		−27.87**	
CAT.N	Top	5.61	10.22	19.29	−11.62	-16.75	10.88	−8.97	-16.97	3.02	1.81
	Bottom	−6.51	−9.07		5.13		−14.12	8.00		1.21	
CSCO.OQ	Top	9.49	33.23***	76.42	1.42	13.36	25.59	18.99*	66.49	0.60	19.66
	Bottom	−23.94	−43.19***		−11.93**		−9.80	−47.50***		−19.07***	
CVX.N	Top	5.28	−4.18	7.44	5.35	10.70	11.51	2.72	17.15	−0.95	1.14
	Bottom	−5.44	−11.62		−5.36		−19.31	−14.43		−2.09	
DD.N	Top	2.33	13.57*	28.46	−0.32	-1.01	2.15	3.46	16.28	4.75	12.45
	Bottom	−2.69	−14.89*		0.69		−1.56	−12.82		−7.70	
DIS.N	Top	5.62	9.23	9.25	5.43	1.73	6.79	−7.17	-5.37	−1.18	3.21
	Bottom	−2.91	−0.01		3.70		−5.15	−1.80		−4.39	
GE.N	Top	7.74	12.16**	19.90	−0.42	2.53	25.34	22.22***	63.40	10.35**	30.19
	Bottom	−26.82	−7.74		−2.96		−10.46	−41.18***		−19.84***	
GS.N	Top	8.68	8.63	26.06	14.38	19.10	20.31	12.04	28.29	14.21	23.01
	Bottom	−18.98	−17.43**		−4.71		−42.88	−16.25*		−8.81*	
HD.N	Top	9.62	24.95**	31.45	−4.36	-0.76	19.32	6.64	-4.58	3.15	-4.77
	Bottom	−3.60	−6.50*		−3.60		−5.64	11.22		7.92	
HPQ.N	Top	8.77	38.51***	94.79	19.95	19.24	19.70	28.71**	90.78	7.03	10.99
	Bottom	−13.69	−56.28***		0.71		−21.47	−62.07***		−3.96	
IBM.N	Top	11.05	20.52***	66.20	10.93*	16.83	31.32	−5.92	-5.70	2.30	-3.61
	Bottom	−10.33	−45.69***		−5.89		−12.16	−0.22		5.91	

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[...continued.]

		Social Media					News Media				
Stock i	Cond.decile	(1) $\overline{CSent}$	(2) $\overline{CAR}$	(3) T-B	(4) $\overline{CAR_{-1}}$	(5) T-B	(6) $\overline{CSent}$	(7) $\overline{CAR}$	(8) T-B	(9) $\overline{CAR_{-1}}$	(10) T-B
INTC.OQ	Top	15.13	26.49***	53.15	18.15**	12.08	29.58	11.22	24.64	15.72*	4.59
	Bottom	−10.16	−26.67***		6.07		−15.52	−13.43		11.13	
JNJ.N	Top	7.02	9.33**	16.66	1.29	3.69	12.51	6.97*	11.08	1.33	4.89
	Bottom	−3.81	−7.33		−2.40		−7.55	−4.11		−3.55	
JPM.N	Top	8.28	18.65*	27.59	1.55	-7.84	19.48	−17.63**	-17.11	−15.00**	-45.10
	Bottom	−17.47	−8.94		9.39		−37.77	−0.51		30.11***	
KO.N	Top	6.49	−0.90	5.31	−0.96	-4.96	15.41	20.54***	34.05	12.91***	13.15
	Bottom	−6.19	−6.21		3.99		−11.09	−13.51*		−0.24	
MCD.N	Top	6.44	24.21***	41.74	6.70	10.00	11.04	−0.02	2.72	2.19	-0.46
	Bottom	−9.20	−17.53***		−3.30		−15.45	−2.75		2.65	
MMM.N	Top	4.68	14.94*	22.85	11.73	9.91	10.25	18.11**	60.85	14.32*	31.98
	Bottom	−2.71	−7.91		1.82		−6.82	−42.74***		−17.67***	
MRK.N	Top	6.27	33.20***	63.75	8.23*	25.12	11.63	42.90***	80.04	20.55***	38.10
	Bottom	−4.29	−30.55***		−16.88**		−8.52	−37.14***		−17.55**	
MSFT.OQ	Top	24.92	16.24	35.80	4.25	6.57	49.02	11.59	8.82	−1.77	-7.44
	Bottom	−17.66	−19.56***		−2.32		−10.14	2.78		5.66	
NKE.N	Top	9.68	60.25***	81.53	17.45**	21.46	9.32	26.36***	29.25	13.35	16.12
	Bottom	−4.99	−21.28***		−4.00		−7.00	−2.89		−2.78	
PFE.N	Top	6.81	12.28	31.42	2.82	7.32	13.26	15.91**	28.89	2.36	3.28
	Bottom	−6.87	−19.14***		−4.51		−13.15	−12.98**		−0.92	
PG.N	Top	4.94	4.82	12.93	5.32	4.45	9.35	−6.13	1.31	−1.79	6.77
	Bottom	−3.07	−8.11		0.88		−6.45	−7.44		−8.56**	
T.N	Top	11.62	2.14	10.31	−0.78	0.55	17.58	0.24	15.77	0.56	11.98
	Bottom	−8.22	−8.17		−1.33		−12.99	−15.53*		−11.42*	
TRV.N	Top	1.39	13.57*	21.10	−0.14	-7.19	1.76	2.06	0.40	−2.05	-7.53
	Bottom	−1.24	−7.53		7.05		−1.22	1.66		5.47	
UNH.N	Top	4.31	28.51***	55.58	14.57*	32.96	8.29	10.07	0.92	4.68	-4.91
	Bottom	−1.94	−27.06***		−18.39***		−4.29	9.15		9.59	
UTX.N	Top	3.52	−2.37	8.59	−6.69	-5.33	6.89	11.89*	21.17	0.86	6.68
	Bottom	−2.84	−10.96*		−1.36		−6.54	−9.28		−5.82	
V.N	Top	5.72	22.52**	13.98	0.68	-5.74	6.65	10.58	-2.51	8.08	1.75
	Bottom	−2.18	8.55		6.42		−3.06	13.09		6.33	
VZ.N	Top	9.92	0.43	4.77	−7.25	-9.22	18.71	10.00**	16.58	5.54	-1.15
	Bottom	−7.68	−4.34		1.98		−13.36	−6.58		6.69	
WMT.N	Top	10.90	28.57***	51.76	13.13**	23.70	19.27	16.13**	45.58	4.05	14.81
	Bottom	−12.82	−23.20***		−10.57**		−24.15	−29.46***		−10.76**	
XOM.N	Top	6.34	6.88*	7.29	−1.07	-13.84	14.75	−18.30*	-28.00	−6.85	-23.52
	Bottom	−10.06	−0.41		12.78**		−24.39	9.70**		16.68***	
Average				**39.00**		**8.21**			**22.16**		**5.62**

Figure 3.4: Returns on long-short strategies conditional on sentiment. This figure reports the average returns, in bps, on long-short strategies intended to exploit the difference between positive and negative overnight sentiment. The plotted values represent strategy returns conditional on social media sentiment (blue), on news media sentiment (red) and, for comparison, on average unconditional returns (black). The top panel depicts returns aggregated from 9:30 am to 4:00 pm 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 9:31 am to 4:00 pm instead, with the overnight return removed.

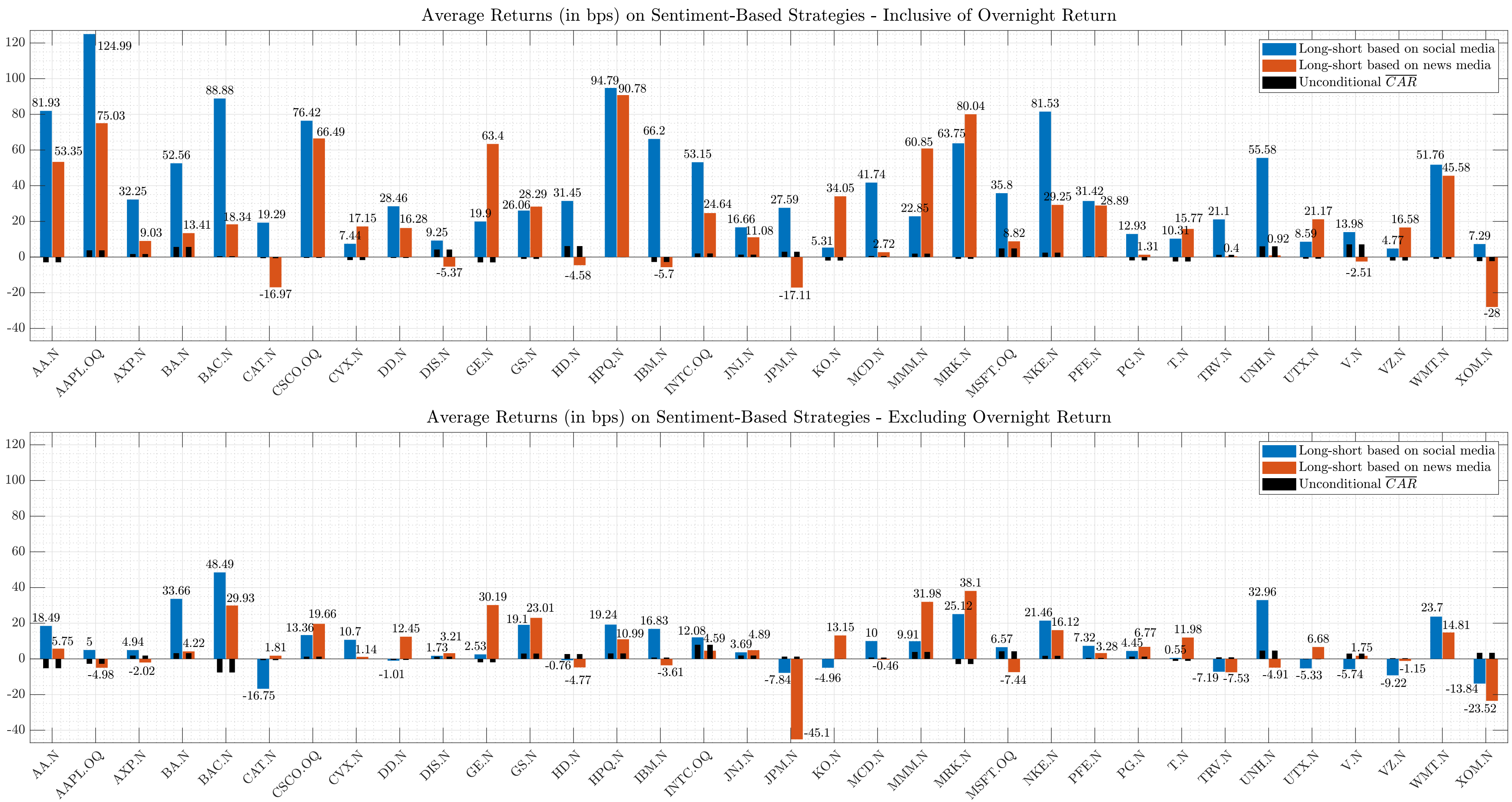

Table 3.2: The first half-hour CARs conditional on the top and bottom overnight sentiment. This table reports the top and bottom deciles of overnight cumulative sentiment for each sample stock and the corresponding cumulative abnormal returns the next day. Columns (1) and (6) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01 pm the previous day to 9:29 am. That is, $\overline{CSent_{i,x}}\,[16{:}01, 9{:}29]$ as defined in Eq.(3.5). Columns (2) and (7) are the average cumulative abnormal returns aggregated from 9:30 am to 10:00 am 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.(3.6). Similarly, Columns (4) and (9) are the corresponding average cumulative abnormal returns but aggregated from 9:31 am to 10:00 am instead, with the overnight return removed. The $\overline{CAR}$s are conditional on sentiment deciles, $\mathcal{D}_{i,10}$ (highest sentiment) and $\mathcal{D}_{i,1}$ (lowest sentiment). In Column (3) and (8), T-B are the returns, in bps, on a long-short strategy intended to exploit this difference. The last row 'Average' indicates the average return on the strategy across all stocks. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are based on confidence bands constructed from bootstrap simulations of the unconditional cumulative returns.

		Social Media					News Media				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stock i	Cond.decile	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B
AA.N	Top	6.72	32.93***	98.79	-6.44	35.35	10.84	25.57**	63.42	-7.42	15.82
	Bottom	-6.39	-65.86***		-41.8***		-17.84	-37.85***		-23.24**	
AAPL.OQ	Top	46.34	58.41***	108.73	-1.09	-11.26	62.32	40.91***	61.34	-8.69***	-18.67
	Bottom	-34.25	-50.32***		10.17**		-43.22	-20.43***		9.99**	
AXP.N	Top	4.03	5.05	36.97	1.62	9.66	10.31	4.36	9.76	-4.89*	-1.29
	Bottom	-3.39	-31.92***		-8.04***		-5.42	-5.4		-3.61	
BA.N	Top	10.11	18.5**	37.91	8.56	19.01	26.51	3.94	13.91	0.99	4.72
	Bottom	-13.32	-19.41***		-10.45***		-34.09	-9.96**		-3.73	
BAC.N	Top	9.01	46.49***	70.35	15.96***	29.96	13.91	15.46	-0.55	3.1	11.03
	Bottom	-31.27	-23.86***		-14***		-25.58	16.01		-7.93*	
CAT.N	Top	5.61	21.44***	46.61	-0.4	10.57	10.88	-7.06	-8.82	4.93	9.95
	Bottom	-6.51	-25.18***		-10.97		-14.12	1.77		-5.02	
CSCO.OQ	Top	9.49	34.91***	66.01	3.1	2.95	25.59	21.55**	49.76	3.16	2.93
	Bottom	-23.94	-31.1***		0.16		-9.8	-28.21***		0.22	
CVX.N	Top	5.28	-10.21	8.48	-0.68	11.74	11.51	2.24	20.9	-1.43	4.89
	Bottom	-5.44	-18.68**		-12.42**		-19.31	-18.66**		-6.33	
DD.N	Top	2.33	20.4***	31.72	6.51**	2.26	2.15	-1.69	5.09	-0.4	1.27
	Bottom	-2.69	-11.32*		4.25		-1.56	-6.79		-1.66	
DIS.N	Top	5.62	16.16**	17.95	12.36***	10.42	6.79	-9.33*	-12.43	-3.34	-3.86
	Bottom	-2.91	-1.78		1.93		-5.15	3.1		0.52	
GE.N	Top	7.74	11.4**	11.55	-1.18	-5.82	25.34	8.81**	31.62	-3.06	-1.59
	Bottom	-26.82	-0.15		4.64		-10.46	-22.81***		-1.47	
GS.N	Top	8.68	10	24.52	15.76*	17.55	20.31	11.4	20.19	13.58	14.92
	Bottom	-18.98	-14.51**		-1.79*		-42.88	-8.79*		-1.35*	
HD.N	Top	9.62	32.03***	34.82	2.72	2.61	19.32	4.94	-1.2	1.45	-1.39
	Bottom	-3.6	-2.78*		0.11		-5.64	6.14		2.84	
HPQ.N	Top	8.77	31.53***	93.05	12.97	17.5	19.7	26.45***	90.	4.77	10.21
	Bottom	-13.69	-61.52***		-4.53		-21.47	-63.55***		-5.44	
IBM.N	Top	11.05	19.05***	57.75	9.46**	8.37	31.32	-11.44	-13.07	-3.22	-10.98
	Bottom	-10.33	-38.71***		1.09		-12.16	1.62		7.76*	

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		Social Media					News Media				
Stock i	Cond.decile	(1) $\overline{CSent}$	(2) $\overline{CAR}$	(3) T-B	(4) $\overline{CAR_{-1}}$	(5) T-B	(6) $\overline{CSent}$	(7) $\overline{CAR}$	(8) T-B	(9) $\overline{CAR_{-1}}$	(10) T-B
INTC.OQ	Top	15.13	19.45***	49.63	11.11**	8.56	29.58	10.94**	32.55	15.43***	12.5
	Bottom	-10.16	-30.18***		2.55		-15.52	-21.62***		2.94	
JNJ.N	Top	7.02	6.88***	17.67	-1.16	4.7	12.51	4.03	8.54	-1.61	2.35
	Bottom	-3.81	-10.79*		-5.86		-7.55	-4.52		-3.96	
JPM.N	Top	8.28	24.08***	37.16	6.98	1.73	19.48	0.29	25.11	2.92	-2.88
	Bottom	-17.47	-13.08**		5.25		-37.77	-24.82***		5.8	
KO.N	Top	6.49	1.1	14.44	1.04	4.17	15.41	15.12***	35.67	7.48***	14.76
	Bottom	-6.19	-13.34*		-3.13		-11.09	-20.55***		-7.28**	
MCD.N	Top	6.44	19.23***	31.4	1.72	-0.35	11.04	0.21	5.77	2.42	2.59
	Bottom	-9.2	-12.16***		2.07		-15.45	-5.57		-0.17	
MMM.N	Top	4.68	11.88**	17.51	8.67*	4.58	10.25	16***	50.51	12.2**	21.64
	Bottom	-2.71	-5.64		4.09		-6.82	-34.51***		-9.43***	
MRK.N	Top	6.27	31.56***	57.74	6.59**	19.1	11.63	39.93***	73.68	17.59***	31.74
	Bottom	-4.29	-26.17***		-12.5***		-8.52	-33.75***		-14.16***	
MSFT.OQ	Top	24.92	1.9	23.04	-10.09***	-6.19	49.02	13.98*	17.87	0.61	1.62
	Bottom	-17.66	-21.14***		-3.9		-10.14	-3.89		-1	
NKE.N	Top	9.68	49.35***	71.45	6.55	11.38	9.32	17.71**	23.48	4.7	10.36
	Bottom	-4.99	-22.1***		-4.83		-7.	-5.77		-5.66*	
PFE.N	Top	6.81	8.29	12.02	-1.18	-12.07	13.26	16.63***	33.58	3.08	7.97
	Bottom	-6.87	-3.74		10.89***		-13.15	-16.95***		-4.89	
PG.N	Top	4.94	6.86**	11.38	7.37*	2.9	9.35	0.71	2.47	5.05	7.93
	Bottom	-3.07	-4.52		4.47*		-6.45	-1.76		-2.88	
T.N	Top	11.62	0.61	10.71	-2.3	0.95	17.58	-7.3	4.55	-6.98	0.77
	Bottom	-8.22	-10.1		-3.25		-12.99	-11.86		-7.75	
TRV.N	Top	1.39	15.65***	29.49	1.94	1.2	1.76	0.78	8.06	-3.33	0.14
	Bottom	-1.24	-13.84**		0.75		-1.22	-7.28		-3.47	
UNH.N	Top	4.31	19.7***	31.45	5.75	8.84	8.29	6.57	6.18	1.18	0.35
	Bottom	-1.94	-11.75**		-3.09		-4.29	0.39		0.83	
UTX.N	Top	3.52	4.2	16.03	-0.12	2.11	6.89	19.81***	25.5	8.77**	11.
	Bottom	-2.84	-11.83**		-2.23		-6.54	-5.69		-2.23	
V.N	Top	5.72	27.25***	25.46	5.4	5.75	6.65	6.52	-9.18	4.02	-4.92
	Bottom	-2.18	1.78		-0.34		-3.06	15.7*		8.93**	
VZ.N	Top	9.92	-6.62	6.2	-14.3**	-7.8	18.71	-1.32	18.99	-5.77	1.26
	Bottom	-7.68	-12.82		-6.5		-13.36	-20.31**		-7.04	
WMT.N	Top	10.9	24.46***	40.26	9.02***	12.2	19.27	16.59***	42.42	4.51	11.64
	Bottom	-12.82	-15.8***		-3.17		-24.15	-25.83***		-7.13**	
XOM.N	Top	6.34	10.41***	29.38	2.46	8.25	14.75	-12.22	-8.12	-0.77	-3.64
	Bottom	-10.06	-18.97**		-5.79		-24.39	-4.1		2.88	
Profit				**37.58**		**6.79**			21.40		**4.86**

Table 3.3: THE FIRST HOUR CARS CONDITIONAL ON THE TOP AND BOTTOM OVERNIGHT SENTIMENT. This table reports the top and bottom deciles of overnight cumulative sentiment for each sample stock and the corresponding cumulative abnormal returns the next day. Columns (1) and (6) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01 pm the previous day to 9:29 am. That is, $\overline{CSent_{i,x}}$ [16:01, 9:29] as defined in Eq.(3.5). Columns (2) and (7) are the average cumulative abnormal returns aggregated from 9:30 am to 10:30 am 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.(3.6). Similarly, Columns (4) and (9) are the corresponding average cumulative abnormal returns but aggregated from 9:31 am to 10:30 am instead, with the overnight return removed. The $\overline{CAR}$s are conditional on sentiment deciles, $\mathcal{D}_{i,10}$ (highest sentiment) and $\mathcal{D}_{i,1}$ (lowest sentiment). In Column (3) and (8), T-B are the returns, in bps, on a long-short strategy intended to exploit this difference. The last row 'Average' indicates the average return on the strategy across all stocks. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are based on confidence bands constructed from bootstrap simulations of the unconditional cumulative returns.

		Social Media					News Media				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stock i	Cond.decile	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B
AA.N	Top	6.72	37.2***	100.31	-2.17	36.87	10.84	21.87**	53.15	-11.13	5.55
	Bottom	-6.39	-63.11***		-39.05		-17.84	-31.28**		-16.68	
AAPL.OQ	Top	46.34	58.64***	109.00	-0.87	-10.99	62.32	41.52***	60.75	-8.07**	-19.27
	Bottom	-34.25	-50.36***		10.12		-43.22	-19.23***		11.19**	
AXP.N	Top	4.03	4.33	39.53	0.89	12.21	10.31	4.99	13.01	-4.26	1.96
	Bottom	-3.39	-35.19***		-11.32		-5.42	-8.01		-6.22*	
BA.N	Top	10.11	22.19***	45.01	12.26	26.11	26.51	1.83	11.16	-1.13	1.97
	Bottom	-13.32	-22.82***		-13.85		-34.09	-9.33**		-3.09	
BAC.N	Top	9.01	42.28***	62.59	11.76	22.20	13.91	9.49	-8.55	-2.87	3.03
	Bottom	-31.27	-20.3***		-10.44		-25.58	18.03		-5.91	
CAT.N	Top	5.61	22.95***	48.94	1.11	12.90	10.88	-9.19	-13.62	2.79	5.16
	Bottom	-6.51	-25.99***		-11.79		-14.12	4.43		-2.36	
CSCO.OQ	Top	9.49	35.32***	67.44	3.51	4.38	25.59	18.56**	54.26	0.17	7.43
	Bottom	-23.94	-32.12***		-0.86		-9.80	-35.69***		-7.25	
CVX.N	Top	5.28	-6.71	9.17	2.81	12.43	11.51	-0.17	16.95	-3.84	0.95
	Bottom	-5.44	-15.89		-9.62		-19.31	-17.12*		-4.79	
DD.N	Top	2.33	17.23***	30.51	3.34	1.05	2.15	-1	9.53	0.3	5.70
	Bottom	-2.69	-13.28*		2.30		-1.56	-10.53		-5.41	
DIS.N	Top	5.62	16.65**	12.67	12.84	5.15	6.79	-9.07	-10.42	-3.08	-1.84
	Bottom	-2.91	3.98		7.69		-5.15	1.35		-1.23	
GE.N	Top	7.74	10.37**	9.77	-2.21	-7.60	25.34	13.53***	38.22	1.67	5.01
	Bottom	-26.82	0.6		5.38		-10.46	-24.69***		-3.34	
GS.N	Top	8.68	8.18	23.84	13.94	16.88	20.31	10.64	19.95	12.81	14.68
	Bottom	-18.98	-15.66***		-2.94		-42.88	-9.31		-1.87*	
HD.N	Top	9.62	35.41***	36.71	6.09	4.50	19.32	10.31	1.78	6.82	1.59
	Bottom	-3.60	-1.3		1.59		-5.64	8.53		5.23	
HPQ.N	Top	8.77	31.81***	90.57	13.24	15.02	19.70	31.89***	95.68	10.21	15.89
	Bottom	-13.69	-58.76***		-1.77		-21.47	-63.8***		-5.69	
IBM.N	Top	11.05	18.85***	57.56	9.27	8.18	31.32	-9.96	-13.68	-1.74	-11.59
	Bottom	-10.33	-38.71***		1.09		-12.16	3.72		9.85**	

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		Social Media					News Media				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stock i	Cond.decile	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B
INTC.OQ	Top	15.13	21.63***	56.39	13.29	15.32	29.58	13.42**	32.20	17.92***	12.14
	Bottom	-10.16	-34.76***		-2.02		-15.52	-18.78**		5.78	
JNJ.N	Top	7.02	5.96**	16.13	-2.08	3.16	12.51	2.87*	6.78	-2.76	0.59
	Bottom	-3.81	-10.17		-5.24		-7.55	-3.91		-3.35	
JPM.N	Top	8.28	19.85**	34.46	2.75	-0.97	19.48	-2.42	18.96	0.21	-9.03
	Bottom	-17.47	-14.62**		3.71		-37.77	-21.38***		9.24	
KO.N	Top	6.49	-1.31	10.00	-1.37	-0.27	15.41	20.65***	38.62	13.02***	17.71
	Bottom	-6.19	-11.3		-1.10		-11.09	-17.97***		-4.69	
MCD.N	Top	6.44	20.31***	31.52	2.80	-0.22	11.04	4.46	10.66	6.67	7.48
	Bottom	-9.20	-11.21**		3.02		-15.45	-6.2		-0.81	
MMM.N	Top	4.68	11.37**	15.09	8.17	2.16	10.25	18.2***	56.55	14.41***	27.68
	Bottom	-2.71	-3.72		6.01		-6.82	-38.34***		-13.27***	
MRK.N	Top	6.27	32.8***	60.38	7.84	21.74	11.63	43.33***	82.40	20.98***	40.46
	Bottom	-4.29	-27.57***		-13.90		-8.52	-39.06***		-19.47***	
MSFT.OQ	Top	24.92	3.2	30.81	-8.80	1.59	49.02	12.06	18.20	-1.3	1.94
	Bottom	-17.66	-27.62***		-10.38		-10.14	-6.13		-3.25	
NKE.N	Top	9.68	47.06***	72.00	4.26	11.93	9.32	19.38**	24.63	6.37	11.50
	Bottom	-4.99	-24.94***		-7.66		-7.00	-5.25		-5.13	
PFE.N	Top	6.81	9.14	15.00	-0.33	-9.09	13.26	17.46***	37.01	3.91	11.40
	Bottom	-6.87	-5.86		8.77		-13.15	-19.54***		-7.48*	
PG.N	Top	4.94	5.26	5.43	5.76	-3.06	9.35	1.59	2.98	5.93	8.43
	Bottom	-3.07	-0.17		8.82		-6.45	-1.39		-2.5	
T.N	Top	11.62	-2.31	7.03	-5.22	-2.73	17.58	-7.5	6.65	-7.18	2.86
	Bottom	-8.22	-9.34		-2.49		-12.99	-14.15*		-10.05*	
TRV.N	Top	1.39	14.71***	29.29	1.00	0.99	1.76	0.56	9.66	-3.55	1.74
	Bottom	-1.24	-14.58***		0.00		-1.22	-9.1		-5.29	
UNH.N	Top	4.31	21.8***	34.37	7.86	11.76	8.29	10.2	5.64	4.8	-0.18
	Bottom	-1.94	-12.57**		-3.90		-4.29	4.55		4.99	
UTX.N	Top	3.52	1.72	14.69	-2.60	0.77	6.89	17.44***	21.75	6.41	7.26
	Bottom	-2.84	-12.97**		-3.38		-6.54	-4.32		-0.85	
V.N	Top	5.72	27.36***	31.51	5.51	11.80	6.65	5.82	-10.02	3.32	-5.76
	Bottom	-2.18	-4.16		-6.28		-3.06	15.85*		9.08*	
VZ.N	Top	9.92	-4.41	2.72	-12.09	-11.28	18.71	2.17	22.58	-2.29	4.85
	Bottom	-7.68	-7.13		-0.81		-13.36	-20.41**		-7.13	
WMT.N	Top	10.90	27.36***	40.08	11.92	12.01	19.27	17.69***	40.56	5.61	9.78
	Bottom	-12.82	-12.72**		-0.10		-24.15	-22.87***		-4.17	
XOM.N	Top	6.34	10.84***	25.27	2.89	4.14	14.75	-15.55*	-11.39	-4.1	-6.91
	Bottom	-10.06	-14.43		-1.25		-24.39	-4.16		2.81	
Profit				**37.52**		**6.74**			**21.84**		**5.30**

Table 3.4: Morning session's CARs conditional on the top and bottom overnight sentiment. This table reports the top and bottom deciles of overnight cumulative sentiment for each sample stock and the corresponding cumulative abnormal returns the next day. Columns (1) and (6) are the average cumulative overnight social and news media sentiment, respectively, with sentiment aggregated from 4:01 pm the previous day to 9:29 am. That is, $\overline{CSent_{i,x}}\,[16{:}01, 9{:}29]$ as defined in Eq.(3.5). Columns (2) and (7) are the average cumulative abnormal returns aggregated from 9:30 am to 12:00 pm 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.(3.6). Similarly, Columns (4) and (9) are the corresponding average cumulative abnormal returns but aggregated from 9:31 am to 12:00 pm instead, with the overnight return removed. The $\overline{CAR}$s are conditional on sentiment deciles, $\mathcal{D}_{i,10}$ (highest sentiment) and $\mathcal{D}_{i,1}$ (lowest sentiment). In Column (3) and (8), T-B are the returns, in bps, on a long-short strategy intended to exploit this difference. The last row 'Average' indicates the average return on the strategy across all stocks. The significance levels of 90%, 95% and 99% (denoted by *, ** and ***, respectively) are based on confidence bands constructed from bootstrap simulations of the unconditional cumulative returns.

		Social Media					News Media				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Stock i	Cond.decile	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B	$\overline{CSent}$	$\overline{CAR}$	T-B	$\overline{CAR_{-1}}$	T-B
AA.N	Top	6.72	32.15***	93.01	-7.22	29.57	10.84	29.31**	75.18	-3.68	27.59
	Bottom	-6.39	-60.86***		-36.79		-17.84	-45.87***		-31.26**	
AAPL.OQ	Top	46.34	60.56***	110.47	1.05	-9.53	62.32	46.95***	63.41	-2.65	-16.61
	Bottom	-34.25	-49.91***		10.58		-43.22	-16.46***		13.96**	
AXP.N	Top	4.03	-1.89	32.56	-5.33	5.24	10.31	6.26	8.09	-2.99	-2.96
	Bottom	-3.39	-34.44***		-10.57		-5.42	-1.82		-0.03	
BA.N	Top	10.11	23.33***	41.35	13.40	22.45	26.51	3.71	9.62	0.76	0.42
	Bottom	-13.32	-18.02***		-9.05		-34.09	-5.9		0.33	
BAC.N	Top	9.01	39.02***	67.61	8.49	27.22	13.91	9.52	-13.41	-2.84	-1.83
	Bottom	-31.27	-28.59***		-18.73		-25.58	22.93		-1.01	
CAT.N	Top	5.61	9.01	23.30	-12.83	-12.74	10.88	-12.51	-21.1	-0.52	-2.32
	Bottom	-6.51	-14.29		-0.09		-14.12	8.59		1.8	
CSCO.OQ	Top	9.49	34.5***	74.94	2.69	11.87	25.59	20.02**	59.45	1.63	12.63
	Bottom	-23.94	-40.44***		-9.18		-9.80	-39.44***		-11***	
CVX.N	Top	5.28	-5.94	7.29	3.58	10.55	11.51	-2.43	15.76	-6.1	-0.25
	Bottom	-5.44	-13.23		-6.97		-19.31	-18.19*		-5.85	
DD.N	Top	2.33	17.54***	35.36	3.65	5.90	2.15	-0.35	14.48	0.94	10.65
	Bottom	-2.69	-17.83**		-2.25		-1.56	-14.83*		-9.71*	
DIS.N	Top	5.62	14.31*	9.63	10.50	2.10	6.79	-6.99	-8.42	-1	0.16
	Bottom	-2.91	4.68		8.39		-5.15	1.43		-1.16	
GE.N	Top	7.74	8.17*	8.62	-4.41	-8.75	25.34	16.97***	53.88	5.1	20.66
	Bottom	-26.82	-0.45		4.34		-10.46	-36.91***		-15.57***	
GS.N	Top	8.68	5.45	25.63	11.21	18.67	20.31	9.45	27.16	11.62	21.89
	Bottom	-18.98	-20.19***		-7.47		-42.88	-17.71**		-10.26***	
HD.N	Top	9.62	27.78***	30.41	-1.54	-1.80	19.32	11.35	1.51	7.86	1.32
	Bottom	-3.60	-2.64		0.26		-5.64	9.84		6.54	
HPQ.N	Top	8.77	28.23**	79.55	9.66	4.00	19.70	27.85**	91.05	6.17	11.26
	Bottom	-13.69	-51.33***		5.67		-21.47	-63.2***		-5.09	
IBM.N	Top	11.05	18.93***	56.09	9.34	6.71	31.32	-4.24	-6.78	3.99	-4.69
	Bottom	-10.33	-37.16***		2.63		-12.16	2.54		8.68	

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		Social Media					News Media				
Stock i	Cond.decile	(1) $\overline{CSent}$	(2) $\overline{CAR}$	(3) T-B	(4) $\overline{CAR_{-1}}$	(5) T-B	(6) $\overline{CSent}$	(7) $\overline{CAR}$	(8) T-B	(9) $\overline{CAR_{-1}}$	(10) T-B
INTC.OQ	Top	15.13	23.87***	56.31	15.53	15.24	29.58	14.38**	38.4	18.88***	18.35
	Bottom	-10.16	-32.45***		0.29		-15.52	-24.02***		0.53	
JNJ.N	Top	7.02	6.23**	16.47	-1.81	3.50	12.51	2.84	5.57	-2.8	-0.63
	Bottom	-3.81	-10.24		-5.31		-7.55	-2.73		-2.17	
JPM.N	Top	8.28	16.74*	26.32	-0.35	-9.11	19.48	-11.68*	1.04	-9.05*	-26.95
	Bottom	-17.47	-9.57		8.76		-37.77	-12.73*		17.9***	
KO.N	Top	6.49	0	7.14	-0.06	-3.13	15.41	20.17***	32.82	12.54***	11.91
	Bottom	-6.19	-7.14		3.07		-11.09	-12.64*		0.63	
MCD.N	Top	6.44	23.75***	37.96	6.24	6.22	11.04	3.52	5.1	5.73	1.92
	Bottom	-9.20	-14.21***		0.02		-15.45	-1.58		3.81	
MMM.N	Top	4.68	14.57**	20.90	11.36	7.96	10.25	17.65***	60.82	13.85**	31.95
	Bottom	-2.71	-6.33		3.40		-6.82	-43.16***		-18.09***	
MRK.N	Top	6.27	31.71***	58.18	6.74	19.54	11.63	44.24***	82.01	21.89***	40.07
	Bottom	-4.29	-26.47***		-12.80		-8.52	-37.77***		-18.18***	
MSFT.OQ	Top	24.92	6.48	36.21	-5.51	6.98	49.02	7.14	11.72	-6.23	-4.53
	Bottom	-17.66	-29.73***		-12.50		-10.14	-4.58		-1.7	
NKE.N	Top	9.68	48.88***	66.38	6.09	6.31	9.32	19.51**	23.13	6.5	10.01
	Bottom	-4.99	-17.5**		-0.22		-7.00	-3.62		-3.51	
PFE.N	Top	6.81	12.28	31.42	2.82	7.32	13.26	15.91**	28.89	2.36	3.28
	Bottom	-6.87	-19.14***		-4.51		-13.15	-12.98**		-0.92	
PG.N	Top	4.94	7.77	10.87	8.28	2.39	9.35	0.98	2.07	5.32	7.53
	Bottom	-3.07	-3.1		5.89		-6.45	-1.09		-2.21	
T.N	Top	11.62	2.87	9.19	-0.05	-0.57	17.58	-2.25	8.12	-1.93	4.33
	Bottom	-8.22	-6.32		0.53		-12.99	-10.37		-6.26	
TRV.N	Top	1.39	12.65**	23.96	-1.06	-4.33	1.76	2.32	5.86	-1.79	-2.07
	Bottom	-1.24	-11.31*		3.27		-1.22	-3.54		0.28	
UNH.N	Top	4.31	20.49***	36.93	6.55	14.32	8.29	4.56	2.11	-0.84	-3.72
	Bottom	-1.94	-16.44***		-7.77		-4.29	2.44		2.88	
UTX.N	Top	3.52	-1.57	7.77	-5.89	-6.15	6.89	16.74***	23.88	5.71	9.38
	Bottom	-2.84	-9.34		0.26		-6.54	-7.14		-3.67	
V.N	Top	5.72	27.04***	22.06	5.20	2.34	6.65	8.46	-4.3	5.96	-0.04
	Bottom	-2.18	4.98		2.85		-3.06	12.76		6	
VZ.N	Top	9.92	0.27	7.15	-7.41	-6.85	18.71	7.61	26.81	3.15	9.08
	Bottom	-7.68	-6.89		-0.57		-13.36	-19.21**		-5.93	
WMT.N	Top	10.90	28.22***	42.99	12.78	14.92	19.27	18.57***	43.14	6.49	12.37
	Bottom	-12.82	-14.77**		-2.15		-24.15	-24.58***		-5.88	
XOM.N	Top	6.34	5.19*	18.12	-2.76	-3.01	14.75	-15.71	-14.35	-4.26	-9.87
	Bottom	-10.06	-12.93		0.25		-24.39	-1.36		5.61	
Profit				**36.24**		**5.45**			**22.14**		**5.60**

3.3.2 After-Hours Media Sentiment Patterns

Are the results obtained in our previous section simply driven by past stock performance? Could it be that that a particularly bearish session is followed by a torrent of negative and pessimistic commentary on news and social media that would simply reflect the continuation of the tone during the trading session? It is well 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 other way around—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.

The 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 as to 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 3.3.1 by swapping the sentiment and CAR variables.

Continuing with CSCO.OQ as an example, we demonstrate the method in Figure 3.5. In the estimation window spanning from 9:30 am to 4:00 pm, we calculate and sort CARs into deciles. In the evaluation window spanning from 4:01 pm to 9:29 am 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 3.5 for the social and news media, respectively. Consistent with the figure legends in previous subsections, thick blue curves indicate average sentiment in the highest deciles, that is, on the days with the highest CARs. Similarly, thick red curves delineate sentiment on the days with the lowest 10% CARs. The 90%, 95% and 99% confidence bands (shown as grey layers) are constructed by performing 2,000 bootstrap simulations with the unconditional of CARs.

The intraday social media sentiment pattern tends to be consistent with daily routines. Following market closure and up to midnight, we observe a quick 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 3.5. From around 7:00 am, social media sentiment resumes its trend until the market opens. This is in striking contrast with the pattern observed for news media sentiment

[24] '(Nearly) nothing to fear but fear itself', 29 Jaunary 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`.

in the bottom panel of Figure 3.5.[25]

News media sentiment appears to be more persistent 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 3.5, 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]

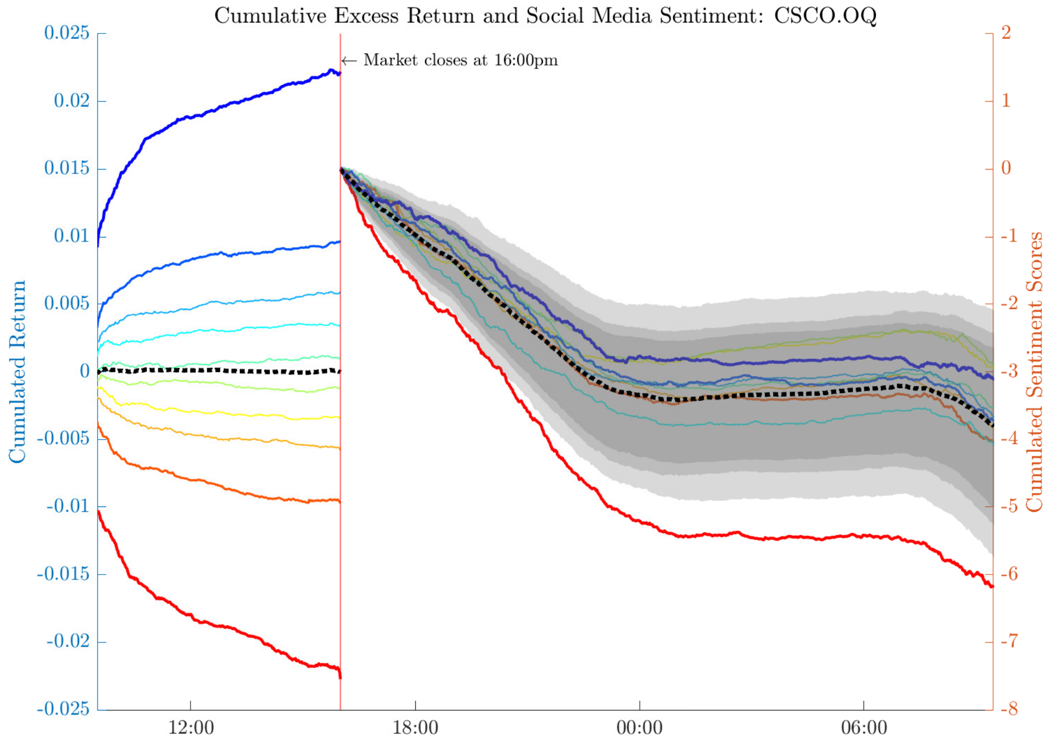
The conditional sentiment expressed in the news media is more positive than the emotions divulged on social media—consistent with the unconditional sentiment patterns in Figures 3.2 and 3.3. Cumulative social media sentiment of CSCO ranges from -3 to -6 (top panel of Figure 3.5, right vertical axis), while the cumulative news media sentiment is bounded between +3 to +9.5 (bottom panel of Figure 3.5, 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.

We perform the analysis for all the stocks in our sample and summarise the results in Table 3.5. Our results confirm the positive correlation between cumulative abnormal returns and the sentiment following trading sessions with excessive CARs. The findings are comparable between the social and news media, with the correlation between the tailed CARs (on the top and bottom decile performing days) and the after-hour sentiment on social (news) media reported at 0.4012 (0.4080) in Table 3.5. This evidence suggests a 'causality loop' whereas trading session performance generates media sentiment following the market closing time, continues overnight, and is 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 further and elaborate on other issues in Section 3.4.

[25] Social and news media patterns observed in Figure 3.5 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 results for CSCO.OQ only. We provide similar plots for AAPL.OQ in Figure B.16 in the Supplementary Online Appendix on page 174 for interested readers. Plots for other stocks in our sample are available upon request.

Figure 3.5: Cumulative Returns and Ensuing Sentiment (CSCO.OQ) Sentiment and returns 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 9:30 am to 4:00 pm 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 4:00 pm to 9:29 am 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 $M = 2,000$.



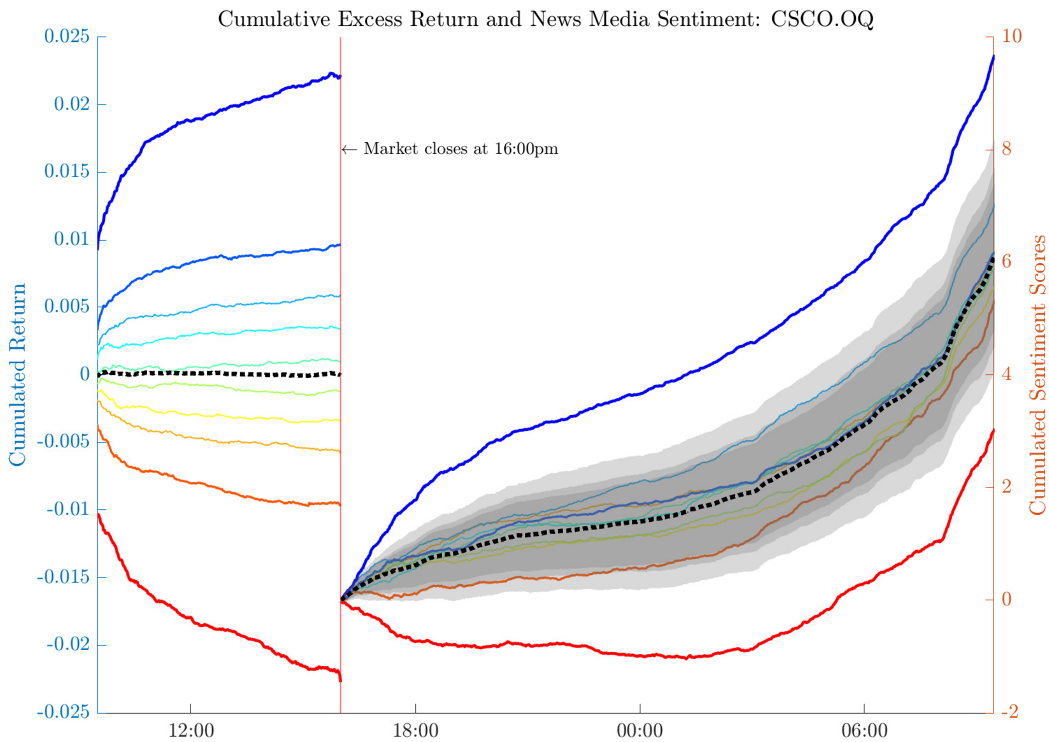


Table 3.5: Cumulative Excess Return and Overnight Sentiment. The table reports the average CARs (in bps) for the top and bottom CAR deciles in Column (1). The corresponding cumulative sentiment from the market close to the next trading day open for the social and news media are presented in Columns (2) and (3), respectively. That is, the CARs are aggregated from 9:30 am to 4:00 pm 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 4:01 pm on day t to 9:29 am on day $t+1$. 'Top' and 'Bottom' represent the average CARs in the lowest and highest CAR deciles. The correlation coefficient between the cumulative excess returns and the ensuing overnight **social** media sentiment, Columns (1) and (2), is 0.4949. The correlation coefficient between the cumulative excess returns and the ensuing overnight **news** media sentiment, Columns (1) and (3), is 0.7086. *, ** and *** denote the significance levels of 90%, 95%, and 99%, respectively. The confidence bands are based on the average cumulative sentiment on n days randomly drawn M times from the entire sample of T days without conditioning on CAR. Specifically, n is set to match the size (in days) of each decile and the number of simulations is set to $M = 2,000$.

Stock i	Cond.decile	(1)	(2)	(3)	Stock i	Cond.decile	(1)	(2)	(3)
		$\overline{CAR}$ [9:30,16:00]	$\overline{CSent}^S$	$\overline{CSent}^N$			$\overline{CAR}$ [9:30,16:00]	$\overline{CSent}^S$	$\overline{CSent}^N$
AA.N	Top	384.97	1.23***	1.53***	JPM.N	Top	257.63	−2.16*	−0.28**
	Bottom	−396.44	−1.03***	−5.30***		Bottom	−243.01	−7.96***	−21.48***
AAPL.OQ	Top	252.52	17.58***	22.94***	KO.N	Top	177.19	1.00***	1.24
	Bottom	−253.38	−10.56***	−9.82***		Bottom	−188.18	−0.02*	0.68
AXP.N	Top	243.90	0.88***	1.90	MCD.N	Top	153.35	0.62***	−0.90
	Bottom	−245.75	−0.33***	1.20		Bottom	−151.68	−1.56***	−2.32
BA.N	Top	225.11	−0.56	4.68***	MMM.N	Top	206.81	0.76**	0.86
	Bottom	−208.38	−3.96***	−0.04		Bottom	−215.55	0.31**	1.61*
BAC.N	Top	354.98	−5.57***	−5.50***	MRK.N	Top	229.48	1.18**	1.64
	Bottom	−347.40	−19.98***	−8.11***		Bottom	−227.59	0.00***	0.84
CAT.N	Top	289.12	1.14***	−0.32	MSFT.OQ	Top	221.76	2.99	22.34**
	Bottom	−297.60	−1.58***	−1.10*		Bottom	−201.58	−0.09***	17.93
CSCO.OQ	Top	222.04	−3.12	9.69***	NKE.N	Top	238.41	2.36***	3.19***
	Bottom	−227.21	−6.18***	3.04**		Bottom	−229.57	0.30*	0.12
CVX.N	Top	207.90	0.25**	1.78***	PFE.N	Top	189.12	0.79***	3.29***
	Bottom	−212.87	−1.41***	−10.97***		Bottom	−180.70	−1.27***	−2.54***
DD.N	Top	228.71	−0.14	−0.01	PG.N	Top	146.79	0.78*	1.09
	Bottom	−237.26	−0.52***	0.02		Bottom	−143.00	0.04***	1.49*
DIS.N	Top	202.69	1.46**	0.56	T.N	Top	157.82	0.62	4.16***
	Bottom	−186.81	0.39	0.02		Bottom	−181.24	−0.93***	−2.02***
GE.N	Top	210.80	−8.94***	8.39***	TRV.N	Top	216.14	0.13**	0.31**
	Bottom	−209.30	−13.95***	−0.13***		Bottom	−207.44	−0.09*	−0.20**
GS.N	Top	249.94	−3.08	−5.68	UNH.N	Top	252.33	0.60***	0.77
	Bottom	−253.52	−7.25***	−19.54***		Bottom	−221.79	0.01***	0.87
HD.N	Top	206.29	2.40***	5.55***	UTX.N	Top	208.01	0.50***	1.05*
	Bottom	−181.86	0.69***	3.66		Bottom	−208.61	−0.08*	0.53
HPQ.N	Top	324.41	−0.74	1.37	V.N	Top	270.82	1.23**	0.11
	Bottom	−330.28	−4.21***	−4.71***		Bottom	−238.23	0.44**	0.48
IBM.N	Top	164.27	2.16***	11.82***	VZ.N	Top	176.56	2.02***	5.92***
	Bottom	−180.74	−1.08***	3.66***		Bottom	−177.10	−0.12***	−1.12***
INTC.OQ	Top	225.97	4.24***	10.45***	WMT.N	Top	167.76	1.48***	4.40***
	Bottom	−220.86	−0.66***	0.95***		Bottom	−173.92	−3.08***	−8.60***
JNJ.N	Top	145.50	2.19***	4.79***	XOM.N	Top	223.26	−0.83	1.15***
	Bottom	−130.97	0.34**	0.88		Bottom	−220.13	−3.32***	−9.29***
					Corr			**0.4012*****	**0.4080*****

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

3.4.1 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 will be biased. At daily frequencies, the most prominent factor to consider is previous day performance. In what follows, we contrast estimates from the two OLS regressions consisting of a baseline and extended regression for each of the stocks in our sample. The extended regression 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:

$$CAR_{i,t}\left[\tau_1,\tau_2\right] = a_i + b_i \times CSent_{i,t}\left[\tau_{-1},\tau_0\right] + e_{i,t} \tag{3.7}$$

where i denotes a firm and $t \in \mathcal{D}_{i,x}$ as defined in Eq.(3.4). 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, $t \in \mathcal{D}_{i,10}$. Further, the extended model is specified as follows:

$$CAR_{i,t}\left[\tau_1,\tau_2\right] = \alpha_i + \beta_i \times CSent_{i,t}\left[\tau_{-1},\tau_0\right] + \gamma_i \times CAR_{i,t-1}\left[\widetilde{\tau}_1,\widetilde{\tau}_2\right] + \epsilon_{i,t} \tag{3.8}$$

where τ_1 and τ_2 define the event window. 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 3.3). That is, on day t we set τ_1 to 9:30 am and τ_2 to 9:31 am .

The main regressor, $CSent_{i,t}\left[\tau_{-1},\tau_0\right]$ is the average cumulative sentiment from **S**ocial or **N**ews media. We set τ_{-1} to 4:01 pm on day $t-1$ and τ_0 to 9:29 am on day t. It is computed by dividing $CSent_{i,t}$ in Eq.(3.3) by the total number of non-missing observations within the same time period. 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 [-1,048; 1,048], assuming consistent minimum or maximum sentiment values (-1 or +1, respectively) are reported every minute from 4:01 pm to 9:29 am.[27] As a result, if not adjusted for

[27]Theoretically, if every consecutive minute from 4:01 pm to 9:29 am contains the maximum score (+1), the accumu-

the volume of media coverage, the CAR series and the $CSent$ series would be at incomparable scales, resulting in inconsistent estimates in Eq.(3.7) and Eq.(3.8).

In Table 3.6, we provide exemplars of regression results based on Eq.(3.7) and Eq.(3.8) 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). 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.(3.8)—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.[28] This is consistent with the evidence provided in the literature on the overnight and intraday return reversals.[29]

We perform the analysis for the remaining 33 stocks and provide a visual summary of the estimated coefficients in Figure 3.6. In the figure, the estimated coefficients from Eqs.(3.7) and (3.8) are contrasted

lated 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.

[28]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.(3.7) and Eq.(3.8), we verified the persistence of the pattern identified. These results are available upon request.

[29]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 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.

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 3.6 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.(3.8) 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.[30] 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 3.6 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 3.6). This is lower than its sensitivity to negative social media sentiment, 1.2074 (Panel C of Table 3.6), 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 3.6 allow us to check the robustness of the results by contrasting the estimates from the baseline and controlled models.[31] The x-axis displays $\hat{\beta}$s from the controlled model in Eq.(3.8) and the y-axis indicates $\hat{b}$s estimated using the baseline model in Eq.(3.7). 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.6, we find that most stocks are clustering along the 45-degree line, implying that the differences in the coefficients are not substantial.

[30] As a way of example, consider CSCO and the estimated coefficients in Eq.(3.8) listed in the 'Controlled' column in Table 3.6. 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 3.6 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 3.6 Panel B.

[31] The respective news media sentiment plots are shown in Figure A.6 in the Appendix.

Therefore, the effect of overnight sentiment on the opening price is not biased by the stock performance pf the previous day.

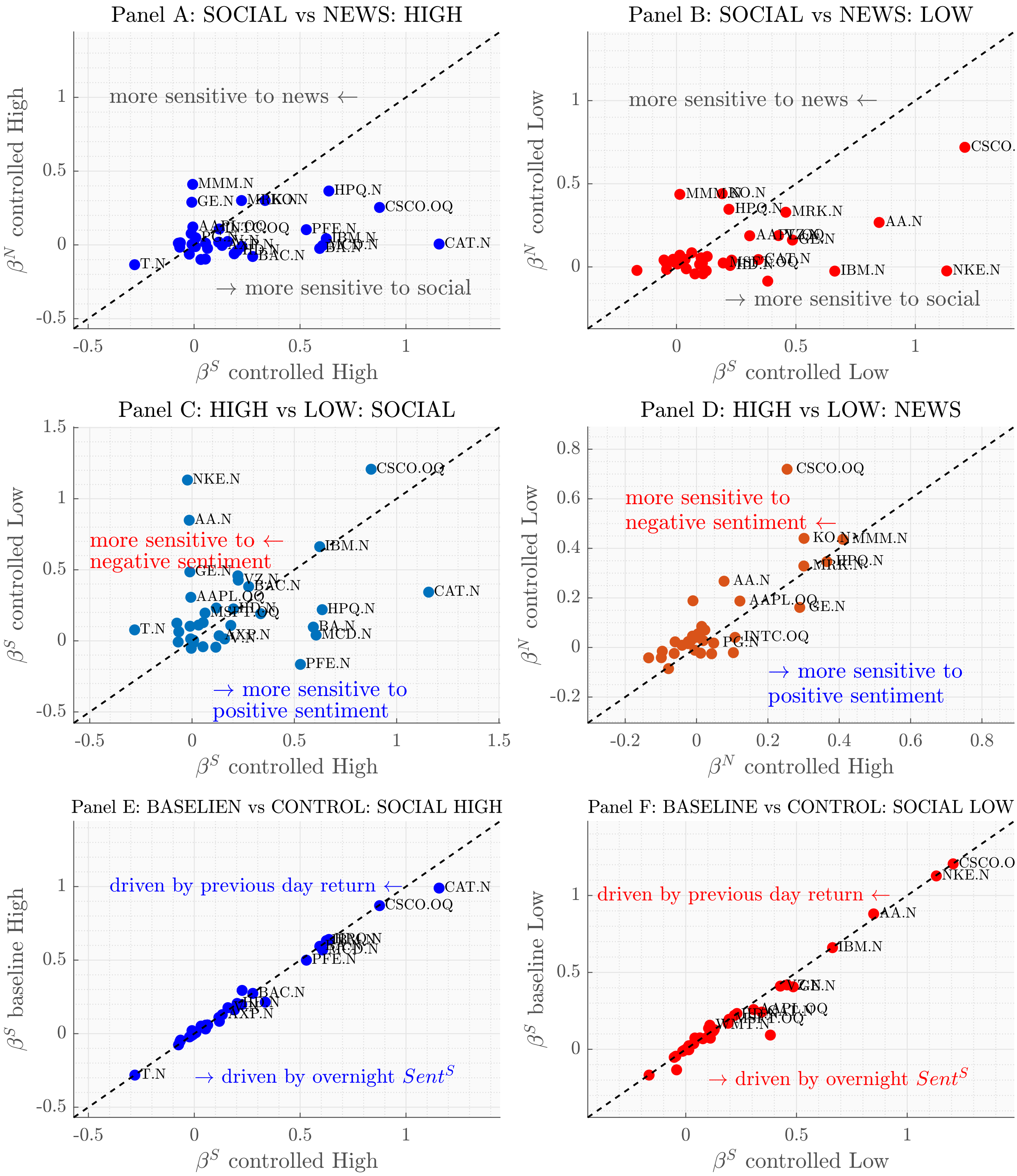
Table 3.6: Sentiment as a Predictor for Returns. The table contains representative regression output for the case of CSCO.OQ based on Eq.(3.7) and Eq.(3.8). The dependent variable is $CAR_{i,t}\,[9{:}30, 9{:}31]$, that is the cumulative abnormal return on CSCO.OQ in excess of the DJIA on day t from 9:30 am to 9:31 am. 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 4:01 pm on the previous day to 9:29 am 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 9:30 am to 4:00 pm. The t-statistics are in parentheses . *, ** 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***
	(8.66)	(8.69)	(7.76)	(7.98)
$CAR_{i,t-1}$		-0.0187		-0.0447*
		(-0.79)		(-1.85)
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***
	(6.12)	(6.2)	(2.5833)	(2.82)
$CAR_{i,t-1}$		-0.1732**		-0.0789
		(-1.94)		(-1.39)
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***
	(7.22)	(7.19)	(5.91)	(7.08)
$CAR_{i,t-1}$		0.0104		-0.2823***
		(0.15)		(-3.69)
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

3.4.2 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

Figure 3.6: Contrasting Betas 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.(3.7) and (3.8) (Panels E and F). Each scatter point represents an intersection of the two slope coefficients from Eq.(3.7) and/or Eq.(3.8). For example, the scatter points for CSCO.OQ in all the panels are constructed based on the regression output reported in Table 3.6. 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 stocks are more sensitive to social media sentiment under positive (negative) sentiment. Panels C and D contrast 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. Similar graphs comparing the baseline and controlled model results for the news media sentiment are provided in Figure A.6 in the Appendix.



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 3.7.

In Table 3.7, 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-dates 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.[32] To address the fact that earnings-related 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.[33]

Our findings suggest that the sentiment measured by TRMI and the overnight sentiment derived in this study are primarily capturing 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) or survey-based consumer confidence sentiment.

3.4.3 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 9:29 am. 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

[32] Refer to Jiang et al. (2012), Bagnoli et al. (2005), Michaely et al. (2013) and Bradley et al. (2014) as mentioned in Section 3.1.

[33] An exemplar of sentiment-event clustering and earnings announcements overlap is provided in the Supplementary Online Appendix in Figure B.12 for Apple, Inc. Similar figures for the remaining DJIA constituents are available upon request.

Table 3.7: 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.

		Social Media sentiment				**News Media sentiment**			
Asset, i	No.days	$\mathcal{D}_{i,1}$ Earnings	Rate	$\mathcal{D}_{i,10}$ Earnings	Rate	$\mathcal{D}_{i,1}$ Earnings	Rate	$\mathcal{D}_{i,10}$ 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%

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 (2019, p. 40, Fig. 2).

We depict our analysis of the optimal τ_{-1} and τ_2 for CSCO.OQ in Figure A.7 for the case of social media. Treating market opening time as an 'event', Panel (a) in Figure A.7 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 9:29 am, 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. [34]

Similar to a quantile function, horizontal axes in both panels show percentiles of the 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 3:29 am to 9:29 am, 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 1,000 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 A.7 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 replying 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.[35] Panel (b) in Figure A.7 shows that varying the intervals of CARs of longer than 15 minutes mitigate the precision of sentiment

[34] Figure A.8 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.

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

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 A.7, 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 A.8, 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 studies.

3.5 Conclusion

In this study, we provide the most comprehensive analysis to date on intraday firm-specific investor sentiment. Using minute-to-minute sentiment scores obtained with textual analysis of over two million blogs, internet message boards and other social and news media sites, we show that investor sentiment of the two different media display distinctive characteristics. Following market closure and up to midnight, we observe a quick build-up in social media sentiment. After midnight, social media activity subsides but quickly reignites at 7:00 am. Of great interest is a prominent 'kink' in the negative social media sentiment at around 7:00 am, which suggests that negative overnight emotions can linger and continue to intensify before the trading begins. However, news media sentiment tends to be more positive, which may result from news commentary having to broadcast a more balanced view.

We find that the accumulated sentiment from the overnight non-trading period can predict the opening stock return. Our results indicate that the cumulative abnormal returns of these stocks are positively related with the top and bottom decile overnight sentiment from the social and news media. In contrast to the prior literature, however, we do not find persistence in this sentiment-return relation. We show that if we remove the overnight returns from the CAR, the relationship between overnight sentiment and the next day's abnormal returns quickly diminish. The fast dissipating effect implies that overnight views are swiftly impounded into stock prices in the first minutes of trading, perhaps through orders submitted before market opening. It is noteworthy, however, that this diminishing effect is asymmetric. On days with the most negative sentiment, overnight sentiment can still predict returns. 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 firm prices than the influence induced by positive sentiment. These results are consistent with Sprenger et al. (2014a), Berkman et al. (2012), Stambaugh et al. (2012, 2014) and Barber et al. (2008) where the negative sentiment boast a higher impact than the positive one.

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 free of the sentiment-return causality loop. In robustness testing of our model, we 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 swings 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 faster than before with the boom of social media, as stock prices are becoming more sensitive to social media sentiment. Our finding that positive and negative sentiment affects the market differently is consistent with several cognitive and psychological biases of noise traders. In this way, we provide investors with a better tool to help understand the novel dynamics of the market in this fast-paced digital era.

Chapter 4

Do Emotions Trump Facts? Evidence from around the World

> *"...As far as markets were concerned, emotions trump facts any day. It isn't events that move markets, but reactions to them, so long as they are shared by a big enough bunch of traders."*
>
> —*The Economist*

Do Emotions Trump Facts? Evidence from around the World

Abstract

The influence of investor sentiment on stock markets has been demonstrated previously, but the majority of the studies are either US-centred or focus on a single source of sentiment. In this study, we contrast the influence of social and news media to investigate how sentiment from these two sources impact markets in Australia, Brazil, Canada, the EU, France, Germany, Hong Kong, India, Japan, Singapore, Spain, Switzerland, the UK and the US. We find that the heightened social and news media sentiment during non-trading periods significantly affect the next-day opening returns even after accounting for previous day market activity. We discover that only the US stock market shows stronger reactions to social media sentiment compared to news, while other markets are more responsive to news media sentiment. Robustness tests demonstrate that the aggregation of sentiment up to three hours before the market open generates the most effective signals in predicting the index opening values. Overall, this study assists in our understanding of the price discovery process in international stock markets, with a novel dataset of high-frequency textual-based sentiment and an approach that helps to disentangle the return-and-sentiment feedback loop.

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

4.1 Introduction

Recent literature has demonstrated that the accurately measured social media sentiment can capture useful aggregate opinions on financial and economic factors known to sway the financial markets' movement (Sprenger et al., 2014b; Yang et al., 2015; Azar and Lo, 2016b). A growing body of literature has also shown that the impact of sentiment on the market is statistically and economically significant at an intraday level in the US market (Sun et al., 2016b; Renault, 2017; Deng et al., 2018; Behrendt and Schmidt, 2018). However, most of these studies concentrate on analysing the sentiment and stock return interactions during trading hours, leading to a mutual sentiment-return causality loop – a tricky endogeneity issue to deal with. Moreover, there has been a dearth of research contrasting the effects of social and news media sentiment on stock markets outside of the US. In this study, we seek answers to the following questions: How does the media sentiment during non-trading hours impact the markets at the opening? What is different when sentiment is measured based on social media compared with traditional financial news? Is the sentiment effect the same around the world and how is it comparable to findings based on the US data? Do optimistic and pessimistic attitudes of investors influence the opening price behaviour differently in various stock markets?

To tackle these questions, we employ 1-minute sentiment scores on 14 global stock markets from the Thomson Reuters MarketPsych Indices (TRMI) database.[1] To our knowledge, these entity-specific sentiment measures are not only the most granular among currently available datasets, but also cover both the well-known developed markets and some affluent emerging markets. The availability of the high-frequency sentiment scores allows us to sever the sentiment-return feedback loop, and from a unique perspective, to analyse the impact of media sentiment during non-trading sessions on the markets' behaviour at the opening. Controlling for the variables known to determine the rate of return, namely, previous day return, volume, realised volatility and the VIX index, we evaluate the impact of sentiment on the overnight return and contrast the effects of social media sentiment with that of the news. We account for the asymmetries in markets' behaviour in response to optimistic and pessimistic attitudes in the media.

We confirm a positive relationship between the social and news media sentiment and overnight returns. For all the countries in our sample, the coefficients on sentiment are positive and at least one media type (either news media, or social media, or both) is statistically significant at the 5% level. The more optimistic (or pessimistic) the media sentiment overnight, the higher (or lower) the next opening price relative to the previous close. We confirm the robustness of this result to different lengths of sentiment aggregation period (ranging from just 30 minutes before markets open to amassing sentiment from the previous day close). We find that the most variability in overnight return is explained when

[1] While TRMI provides data for additional markets, the sparsity of these data prevents a meaningful cross-country comparison. For a brief summary of this database, see https://www.marketpsych.com/data/.

sentiment is aggregated over the period of just three hours before the market opening.

We show that the US is the only market that is more sensitive to social media sentiment than news. In other markets, such as Hong Kong, Japan and the UK, news sentiment asserts stronger impact on opening values than social media sentiment does. In the US market, a one-standard-deviation increase in social media sentiment leads to a 1.17% increase in the DJIA overnight returns, and this effect is statistically significant at the 1% level. In contrast, a one-standard-deviation rise in news media sentiment only causes a 0.8% rise in the DJIA overnight returns, which is not statistically significant. In Japan, the overnight return on the Nikkei225 gains 15.59% on a one-standard-deviation increase in social media sentiment, and rises remarkably by 28.16% on a comparable unit increase in news media sentiment. We find that Japan, Hong Kong, India and France appear to be swayed by news media sentiment much more strongly than are Canada, Singapore and the UK. The responses to news media sentiment in Australia and the US appear to be of little consequence.

Consistent with other studies, we show that information is absorbed faster in markets with higher liquidity and greater media attention. For instance, examining global sentiment and the domestic sentiment of 11 Asian stock markets, Chen et al. (2013) argues that the returns in Asian markets are subject to investor sentiment more than the developed markets due to the arbitrage restrictions. Similarly, we find that the magnitude of market reactions to sentiment in the US is smaller than those in other markets. This finding is intuitive given that the US financial markets are among the most efficient and liquid markets. Moreover, our data statistics reveal that Asian markets (Singapore, Hong Kong, India and Japan) exhibit overall positive tonality in both media sources, whereas properties of the EU market sentiment based on news and social media are largely consistent with characters of the France and Germany stock markets.

It is important to distinguish large sentiment swings in the market because past research have shown that the predictive power of sentiment is concentrated in high-sentiment periods (e.g., Stambaugh et al., 2012). Hence, we explicitly account for the extreme sentiment readings, represented by the top (most positive) and bottom (most negative) deciles, and examine its effects. We uncover substantial differences in return responses at these extreme sentiment magnitudes. When messages in social and news media show trumped emotions, the neutral sentiment is overwhelmed by the heightened positive and negative sentiment. In fact, we find that the markets in Australia, Canada, India, Japan, the UK and the US are more sensitive to the mounted negative sentiment compared to positive one. Hong Kong, in contrast, is the only market that exhibits higher responses to heightened positive sentiment. our results reconfirm that negative sentiment in general affects stock markets at a higher extent than positive sentiment. Our findings side with Akhtar et al. (2012), which finds that due to psychological reasons, investors and the market react to negative monthly consumer sentiment announcements more prominently than the positive sentiment counterpart.

One may argue that these results could be driven by the selection of a specific period of sentiment accumulation. To verify the robustness of our results, we test a range of durations for sentiment aggregation and confirm that our findings are robust. Specifically, we find that windows spanning from 30 minutes to six hours before the market opening contain consistent predictive power. Shorter spans weaken the return predictability; we demonstrate that estimation windows of less than 30 minutes (for example, 15 minutes) do not provide consistent results. Sentiment cumulated within such short periods tends to be more volatile compared to sentiment accumulated over more extended periods. This variation is primarily due to the sparsity of available observations and small sample size within such short intervals. On the contrary, amassing sentiment from the previous close to the next open may to some extent dilute the predictive ability of overnight sentiment.

This study brings about two main implications. Firstly, the differences between the US and other markets suggest that scholars and practitioners should be cautious in extrapolating evidence from one market to another. In this respect, we side with Xiong et al. (2020) who arrived at a similar conclusion. Reasons to support this implication are in twofold. Firstly, the geographic locations, time zones, starting and ending points of trading sessions, and thus the corresponding information accumulation and transmission processes vary from one market to the other. Moreover, the social media sentiment measures used for all markets greatly depend on the US social media platforms. If such sentiment is constructed from social media sources that largely coincide with the US markets' trading sessions, then for other global markets, news media sentiment measures would constitute a more appropriate informative signal, compared with their social media counterparts. The dissimilarities in both the exchange's distinctive characteristics and the specific sentiment measures on them imply that it would be unwise to adopt the US evidence to other markets hastily.

Secondly, our results help paint a more complete picture of the propagation of overnight investor sentiment and its impact on market behaviour. The important practical implications to investors and regulators are that these novel sentiment measures can be used to quantify the economic impact of investor sentiment on the overnight returns and on the intraday return patterns. Our results offer great insights on how the unstructured data from social and news media can sway markets around the globe. These findings are of great importance for investors and regulators in a highly connected world where social media platforms such as Twitter, Facebook and StockTwits are gaining increasing prevalence in everyday life.

We contribute to the behavioural finance literature by focusing on the causal relationship between the highly granular textual analytical sentiment and the overnight stock returns. We differentiate social media influences from that of traditional news, and perform a comprehensive comparison across 14 of the most affluent financial markets. As pointed out by Baker et al. (2012), the majority of studies investigating the return predictability from investor sentiment (e.g., Sun et al., 2016b; Renault, 2017;

Heston and Sinha, 2017), are US centred due to limited data availability for other markets. Using novel dataset of sentiment measures that are entity-specific and extended to broader market bases, our study mitigates the data availability problem and thus contribute to this line of literature.

In addition, the existent studies often apply sentiment measures that only account for a single source of sentiment. For example, Tetlock (2007) considers sentiment contained in news columns from the *Wall Street Journal*, while Garcia (2013) examines effects from the *New York Times*. Chen et al. (2014) focuses on the stock message board *seekingalph.com*, Sprenger et al. (2014c) analyses short-period Twitter content, Siganos et al. (2014) extracts sentiment from Facebook, and Da et al. (2011) derives their sentiment measure from the Google Search Volume index. Although Fang and Peress (2009) synthesised several popular US newspapers (*USA Today*, the *Wall Street Journal*, the *New York Times* and the *Washington Post*), study directly contrasting the rising social media with the traditional financial news remains rare. Therefore, Our research relying on multiple media sources is in line with Chen et al. (2018) , Ahoniemi et al. (2015), Boudoukh et al. (2018) and Lou et al. (2019), which demonstrate the crucial role textual analytical sentiment plays in the current digital world.

The debate on whether sentiment is a momentum or contrarian return predictor remains highly contentious. Hence, examining the return predictability in the several international markets, we also add value to the literature on sentiment contagion and its return predictability in international markets (e.g., Baker et al., 2012; Chen et al., 2013; Bai, 2014; Hudson and Green, 2015; Feldman and Liu, 2017). Using weekly Google search index, Gao et al. (2019) finds evidence supporting that sentiment is a contrarian predictor in stock markets around the world. In 36 out of their 38 country samples, the authors find a negative relationship between sentiment and the next week's market returns. In contrast, Han and Li (2017) finds that investor sentiment is a reliable momentum predictor at monthly frequency in China. That is, there is a positive relation between sentiment and the subsequent returns. Our results provide additional evidence on this undetermined topic. We differ from the prior research in that we use alternative sentiment measures that are available at a much higher (intraday) frequency. It allows us to gauge the emotional swings more precisely and conduct 'anatomical' observations across the international markets. To the best of our knowledge, we are the first to employ the textual-based 1-minute sentiment scores to examine a sentiment-return relationship across global markets.

The rest of the paper proceeds as follows. Section 4.2 introduces the TRMI dataset in detail, provides descriptive statistics, elaborates data pre-processing procedures and presents model specifications. Section 4.3 then presents our main results, focusing on the comprehensive comparison of the UK and US markets at first, followed by a summary of the results of all the sample markets. Section 4.4 focuses on an examination of the model effectiveness by considering a range of robustness checks. Finally, Section 4.5 concludes.

4.2 Data and Methodology

4.2.1 Data Source

Our sentiment data are from Thomson Reuters MarketPsych Indices (TRMI). The sentiment scores are calculated using a proprietary machine-learning algorithm that scrapes texts about a specific index from the top social media platforms and the most popular financial news media. Specifically, we investigate 14 market indices as listed in Table 4.1. For each index in Table 4.1, TRMI scans and analyses English language articles and posts that referring to the particular index, and creates the "TRMI company group index". Social media source of TRMI comes from the top 30% of over two million blogs, stock message boards and other social media sites, for example, *SeekingAlpha*, *Yahoo!Finance* and *StockTwits*. And news media source of TRMI includes leading professional financial news presses, such as *Wall Street Journal*, *the New York Times* and *the Financial Times*. A more detailed description about our dataset is provided in Gan et al. (2019) (Section 3.1 and the Appendix B. Supplementary data). The TRMI algorithm then scores the index's specific sentiment on social and news media based on the Loughran and McDonald (2014) financial dictionary.[2] We use 1-minute sentiment scores from 1 January 2011 to 30 November 2017 from the TRMI company group indices, an aggregated sentiment score that mimics and targets a specific entity (representative equity index). We extract daily stock market data for the same sample period from Oxford-Man library's country index archives.

Table 4.1: Data Sources. Sentiment variables are obtained from the Thomson Reuters MarketPsych; overnight returns, daily returns and daily average realised volatility are from the Oxford-Man Institute of Quantitative Finance. The TRMI data are measured at UTC time, which is adjusted to local exchange time to match the trading hours. Changes in daylight saving times across countries have also been taken into account.

TRMI Index	Resembling Indices	Oxford-Man	Time Zone	Trading Hours
MPTRXUS30	DJIA 30	DJIA	UTC-5(-4)	9:30-16:00
MPTRXCA250	S&P/TSX Composite	S&P/TSX Composite	UTC-5(-4)	9:30-16:00
MPTRXBR50	IBRX 50	Bovespa	UTC-3(-2)	10:00-17:00
MPTRXGB100	FTSE 100	FTSE 100	UTC(+1)	8:00-16:30
MPTRXCH20	Swiss Market	Swiss Market	UTC+1(+2)	9:30-17:00
MPTRXDE30	Deutsche Borse DAX 30	DAX 30	UTC+1(+2)	9:00-17:30
MPTRXES35	IBEX 35	IBEX 35	UTC+1(+2)	9:00-17:30
MPTRXEU50	EURO STOXX 50	EURO STOXX 50	UTC+1(+2)	9:00-17:30
MPTRXFR40	CAC 40	CAC	UTC+1(+2)	9:00-17:30
MPTRXIN50	Nifty 50	S&P CNX Nifty	UTC+5:30	9:15-15:30
MPTRXHK50	Hang Seng	Hang Seng	UTC+8	9:30-12:00; 13:00-16:00
MPTRXSG30	FTSE Straits Times	FTSE Straits Times	UTC+8	9:00-12:00; 13:00-17:00
MPTRXJP225	Nikkei 225	Nikkei 225	UTC+9	9:00-11:30; 12:30-15:00
MPTRXAU500	ASX All Ordinaries	ASX Ordinaries	UTC+10(+11)	10:00-16:00

One could argue that there might be substantial differences among local languages in social and news media. However, we do not examine non-English media sources such as Japanese, Spanish and Cantonese for reasons of data comparability. Moreover, TRMI sentiment scores are based on financial

[2]TRMI covers a plethora of securities and markets, including more than 12,000 companies, 36 commodities and energy subjects, 187 countries, 62 sovereign markets, 45 currencies and since 2009, more than 150 cryptocurrencies. For more details, see *Thomson Reuters MarketPsych Indices 2.2 User Guide, 23 March 2016, Document Version 1.0.*

dictionary constructed from English terms, while financial dictionaries could be easily obtained for other languages, the sentiment scoring algorithm could not guarantee convergence. At the time of our analysis, TRMI did have Japanese-based sentiment measures, we chose English-based sentiment to keep the measurement consistency across all markets in our sample. Employing local language sentiment data from other providers may put the comparability of our results in jeopardy.

Figure 4.1: Heatmap of News Media sentiment. This figure offers a visualization of the representative TRMI news media indices and the proportion of non-missing data by day-of-the-week and by minute-of-the-day (horizontal axis). Three major markets are presented in the figure. By far, the DJIA is the most sentiment-rich as evidenced from the heatmaps' color saturation in the panels on the left. The peaks of news media activity fall within the trading times of the markets for the DJIA and FTSE100, but only transient spikes corresponding to post opening and post closing market times are observed for the Nikkei225. Japan's financial market reliance on the US and UK markets is further evidenced by substantially low news media activity on Mondays, with activity picking up towards the market open times in Tokyo.

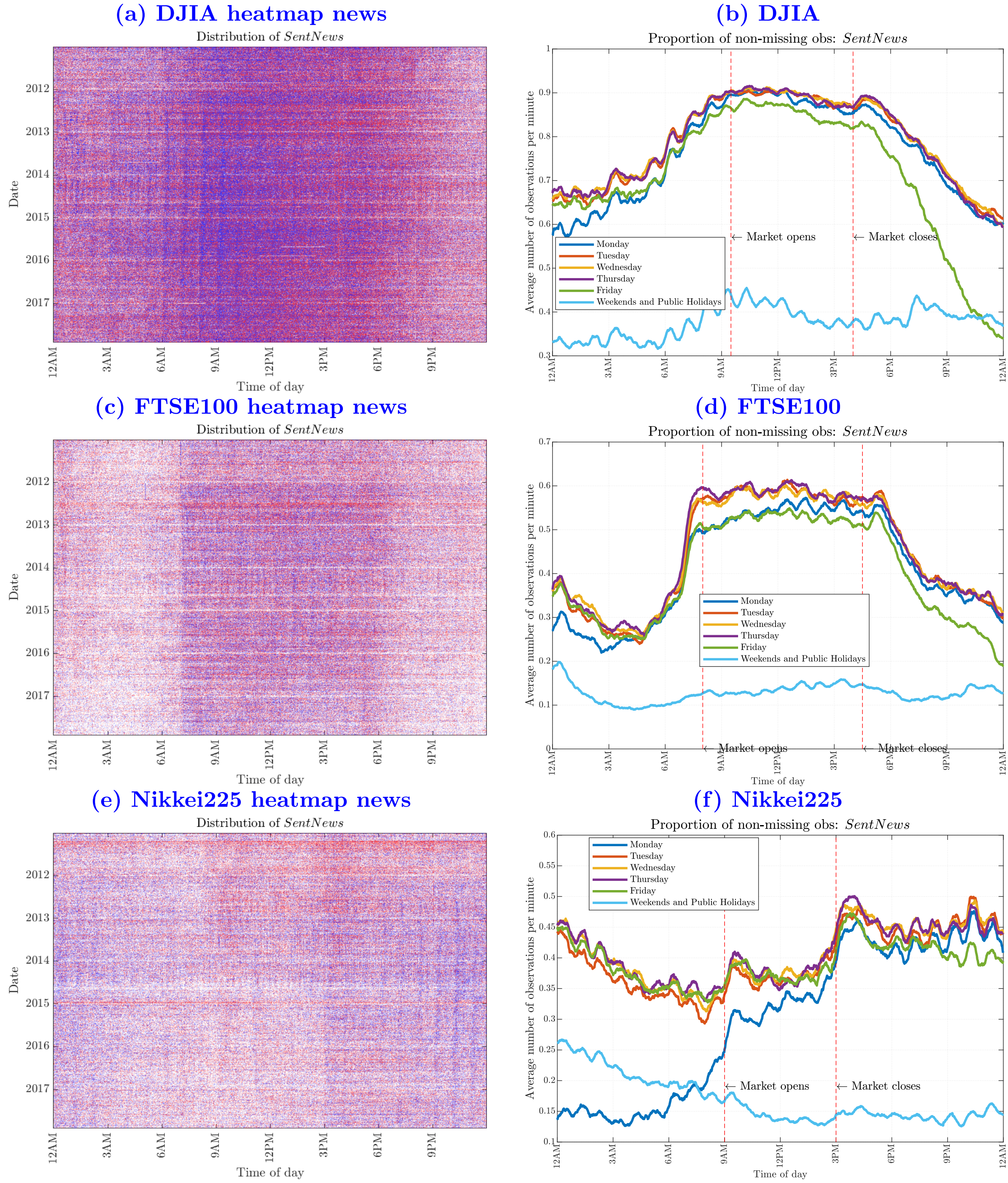
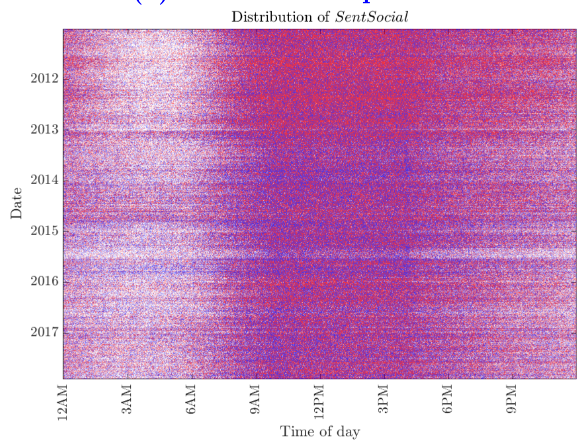
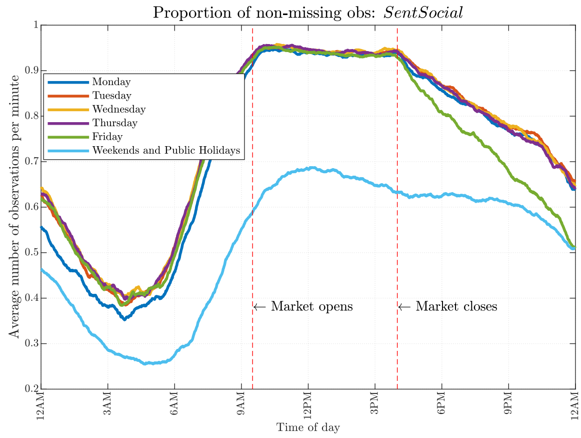


Figure 4.2: Heatmap of Social Media Sentiment This figure offers a visualization of the representative TRMI social media indices, and the proportion of non-missing data by day-of-the-week and by minute-of-the-day (the horizontal axis). By far, the DJIA is the most sentiment-rich as evidenced from the heatmaps' color saturation in the panels on the left. The peaks of social media activity fall within the trading times of the markets for the DJIA, but only transient spikes corresponding to post opening and post closing market times are observed for the FTSE100 and the Nikkei225. Japan's financial market reliance on the US and UK markets is further evidenced by substantially low social media activity on Mondays, with activity picking up towards the trading hours in New York.

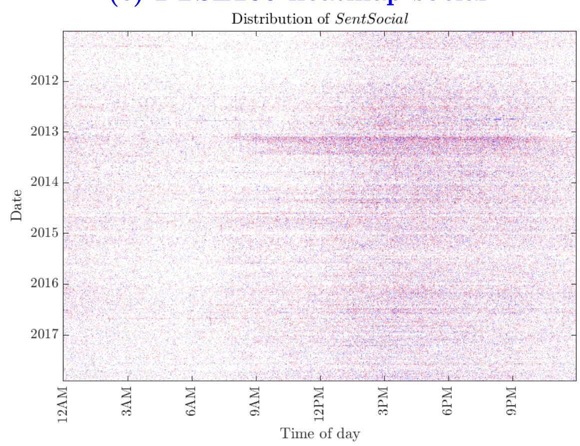
(a) DJIA heatmap social



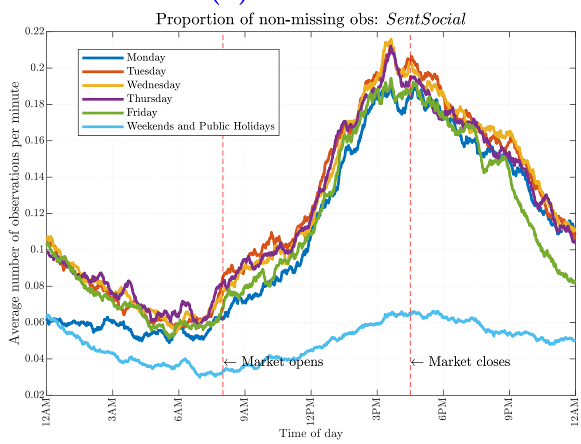
(b) DJIA



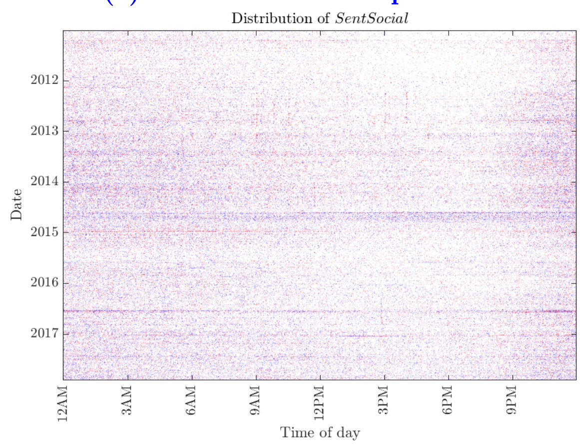
(c) FTSE100 heatmap social



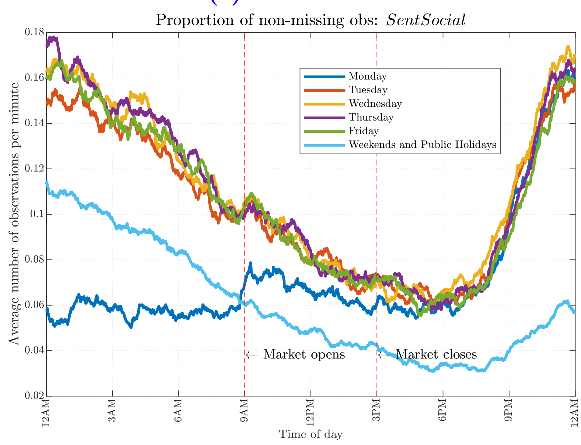
(d) FTSE100



(e) Nikkei225 heatmap social



(f) Nikkei225



Our sentiment variables range from -1 (maximally negative tone) to 1 (maximally positive tone), with a sentiment score of zero representing neutral tonality. Heatmaps, day-of-the-week and time-of-day groupings enable visualisation of the vast high-frequency sentiment and stock return data to help identify patterns and irregularities in our dataset. In Figures 4.1 and 4.2 (panels on the left), using the DJIA, FTSE100 and Nikkei225 indices as the most prominent examples, we allot all 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 12:00 am to 11:59 pm 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, while missing data are shown as blank. A mixture of positive and negative sentiment scores brings out an overall purple hue, attesting to the frequent reversal in sentiment polarity at high frequencies. A strong tendency of the DJIA social media to coincide with the exchange trading hours can be observed by contrasting the saturation of Panel (a) in Figure 4.1 and Figure 4.2 data in the heatmaps. Coincidentally, such a pattern in the news media is less obvious but with more pronounced threads weaving through each morning 'on-the-hour' (i.e., pronounced ridges at the 6:00, 7:00, 8:00 and 9:00 marks in the middle-left panel). In striking contrast, the flow of sentiment data for the FTSE100 and Nikkei225 indices exhibit a more pronounced activeness in the news media segment, coinciding with the exchange trading hours much closer than its social media counterpart (Panels (c) and (e) in Figures 4.1 and 4.2). This points to substantial dissimilarities in information flows in the UK and Japan markets compared to the US. Panels on the right-hand side display the proportions of non-missing observations in variables on the left-hand side and capture intraday and day-of-the-week patterns in these variables including non-trading days (e.g., weekends and public holidays). Figures 4.1 and 4.2 highlight the nontrivial nature of sentiment analysis due to the irregularity of the data, especially in light of the asynchronicity with the returns.

4.2.2 Model Specifications

To evaluate the impact of cumulative sentiment from social or news media during non-trading hours on overnight returns we employ a framework from Fraiberger et al. (2018). Specifically, we estimate the following set of baseline and hypothesis-specific regressions to capture various media sentiment effects and to control for potential confounding factors:

$$
\begin{aligned}
Ro_t =& \alpha + \beta_2 Rc_{t-1} + \beta_3 VLM_{t-1} + \beta_4 RV_{t-1} + \beta_5 VIX_{t-1} + \epsilon_t, && (4.1)\\
Ro_t =& \alpha + \beta_1 Sent_t^k + \epsilon_t, && (4.2)\\
Ro_t =& \alpha + \beta_1 Sent_t^k + \beta_2 Rc_{t-1} + \beta_3 VLM_{t-1} + \beta_4 RV_{t-1} + \beta_5 VIX_{t-1} + \epsilon_t, && (4.3)\\
Ro_t =& \alpha + \beta_1 Sent_t^k + \gamma_1 D_t^{-k} + \gamma_2 D_t^{+k} + \gamma_3 D_t^{-k} \times Sent_t^k + \gamma_4 D_t^{+k} \times Sent_t^k \\
& + \beta_2 Rc_{t-1} + \beta_3 VLM_{t-1} + \beta_4 RV_{t-1} + \beta_5 VIX_{t-1} + \epsilon_t, && (4.4)
\end{aligned}
$$

where Ro_t indicates the overnight return of an aggregate country index on day t (in per cent) and is computed as $Ro_t = \log(Po_t/Pc_{t-1}) \times 100$ with Po_t and Pc_t denoting open and close index values on day t.[3]

Eq.(4.1) is a baseline model that includes a set of controls but omits the sentiment. Comparing models that include sentiment to this benchmark allows for an evaluation of changes in the model predictability when sentiment variables are present. An alternative benchmark model in Eq.(4.2) that only includes the sentiment variable assists in determining whether the overnight sentiment subsumes information from the previous day trading activity captured by the controls in Eq.(4.1). In Eq.(4.3), we focus on the single sentiment variable while accounting for the set of controls. Finally, our most flexible model in Eq.(4.4) allows for asymmetric effects and the pockets of heightened sentiment via binary regressors and their interactions with the sentiment variables.

We incorporate control variables that have been known to influence the market opening indices. That is, Rc_{t-1} is the close-to-close return of the country index on day $t-1$ (in per cent), calculated as $Rc_{t-1} = \log(Pc_{t-1}/Pc_{t-2}) \times 100$. The lagged close-to-close return is included to control for the daily return autocorrelation effect resulting from possible market microstructure phenomenon, such as non-synchronised trading, bid-ask bounce and trading costs. VLM denotes the de-meaned log number of trades and is used to proxy for the changes in market liquidity. RV is the de-meaned daily average realised volatility (in per cent), to account for changes in short-run market frictions other than the return autocorrelation. VIX is the de-meaned log VIX index, which controls for the general sentiment swings in the global market.[4] While $Sent$ stands for investor sentiment, the superscript k denotes the source of sentiment data and can be either S or N depending on whether the source of the sentiment is social or news media.

Our aim is to investigate the effect of sentiment on overnight returns in Eqs.(4.1)–(4.4) above,

[3]Eqs.(4.1)–(4.4) are estimated for each country separately. All variables, coefficients, and error terms are, therefore, country-specific. We omit country subscript for simplicity. That is, instead of $Ro_{t,i}$ we use Ro_t without loss of generality. A summary of country-specific equity indices, including the list of data sources, time zones and trading hours is provided in Table 4.1.

[4]Different from Fraiberger et al. (2018) that take the *detrended* log trading volume and the *detrended* volatility, we use the *de-meaned* variables of log trades, realised volatility and VIX to improve the comparability of regression constants. The *de-meaned* results are computed as the daily observations in excess of sample averages.

while allowing for a number of alternative control variables commonly used in the literature.[5] There are several reasons why this causal relation deserves attention. Firstly, the exploration of close-to-open sentiment allows us to have a benchmark analysis. Moreover, measuring media sentiment over the non-trading periods helps us to avoid any endogeneity concerns by breaking the return-and-sentiment loop effectively. The use of overnight sentiment also benefits us by being a more accurate signal-to-noise proxy for what can be a very "noisy" measure. Furthermore, a growing body of evidence shows that nowadays, overnight information flow and the emotions expressed within them are of greater importance than it used to be (Ahoniemi et al., 2015). As the world is connected more than ever before, both regional and global events can trigger investor reactions in all markets. Thus, it stands to reason that one needs to consider the similarities and differences between the US market and other global markets.

In our setup, $Sent_t^k$ is the focal independent variable, the **standardised**[6] average cumulative sentiment before market open on day t, from media type k, where $k = N$ represents the news media, and $k = S$ indicates the social media. For our main discussion, we define $Sent_t^k$ over the window at which we aggregate sentiment from the previous day $(t-1)$ close to the current day (t) open. For robustness, we probe a number of different windows over the non-trading hours to gauge emotions between two consecutive trading days. While the results of close-to-open sentiment analysis are reported here, the exploration of various sentiment windows and robustness checks are discussed in Section 4.4.

Our key independent variable, $Sent_t^k$, is constructed from the intraday sentiment scores provided by TRMI. On each day, we use the unequally-distanced data at 1-minute frequency to compute the average cumulative sentiment. To maintain the comparability with different levels of media coverage volume across markets, we avoid pre-filling the missing observations.[7] Specifically, if $x_{t,j}^k$ denotes raw sentiment from the media type k on day t at time j, the close-to-open average cumulative sentiment on day t is the cumulative sum of all the 1-minute sentiment scores (positive and negative) from the market closing time (τ_c) on day $t-1$ to the market open time (τ_o) on day t, divided by the number of non-missing observations over the same duration.[8] In other words, the (average) cumulative overnight sentiment is computed as follows:

$$X_t^k = \frac{1}{n_t^k} \sum_{j=\tau_c}^{\tau_o} x_{t,j}^k,$$

[5]A detailed list of variable names and definitions is provided in Table A.5 of the Appendix.

[6]Unlike Fraiberger et al. (2018), which *normalise* the news-based sentiment index, we use the term *standardise* instead. While several studies use the term *normalisation* and *standardisation* interchangeably, we differentiate them. Standardisation is the process of de-meaning and unifying variance, in other words, obtaining the z-score, while *normalisation* is the process of re-scaling variables between 0 and 1.

[7]The TRMI sentiment data we used span across 24 hours at the highest possible frequency of one minute. However, when there is no postings on the social media or no articles in the news media about a specific entity, sentiment scores are represented as *not-a-number*.

[8]Market closing and opening times are listed in Table 4.1.

where n_t^k is the cardinality of a set of overnight sentiment scores from the media type k terminating on day t (i.e., the number of non-missing elements). The above definition implicitly assumes that $\tau_c \in t-1$ and $\tau_o \in t$. If the entire overnight period contains no observations, we assign a value of zero to the cumulative sentiment for that overnight period to maintain a neutral emotion. Given the diversity of the markets in our sample and the sentiment variability of its participants, it is important to standardise the average cumulative sentiment. We compute it as follows:

$$Sent_t^k = \frac{X_t^k - \overline{X^k}}{\sigma_{X^k}},$$

where $\overline{X^k}$ is the mean score of X_t^k averaged across days, while σ_{X^k} is the sample standard deviation.[9]

To account for the impact from polarised (strong positive or negative) average cumulative sentiment, we further include two binary regressors, D_t^{+k} and D_t^{-k}, in Eq.(4.4) to indicate the top and bottom decile days of $\{Sent_t^k\}_{\forall t}$. Furthermore, we add interaction terms between these dummy variables and sentiment to capture the magnitude of the effect from the highly polarised cumulative sentiment.[10]

4.2.3 Descriptive Statistics

The re-scaling and transformation of the variables helps generate a easily comparable regression coefficients across all 14 markets. For example, as shown in Panels (a) and (c) of Table 4.2, the number of trades (VLM_{t-1}) and the VIX index (VIX_{t-1}) are at much higher magnitudes than the other variables. However, the realised volatility (RV_{t-1}) is at a much lower level compared to the other variables. This scale difference presents difficulty in interpreting regression coefficients.

We standardise the $Sent^S$ and $Sent^N$ variables to improve the comparability of these key independent variables across multiple markets. Since standardisation results in zero means and unit standard deviations in sentiment variables, the interpretation of the coefficient estimates and their economic significance is simplified. This re-scaling procedure (as shown in Panels (b) and (d) in Table 4.2), ensures that the regression models are not only effectively comparing variations between the inputs and output but also precisely quantifying the causality we set out to measure at an easily understandable and comparable level. Hence, our subsequent discussions are based on the transformed variables, unless stated otherwise.

[9]That is, $\overline{X^k} = \frac{\sum_{t=1}^{T} X_t^k}{T}$ and $\sigma_{X^k} = \sqrt{\frac{\sum_{t=1}^{T}(X_t^k - \overline{X^k})^2}{T-1}}$.

[10]In a set of unreported results, we tested for different magnitudes of "polarised" average cumulative sentiment, constructing dummy variables based on the top and bottom *quintiles* instead of *deciles*, and the results are consistent.

Table 4.2: Descriptive Statistics. The table presents the summary statistics of the data used in our analysis. The left-hand side 'raw data' panels contain descriptive statistics of original data before applying any transformations. The right-hand side 're-scaled data' panels display descriptive statistics of each regression variables after we made the following transformations: Ro and Rc are expressed in percentage; $Sent^k$'s are standardised to have zero means and unit standard deviations; VLM and VIX take logarithm formats first and are then de-meaned; and RV is de-meaned and transformed to per cent. The daily sentiment data are constructed by aggregating 1-min sentiment data from the previous day close to the next day open. For example, for the US market the overnight sentiment on day t is constructed by aggregating 1-min sentiment data from 4:01 pm on day $t-1$ to 9:29 am on day t. Similarly, for the UK market, the aggregation window is from 4:31 pm to 7:59 am. Summary statistics for the other 12 markets are omitted for brevity. Time subscripts in the variables are omitted since the distinction between t and $t-1$ is of no consequence to the univariate descriptive statistics.

DJIA	(a) Raw data				(b) Re-scaled data			
	mean	std	min	max	mean	std	min	max
Ro	0.0000	0.0010	-0.0063	0.0084	0.0039	0.0979	-0.6307	0.8366
$Sent^S$	-0.0055	0.0450	-0.2872	0.1934	0.0000	1.0000	-6.2605	4.4206
$Sent^N$	0.0120	0.0449	-0.1838	0.1760	0.0000	1.0000	-4.3593	3.6532
Rc	0.0004	0.0084	-0.0556	0.0402	0.0411	0.8383	-5.5624	4.0179
VLM	16,009.9	6,353.6	4,899.0	23,412.0	0.0000	0.4046	-1.1030	0.4612
RV	0.000064	0.000178	0.000002	0.005946	0.0000	0.0178	-0.0062	0.5882
VIX	16.36	5.60	9.14	48.00	0.0000	0.2873	-0.5366	1.1219
FTSE100	**(c) Raw data**				**(d) Re-scaled data**			
	mean	std	min	max	mean	std	min	max
Ro	0.0002	0.0062	-0.0666	0.0317	0.0227	0.6243	-6.6640	3.1714
$Sent^S$	0.0042	0.0777	-0.2668	0.2662	0.0000	1.0000	-3.4886	3.3728
$Sent^N$	-0.0248	0.0624	-0.2881	0.2000	0.0000	1.0000	-4.2180	3.5995
Rc	0.0001	0.0094	-0.0495	0.0373	0.0126	0.9352	-4.9549	3.7257
VLM	68,291.7	21,294.6	11,899.0	314,308.0	0.0000	0.2940	-1.7043	1.5697
RV	0.000047	0.000073	0.000004	0.001596	0.0000	0.0073	-0.0043	0.1549
VIX	16.36	5.60	9.14	48.00	0.0000	0.2873	-0.5366	1.1219

4.2.4 Model Validity

Prior to estimating the models in Eqs.(4.1)–(4.4), we assess the pairwise correlations between all continuous variables to alleviate concerns over possible collinearity or omitted variable bias (OVB). The implications of collinearity and OVB could be dire, potentially resulting in biased estimates, high standard errors of the regression estimates, large changes in the coefficients when adding predictors, and opposite sign of the coefficients to what are anticipated from theory. Using the DJIA and FTSE100 as examples (Table 4.3 Panels (a) and (b), respectively), we demonstrate our pre-estimation assessment procedure. Unsurprisingly, the highest correlation in the set of DJIA data is 0.44 between VIX_{t-1} and RV_{t-1}, followed by 0.38 between $Sent^S$ and VLM_{t-1} and 0.37 between $Sent^S$ and $Sent^N$. Similarly, the highest correlation in the set of FTSE100 data is 0.60 between VIX_{t-1} and RV_{t-1}, followed by 0.35 between VLM_{t-1} and RV_{t-1} and 0.30 between $Sent^S$ and $Sent^N$. In the case of the US market, we also note that $Sent^S$ shows stronger correlations with other variables than $Sent^N$. In the UK market, however, such a difference in correlation with other variables between $Sent^S$ and $Sent^N$ is less prominent, implying an important distinction between the FTSE100 and DJIA in terms of information transmission from the two media sources. Furthermore, the magnitudes of correlation coefficients in Table 4.3 indicate no evidence of collinearity and a low possibility of omitted variable bias in the model.[11]

Table 4.3: Pairwise correlation coefficients: DJIA and FTSE100 close-to-open. To assist in checking possible omitted variable bias, this table lists the pairwise Pearson correlation coefficients and their respective significance levels between variables in Eq.(4.3). The sentiment is aggregated from the previous day close to the next day open, from 4:01 pm on day $t-1$ to 9:29 am on day t. The correlation coefficients with p-values below 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

(a) DJIA pairwise correlations

	Ro_t	$Sent_t^S$	$Sent_t^N$	Rc_{t-1}	VLM_{t-1}	RV_{t-1}	VIX_{t-1}
Ro_t	1.00						
$Sent_t^S$	0.05**	1.00					
$Sent_t^N$	0.04*	0.37***	1.00				
Rc_{t-1}	0.05**	0.03	0.04	1.00			
VLM_{t-1}	0.11***	0.38***	-0.01	-0.01	1.00		
RV_{t-1}	-0.01	-0.11***	-0.05**	-0.16***	-0.04	1.00	
VIX_{t-1}	-0.05*	-0.33***	-0.07***	-0.15***	-0.33***	0.44***	1.00

(b) FTSE100 pairwise correlations

	Ro_t	$Sent_t^S$	$Sent_t^N$	Rc_{t-1}	VLM_{t-1}	RV_{t-1}	VIX_{t-1}
Ro_t	1.00						
$Sent_t^S$	0.06***	1.00					
$Sent_t^N$	0.23***	0.30***	1.00				
Rc_{t-1}	-0.01	0.03	0.01	1.00			
VLM_{t-1}	0.06**	0.00	-0.05**	-0.08***	1.00		
RV_{t-1}	0.07***	-0.09***	-0.14***	-0.13***	0.35***	1.00	
VIX_{t-1}	-0.03	-0.16***	-0.26***	-0.11***	0.20***	0.60***	1.00

As shown in Table 4.3, the correlation between overnight social media and news media sentiment is around 0.3 (that between $Sent^S$ and $Sent^N$ is 0.37 in Panel (a) and 0.30 in Panel (b)). As a result, the top/bottom decile dummy indicators that we generated based on these overnight sentiments may contain the same "tail event" days, involving a possible double-counting problem if strong overlapping rate of these dummy variables existed and we had incorporated them together. Thus, another important procedure before the estimation of regression coefficients is to check the coincidence rates in the dummy variables to identify the heightened sentiment levels. We make this evaluation for every country and report the results of the DJIA and the FTSE100 in Table 4.4 for illustration. Both Panels of Table 4.4 show that the coincidence rates between D_t^{-S} and D_t^{+S}, and that between D_t^{-N} and D_t^{+N} are zeros, which are intuitively correct by construction. Surprisingly, we discover a low coincidence rate in polarised emotions across social and news media sources in both the DJIA and FTSE100 datasets. In particular, the coincidence rates of the most negative sentiment (bottom decile) days across social and news media (D_t^{-S} and D_t^{-N}) is only 3.39% for the DJIA and 2.65% for the FTSE100. Similarly, the coincidence rates between the most positive (top decile) social and news media days (D_t^{+S} and D_t^{+N}) are 2.76% for the DJIA and 1.90% for the FTSE100. We also find that all the coincidence rates are lower than 1% between the dummy variables that indicate the opposite polarities across different

[11] In Table A.8 in the appendix, we report the results of variance inflation factors (VIF) to assess the severity of multicollinearity. While proper collinearity diagnostic tests such as in Farrar and Glauber (1967) and Belsley et al. (1980) may be performed, the magnitudes of the correlation coefficients and the VIFs do not warrant this test. The reported results include DJIA and FTSE only, the results for other markets are similar and available upon request.

media sources (i.e., D_t^{+S} and D_t^{-N}, D_t^{+N} and D_t^{-S}). This evidence further corroborates our assertion that only a diminutive possibility of coincidence exists in the extremely positive (negative) sentiment across one media source to the other. The coincidence rates of highly negative sentiment from social and news media are higher than the coincidence rates of highly positive sentiment from these two sources.

Table 4.4: Coincidence rates in extreme sentiment. The case of close-to-open overnight sentiment for the DJIA and FTSE100 datasets. We check the coincidence rates (in per cent) amongst the four dummy variables representing strong positive or negative sentiment from social and news media. The dummy variables are based on sentiment aggregated from the previous day close to the next day open, that is, from 4:01 pm on day $t-1$ to 9:29 am on day t. Similarly, for the UK market, the aggregation window is from 4:31 pm to 7:59 am. The coincidence rates for the other 12 markets are similar and omitted for brevity. $D_t^{\pm S}=1$ if the average cumulative **S**ocial media sentiment belongs to the top (+) or bottom (−) decile, $D_t^{\pm N}=1$ if the average cumulative **N**ews media sentiment is ranked in the top (+) or bottom (−) decile.

(a) DJIA sentiment coincidence rates

	D_t^{-S}	D_t^{+S}	D_t^{-N}	D_t^{+N}
D_t^{-S}	100%			
D_t^{+S}	0.00%	100%		
D_t^{-N}	3.39%	0.35%	100%	
D_t^{+N}	0.12%	2.76%	0.00%	100%

(b) FTSE100 sentiment coincidence rates

	D_t^{-S}	D_t^{+S}	D_t^{-N}	D_t^{+N}
D_t^{-S}	100%			
D_t^{+S}	0.00%	100%		
D_t^{-N}	2.65%	0.29%	100%	
D_t^{+N}	0.23%	1.90%	0.00%	100%

4.3 Sensitivity to Overnight Sentiment in Global Markets

In this section, we conduct a formal analysis of the global market sensitivity patterns based on overnight (close-to-open) social media and news sentiment data. For each country in the sample, we estimate Eqs.(4.1) through (4.4) with the ordinary least squares (OLS) regression. For illustration purposes, Tables 4.5 and 4.6 report the estimates using the DJIA and FTSE100 data, respectively.[12] We summarise the results for the 14 countries in Table 4.7 to contrast the similarities and the differences in market responses to changes in social and news sentiment.

We report the estimates of the baseline model in Column (1) of Tables 4.5 and 4.6. This model does not include the key independent variable, $Sent_t^k$, but does incorporate four variables controlling for the impact on overnight returns from the previous day's trading activities (Rc_{t-1}, VLM_{t-1}, RV_{t-1} and VIX_{t-1}). In the case of the US market, from Table 4.5, we observe that the previous day return and trading volume significantly impact the DJIA's overnight return on the following day. The estimated

[12] The detailed estimates for other countries are obtained in the similar manner but are omitted here for brevity. For each market and model specification, we use the maximum available number of observations, which leads to variations in sample sizes, e.g., due to the inclusion of lagged variables or difference in non-trading days across countries.

positive coefficients suggest that the higher the previous day's return and volume, the higher the index values at the next day's opening time. In other words, daily return autocorrelation and changes in the market liquidity significantly impact the DJIA's overnight return. In contrast, for the UK market, it is the change in daily realised volatility and the variation in the VIX index that strongly influence the FTSE100's overnight returns (Table 4.6, Column 1). A heightened level of realised volatility on the previous day leads to a statistically significant increase in the overnight return of the FTSE100. The increased global "fear" index (VIX) on the previous day, however, triggers a decline in the index at the market opening the following morning.

We proceed by gradually introducing sentiment variables based on model variations in Eqs.(4.2) through (4.4) and report our results in Tables 4.5-4.6. Columns (2) to (4) contain results based on the social media while Columns (5) to (7) are based on the news media. For the US market, we observe that while the impact of overall sentiment from social media in Column (2) is significant and the coefficient is of expected positive sign, the impact is marginal. Moreover, after controlling for previous day market activity, this effect is insignificant (refer to Column (3)). However, when we consider the asymmetry and the effects of extreme sentiment, the evidence is consistent with our expectations: The impact of extreme negative sentiment is much more pronounced, while the effect of extreme positive sentiment is not significant. This evidence is consistent with Gan et al. (2019) in that sentiment from extreme deciles often possesses a higher signal-to-noise ratio compared to sentiment in moderate deciles. Furthermore, a large body of empirical literature has shown that influences from negative investor sentiment prevail over positive sentiment (e.g., Akhtar et al., 2012; Stambaugh et al., 2012, 2014; Sprenger et al., 2014a, among others).

Consistent with our prior study based on individual stocks (constituents of the DJIA index), the accumulated positive overnight social media sentiment leads to significant increases in the overnight market return. Without controlling for the previous day's trading activities, a one-standard-deviation increase (decrease) in cumulative social media sentiment is associated with 0.53% higher (lower) opening returns the next day (Column 2 of Table 4.5). Similarly, a one-standard-deviation increase (decrease) in cumulative social media sentiment in the FTSE100 is related to 3.91% upswings (drops) in the next day's opening returns (Column 2 of Table 4.6). When we control for the impact on overnight returns from the previous day's trading activities in Column (3) in Tables 4.5-4.6, we observe that the economic magnitudes of influence from social media sentiment shrink for both the DJIA and FTSE100. Moreover, in Table 4.5, the t-statistics of $Sent^S$ for the DJIA become insignificant (0.53), while the significance and magnitude of the news media sentiment remained largely intact. Although the social media sentiment coefficient for the FTSE100 subsided from 0.0391 to 0.0355, it remained significant at the 5% level (t=2.36). The overall model fit for both markets improved compared with Column (2), with the adjusted R^2 increasing from 0.23% to 1.1% for the DJIA (Table 4.5), and from 0.34% to

1.52% for the FTSE100 (Table 4.6).

The model in Eq.(4.4) controls for the most optimistic and pessimistic days, using dummy variables indicating the top (D_t^{+S}) and bottom (D_t^{-S}) deciles of $Sent^S$, as well as their interaction terms with $Sent^S$. The model estimates, in Column (4) of Tables 4.5 and 4.6, highlight the asymmetry in sentiment impact. For the DJIA index, in Table 4.5 Column (4), while the social media sentiment coefficient is significant, only the large negative swings appear to impact the index returns at the opening. We find no such evidence for the news media sentiment. In contrast, the results of Table 4.6 for the FTSE100 reveal the opposite - it is the sentiment based on news media rather than social media that exhibits significant impact and, consistent with the DJIA results, it is the large negative sentiment that has the most pronounced influence. All else being equal, a three-standard-deviation increase in pessimistic sentiment (i.e., a decrease in $Sent^S$) brings about approximately 21.5% decrease in overnight returns.[13] We focus on a three-standard-deviation change rather than the ad hoc one-standard-deviation in interpretations of the results of Eq.(4.4), because only under such a magnitude are the dummy variables representing the top and bottom deciles of sentiment switched on. Milder magnitudes of change, such as one standard deviation, do not constitutes the top and bottom decile events. The interpretation of the $Sent^S$ and $Sent^N$ coefficients alone, however, does not involve this consistency, so we stick to the ad hoc one-standard-deviation change interpretation for Eqs.(4.2) and (4.3).

We observe that, unlike in the US market, news media sentiment in the UK market displays more profound role in determining overnight returns. All else equal and controlling for other market variables, a one-standard-deviation increase in news media sentiment of the FTSE100 generates approximately 14.91% increase in the overnight returns (Column (6) of Table 4.6) at the 1% significance level. Such an effect from the social media, however, only results in 3.55% rises in the overnight returns (Column (3)). Similar to the social media patterns in the US market, negative news sentiment in the UK exerts a greater impact than positive news sentiment (Column (7) of Table 4.6).

Overall, we find that, with the exception of the US and Brazil markets, the news media sentiment displays more pronounced influence on overnight returns. To assist in contrasting the effects of social and news media on the international financial markets, we refrain from reporting results individually for each market as we have done in Tables 4.5 and 4.6 for illustrative purposes. Instead, we detail the results of country-level regressions based on Eq.(4.4) in Table 4.7 where Panels (a) and (b) contain the results based on social and news media, respectively.

The coefficients of $Sent^S$ and $Sent^N$ in Table 4.7 bring about several insights. Firstly, except for the IBEX35 index for social media, all the coefficients of $Sent^S$ and $Sent^N$ are positive, suggesting

[13] For example, the effect from a three-standard-deviation increase in **negative** sentiment can be estimated with $Sent^S = -3$, $D_t^{-S} = 1$, and $D_t^{+S} = 0$ as: $0.0117 \times (-3) + (-0.05) \times 1 + (-0.0433) \times (-3) = -0.2150$ based on values in Table 4.5 Column (4).

Table 4.5: SENTIMENT SENSITIVITY OF THE DJIA. This table summarises the regression results based on Eqs.(4.1) through (4.4) for the Dow Jones Industrial Average index. The dependent variable, Ro, is the overnight (close-to-open) index return in per cent. The main independent variables are the standardised average cumulative sentiment based on social and news media ($Sent_t^S$ and $Sent_t^N$, respectively) from the previous day market closing time to the next day open. D_t^{-k} and D_t^{+k} are dummy variables indicating the bottom and top sentiment deciles. Rc_{t-1} is the close-to-close index return on the previous day in per cent. VLM_{t-1} is the de-meaned logarithm of the number of trades on the previous day. RV_{t-1} is the de-meaned realised volatility on the previous day in per cent. VIX_{t-1} is the de-meaned logarithm of VIX on the previous day. p-values below 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

Dependent variable = overnight DJIA return on day t (in percent)							
		Social Media ($k = S$)			News Media ($k = N$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	0.0037	0.0039*	0.0037	0.0039	0.0039*	0.0037	0.0030
	(1.39)	(1.68)	(1.41)	(1.32)	(1.68)	(1.40)	(1.02)
$Sent_t^k$		0.0053**	0.0014	0.0117***	0.0040*	0.0040*	0.0008
		(2.24)	(0.53)	(2.71)	(1.72)	(1.71)	(0.19)
D_t^{-k}				-0.05**			0.0203
				(-2.32)			(0.76)
D_t^{+k}				0.0032			-0.0199
				(0.12)			(-0.75)
$D_t^{-k} \times Sent_t^k$				-0.0433***			0.0131
				(-3.41)			(0.90)
$D_t^{+k} \times Sent_t^k$				-0.0130			0.0178
				(-0.90)			(1.15)
Rc_{t-1}	0.0056**		0.0056**	0.0062**		0.0055*	0.0056**
	(1.98)		(1.98)	(2.20)		(1.95)	(1.98)
VLM_{t-1}	0.0256***		0.0245***	0.0204***		0.0259***	0.0259***
	(4.13)		(3.79)	(3.11)		(4.19)	(4.17)
RV_{t-1}	-0.0046		-0.0055	-0.0187		-0.0016	0.0037
	(-0.03)		(-0.04)	(-0.13)		(-0.01)	(0.02)
VIX_{t-1}	-0.0012		-0.0001	0.0044		-0.0001	-0.0005
	(-0.12)		(-0.002)	-0.44		(-0.01)	(-0.05)
adj.R^2	0.0114	0.0023	0.0110	0.0168	0.0013	0.0125	0.0116
F-stat	6.00	5.02	4.85	4.29	2.96	5.39	3.27
p-value	0.00	0.03	0.00	0.00	0.09	0.00	0.00
Nobs.	1,738	1,739	1,738	1,738	1,739	1,738	1,738

Table 4.6: Sentiment Sensitivity of the FTSE100. This table summarises the regression results of Eqs.(4.1) to (4.4) of the FTSE100 Index. The dependent variable Ro is the overnight return (close-to-open) of FTSE100 in per cent. The main independent variables are the standardised average cumulative sentiment on social media ($Sent_t^S$) and news media ($Sent_t^N$) from the previous day closing to the next day open. D_t^{-k} and D_t^{+k} are dummy variables that indicate the bottom and top decile average cumulative sentiment days. Rc_{t-1} is the close-to-close return on the previous day in per cent. VLM_{t-1} is the de-meaned log number of trades on the previous day. RV_{t-1} is the de-meaned realised volatility on the previous day in per cent. VIX_{t-1} is the de-meaned log(VIX) on the previous day. p-values below 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

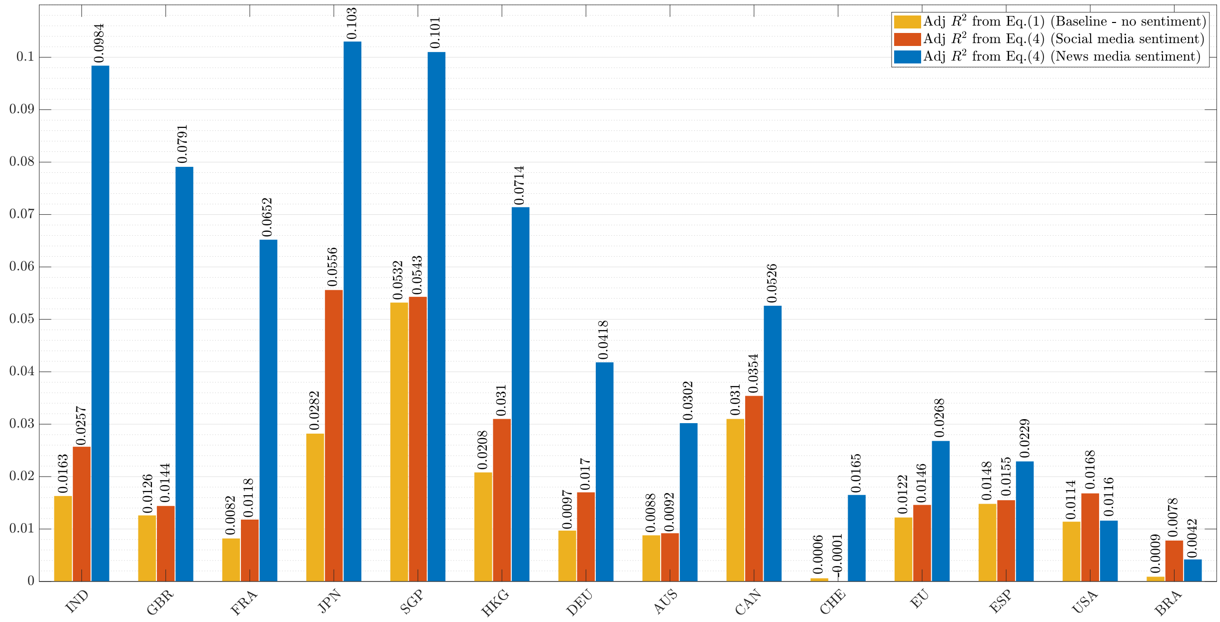
FTSE100 dependent = overnight return on day(t) in percent							
		Social Media ($k = S$)			**News Media** ($k = N$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	0.0227	0.0227	0.0227	0.0325*	0.0227	0.0227	0.0487***
	(1.53)	(1.52)	(1.53)	(1.95)	(1.56)	(1.57)	(3.04)
$Sent_t^k$		0.0391***	0.0355**	0.0186	0.1447***	0.1491***	0.1227***
		(2.62)	(2.36)	(0.71)	(9.93)	(9.95)	(4.82)
D_t^{-k}				-0.0889			0.5100***
				(-0.44)			(2.97)
D_t^{+k}				-0.0009			-0.0197
				(-0.00)			(-0.11)
$D_t^{-k} \times Sent_t^k$				0.0044			0.3833***
				(0.04)			(4.03)
$D_t^{+k} \times Sent_t^k$				-0.0002			-0.0351
				(-0.00)			(-0.33)
Rc_{t-1}	0.0008		0.0003	0.0004		0.0045	0.0057
	(0.05)		(0.02)	(0.03)		(0.28)	(0.37)
VLM_{t-1}	0.0825		0.0787	0.0808		0.0874*	0.1017*
	(1.52)		(1.45)	(1.49)		(1.66)	(1.94)
RV_{t-1}	10.834***		10.808***	10.697***		10.461***	11.083***
	(4.04)		(4.04)	(3.99)		(4.01)	(4.27)
VIX_{t-1}	-0.2453***		-0.2246***	-0.2285***		-0.1062*	-0.1078*
	(-3.79)		(-3.45)	(-3.49)		(-1.65)	(1.68)
adj.R^2	0.0126	0.0034	0.0152	0.0144	0.0532	0.0655	0.0791
F-stat	6.56	6.84	6.37	3.82	98.7	25.3	17.6
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nobs.	1,738	1,739	1,738	1,738	1,739	1,738	1,738

a direct effect of overnight sentiment on overnight returns. That is, positive (negative) sentiment over the non-trading hours is associated with an increase (decrease) in the next day opening prices relative to the previous day closing. Secondly, since we employ standardised sentiment variables, we can directly contrast the coefficients between social and news media effects, in addition to comparing sentiment effects across counties. We find that only the US market exhibits a stronger reaction to social media sentiment compared with the news, as evident by the magnitude of $Sent^S$ relative to $Sent^N$. In contrast, the rest of the countries in our sample display greater responses to news media. Moreover, social media sentiment have little impact in the UK, Canadian, Swiss and Spanish stock markets. While the estimated coefficient of $Sent^S$ for Brazil is insignificant, the heightened negative social media sentiment, D_t^S, has a hefty detrimental impact on the Bovespa's overnight returns. Other markets, for instance, France, Germany, Hong Kong, India, Japan and Singapore, are sensitive to both social and news media, given the significance of both $Sent^S$ and $Sent^N$ coefficients. However, these markets appear to be more responsive to news media sentiment than social media. Since the performance of EU's STOXX index is largely driven by Germany and France, the estimates for STOXX index are consistent with these two markets. Lastly, the only market that is similar to the US in its response to media sentiment is Australia, where the social media exerts significant influences on opening returns, while news media sentiment is largely muffled. This finding is consistent with Bertram (2004) that the general performance of the ASX is mainly affected by overnight sessions when any material market-moving information arrives from the larger trading venues (e.g., US and Europe). It is worth noting, however, that the magnitude of the social media impact on the US market is smaller compared with Australia. Given that the US financial markets are among the most efficient, this result is not surprising.

A closer look at the binary regressors and interaction terms in Table 4.7 further illustrates the asymmetric effect of media sentiment on overnight returns. The results in Panel (a) suggest that the US, Brazil and Japan markets are prone to excessive negative swings in social media sentiment, while Hong Kong is the only country in our sample that is more sensitive to extreme positive social media sentiment. This asymmetry is more pronounced for the news media in Panel (b). We find that the overnight market returns in the UK, Australia, France, Japan, and India are highly sensitive to excessive negative swings in news media sentiment. The Canadian market is highly sensitive to both negative and positive swings in news sentiment but displays no association with social media. Thus, the Canadian market presents a striking contrast to the US, where social media sentiment is clearly dominant. To the contrary, Hong Kong offers an interesting case - it is the only market that shows statistically significant reaction to positive but not the negative swings across social and news media.

In Figure 4.3, we evaluate the increments in the proportion of the overnight return variation explained by adding sentiment-based variables. Specifically, we contrast the adjusted R^2 in Table 4.7

Figure 4.3: Proportion of the overnight return variation explained. The figure contrasts adj.R^2s from the baseline regression model in Eq.(4.1) (absent sentiment data) with adj.R^2s from Eq.(4.4) based on social and news media sentiment. The country plots are ordered on the basis of the difference between the adj.R^2s from Eq.(4.4) for news and social media.



based on Eq.(4.4) for social and news media, respectively, with the adjusted R^2 from a baseline model in Eq.(4.1) that contains no sentiment data. This allows for the "value added" assessment of the sentiment signal.[14] From the figure, we observe that in India, France and UK, the signal contained in the news media sentiment data more than doubles the proportion of the explained overnight return variation. On the other hand, the US and Brazil are the only countries in our sample where social media sentiment offers relatively larger explanatory power compared to news media. The addition of social media variables in Switzerland and news media variables in Brazil show no significant improvements, resulting in low R^2s and F-statistic below conventional critical values (see Table 4.7). The R^2 levels in Figure 4.3 may appear low, they are nonetheless consistent with the R^2 bounds in the empirical stock return forecasting literature. For instance, Fama and French (1988), Zhou (2010), and Kan and Zhou (2006) present close to or less than 1% monthly return forecasting R^2 statistics. According to Rapach and Zhou (2013), the monthly R^2 statistics below 1% can still be economically relevant. Contrasting R^2 in models with and without sentiment variables allows us to assess the importance of news versus social media in the global markets, with their specific information processing limitations, market inefficiencies, and any cultural or psychological influences.

Given the complexity of the model in Eq.(4.4), we provide visual summaries of our findings in Figures 4.4 and 4.5 where we assess the overall impact of one and three standard deviations changes in

[14] We would like to point out that our aim is not to compare information environment or market efficiency across countries, although it could be an interesting research question for future studies. As noted in Bartram et al. (2009), there are large variations across countries in uncertainty about country fundamentals, financial development, and information environment, all of which determine the cross-country variation in R^2.

overnight sentiment on the index return. In these figures, we contrast the sensitivity of index returns to changes in news versus social media sentiment. If the impact of social and news media are equivalent, then the country would lie on the 45-degree line. With the exception of the US, our results in Figure 4.4 convey that the one-standard-deviation change in news media sentiment has a higher impact on index returns than social media.

To assist with interpretation of the results in Table 4.7 and to contrast the effects of news versus social media, we plot the estimated coefficients from Panel (a) against the estimated coefficients from Panel (b) along with a 45reference line. To that end, Figure 4.4 contrasts market sensitivities to overnight news sentiment ($Sent^N$) and social media sentiment ($Sent^S$). Countries plotted above (below) the 45line exhibit stronger sensitivity to news (social) media sentiment. Considering the standardisation of the country-specific sentiment scores and the inclusion of controls, the coefficients of $Sent^N$ and $Sent^S$ from Eq.(4.4) represent the magnitude of change in country index returns (in per cent) in response to a one-standard-deviation change in sentiment after controlling for other factors that are known to determine the rate of market index return. Each point on the graph represents an intersection of the estimated $Sent^N$ and $Sent^S$ from Eq.(4.4), while the sizes of the plotted points are scaled to represent the absolute values of the larger t-statistic of the corresponding coefficients. For example, the US is the only country in our sample whose broad market index exhibit a dependency on daily social media sentiment fluctuations. Although the magnitude of the coefficient is small, it is worth noting that the US market is among the most efficient markets, and the coefficient (however small) is still significant after accounting for other factors known to determine index returns.[15] Unlike the US, markets in other countries are more sensitive to sentiment from news than social media. France, Hong Kong, India and Japan appear to be swayed by news media sentiment much more strongly than Canada, Singapore, and the UK. Response to daily news media sentiment in Australia and the US appears to be of little consequence judging by the t-statistics on $Sent^N$ from Table 4.7.

Figure 4.5 is designed to contrast the total effects from large swings in news and social media sentiment. Given the three-standard-deviation change in the relevant sentiment type, a response in the market index return is calculated based on estimated coefficients from Table 4.7. This allows us to consider the full complexity of sentiment variables in Eq.(4.4), including overall sensitivity to sentiment and polarised emotions via binary regressors and the interaction terms. The horizontal axis in Figure 4.5 represents expected overnight returns conditional on strong social media sentiment ($Sent^S = \pm 3\sigma$), and the vertical axis indicates expected overnight returns conditional on strong news media sentiment ($Sent^N = \pm 3\sigma$). Here, $\sigma = 1$ for all countries and sentiment media types due to the standardisation of the sentiment scores that facilitates the comparison. Each blue mark in the figure represents the

[15]Specifically, we account for previous day close-to-close returns (Rc_{t-1}), volume (VLM_{t-1}), realised volatility (RV_{t-1}), and the global fear index (VIX_{t-1}).

intersection of predicted index return from large positive changes in social media sentiment (x-axis) and news media sentiment (y-axis). Similarly, each red mark represents the intersection of predicted index return from large negative changes in sentiment.[16]

In Figure 4.5, the location of scatter points along the horizontal axis indicate the total effect from social media sentiment on market returns. The deviation of scatter points along the vertical axis and away from the origin attests to the magnitude of the total effect from news media sentiment. If market returns are positive in response to positive sentiment from social and news media, the scatter points would be located in the shaded blue area in Quadrant I. Similarly, if market returns are negative in response to negative sentiment from social and news media, the scatter points would be located in the shaded red area in Quadrant III. If the effects of social and news media are equivalent, the scatter points would be plotted along the 45 line. Points concentrating around the origin display smaller magnitudes of sensitivity to sentiment. Contrasting the red and blue scatter points reveals that negative sentiment effects from news media appear to be stronger than positive ones. For example, a negative three-standard-deviation change in news media sentiment results in -96 bps in FTSE100, while a positive three-standard-deviation change in news media sentiment accounts for only +31 bps. Another interesting observation is that Hong Kong market reacts negatively to both positive and negative extreme news media sentiment. Points placed in Quadrants II and IV, however, indicate sensitivity to only one type of media source. For example, the red dots at the bottom right (namely, Australia, France, Germany and Singapore) indicate sensitivity to only negative news sentiment but not negative social media sentiment. We have performed similar analysis with the two-standard-deviation change in the relevant sentiment variables and found qualitatively similar results.

Together, Figures 4.4 and 4.5 aid in our understanding of the multitude of the results in Table 4.7. Figure 4.4 indicates that, with the exception of the US, markets are more easily swayed by variations in the news sentiment rather than social media. The consequences of this is that scholars should and must refrain from adopting the US evidence naively in the context of other markets. Figure 4.5 contrasts the strong polarised (positive and negative) sentiment effects across different media types, which brings out new insights to the literature of the influence of media sentiment on the stock returns.

[16]More precisely, the x coordinates for the blue marks in Figure 4.5 are calculated as $E\left[Ro|Sent^S = +3, D^{+S} = 1, D^{+N} = 0, D^{-S} = 0, D^{-N} = 0\right]$ with estimates from Table 4.7.(a) for the social media sentiment. The y coordinates are $E\left[Ro|Sent^N = 3, D^{+S} = 0, D^{+N} = 1, D^{-S} = 0, D^{-N} = 0\right]$ with estimates from Table 4.7.(b) for the news media sentiment. Therefore, blue marks in Figure 4.5 represent relative sensitivities of market index returns to extreme positive sentiment shifts. Similarly, the coordinates for the red marks are calculated by passing the negative three-standard-deviation change in the relevant sentiment type through model estimates in Table 4.7. That is, the (x, y) coordinates of the red marks are represented by the values $E\left[Ro|Sent^S = -3, D^{+S} = 0, D^{+N} = 0, D^{-S} = 1, D^{-N} = 0\right]$ and $E\left[Ro|Sent^N = -3, D^{+S} = 0, D^{+N} = 0, D^{-S} = 0, D^{-N} = 1\right]$.

Table 4.7: Global market sensitivity to overnight sentiment. This table summarises the regression results of all the sample indices based on Eq.(4.4). The dependent variable Ro_t is the overnight return (close-to-open) of each index in per cent. The main independent variables are the standardised average cumulative sentiment on social media ($Sent_t^S$, Panel (a)) and news media ($Sent_t^N$, Panel (b)) from the previous day closing to the next day open. D_t^{-k} and D_t^{+k} are binary regressors indicating the bottom and top decile average cumulative sentiment days, respectively. The corresponding t-statistics is provided in parentheses. The estimates with p-values below 10%, 5% and 1% are indicated by *, **, and ***, respectively. Control variables include: the close-to-close return on the previous day (Rc_{t-1}, in per cent), the de-meaned log number of trades on the previous day (VLM_{t-1}), the de-meaned realised volatility on the previous day (RV_{t-1}, in per cent), and the de-meaned log(VIX) on the previous day (VIX_{t-1}). The estimated coefficients for control variables are omitted for brevity. The adjusted R^2 and F-statistics for each country regression are at the bottom row of each panel. For the F-test, the unrestricted and restricted models are Eq.(4.4) and Eq.(4.1), respectively. The F critical values with $df_1 = 5$, $df_2 = 1738 - 5 - 1$ are 1.85, 2.22, and 3.03 for the 10%, 5% and 1% significance levels, respectively.

Panel (a) Social Media

Country Index	US DJIA	UK FTSE100	Canada TSX	Brazil Bovespa	Australia AORD	Switzerland Swiss	Germany DAX30	Spain IBEX35	EU STOXX	France CAC40	HK HangSeng	Japan Nikkei225	India Nifty	Singapore FTStraits
constant	0.0039	0.0325*	0.0214***	0.0545***	0.0079	0.0243	0.0371*	0.0685***	0.0154	0.0276	0.0810***	0.0649***	0.0379**	0.0601***
	(1.32)	(1.95)	(3.04)	(2.84)	(1.05)	(1.57)	(1.89)	(3.20)	(1.32)	(1.45)	(3.46)	(2.89)	(2.48)	(5.21)
$Sent_t^S$	0.0117***	0.0186	0.0105	0.0329	0.0257**	0.0215	0.1230***	-0.0074	0.0424**	0.0766**	0.1191***	0.1559***	0.0721***	0.0480**
	(2.71)	(0.71)	(0.95)	(0.99)	(2.10)	(0.87)	(4.06)	(-0.21)	(2.26)	(2.47)	(3.20)	(4.48)	(3.018)	(2.25)
D_t^{-S}	-0.05**	-0.0889	-0.1046	-0.2972*	-0.0618	-0.0011	-0.0821	-0.2307	-0.0784	-0.2354	-0.0939	0.5516**	-0.0840	-0.0335
	(-2.32)	(-0.44)	(-1.25)	(-1.66)	(-0.90)	(-0.01)	(-0.35)	(-1.01)	(-0.68)	(-1.15)	(-0.36)	(2.34)	(-0.52)	(-0.39)
D_t^{+S}	0.0032	-0.0009	0.1066	0.0194	-0.0334	0.056	0.0442	0.0217	0.1576	-0.0953	0.4420*	0.3680	-0.1702	-0.0126
	(0.12)	(-0.00)	(1.22)	(0.66)	(-0.57)	(0.33)	(0.21)	(0.11)	(1.50)	(-0.44)	(1.71)	(1.32)	(-1.17)	(-0.12)
$D_t^{-S} \times Sent_t^S$	-0.0433***	0.0044	-0.0472	-0.0801	-0.0588	0.0130	-0.1431	-0.0396	-0.0693	-0.1535	-0.1016	0.2861**	-0.0446	-0.0414
	(-3.41)	(0.04)	(-0.96)	(-0.73)	(-1.51)	(0.12)	(-1.07)	(-0.30)	(1.06)	(-1.35)	(-0.70)	(2.18)	(-0.50)	(-0.83)
$D_t^{+S} \times Sent_t^S$	-0.0130	-0.0002	-0.0394	-0.0721	-0.0047	-0.0457	-0.1179	-0.0379	-0.1066*	0.0079	-0.2506*	-0.2355	0.0540	-0.0364
	(-0.90)	(-0.00)	(-0.84)	(-0.84)	(-0.14)	(-0.49)	(-0.98)	(-0.36)	(-1.77)	(0.07)	(-1.74)	(-1.44)	(0.64)	(-0.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.0168	0.0144	0.0354	0.0078	0.0092	-0.0001	0.017	0.0155	0.0146	0.0118	0.031	0.0556	0.0257	0.0543
F-stat	4.29	3.82	8.08	2.51	2.8	0.871	4.35	4.04	3.86	3.31	7.18	12.4	6.10	12.1

Panel (b) News Media

Country Index	US DJIA	UK FTSE100	Canada TSX	Brazil Bovespa	Australia AORD	Switzerland Swiss	Germany DAX30	Spain IBEX35	EU STOXX	France CAC40	HK HangSeng	Japan Nikkei225	India Nifty	Singapore FTStraits
constant	0.0030	0.0487***	0.022***	0.0514***	0.0158**	0.0266*	0.0465**	0.0524**	0.0219*	0.0403**	0.0891***	0.0601***	0.0281*	0.0619***
	(1.02)	(3.04)	(3.15)	(2.69)	(2.12)	(1.72)	(2.39)	(2.46)	(1.89)	(2.17)	(3.87)	(2.73)	(1.91)	(5.54)
$Sent_t^N$	0.0008	0.1227***	0.0615***	0.0647**	0.1702	0.0585**	0.1478***	0.0716**	0.0745***	0.1720***	0.1996***	0.2816***	0.1675***	0.1014***
	(0.19)	(4.82)	(5.49)	(2.16)	(1.46)	(2.37)	(5.02)	(2.16)	(4.22)	(6.04)	(5.53)	(7.82)	(7.69)	(5.87)
D_t^{-N}	0.0203	0.5100***	-0.1250*	0.0973	0.1702**	-0.1022	0.1534	0.2972	0.0209	-0.3483*	0.1766	0.4961**	0.4597**	-0.1119
	(0.76)	(2.97)	(-1.85)	(0.36)	(2.36)	(-0.60)	(0.60)	(1.18)	(0.16)	(-1.85)	(0.65)	(2.25)	(2.25)	(-0.94)
D_t^{+N}	-0.0199	-0.0197	-0.1803**	0.1602	0.0945	0.1919	-0.1957	0.1634	0.0876	0.0480	0.8705***	-0.0638	-0.1476	0.0486
	(-0.75)	(-0.11)	(-2.12)	(0.90)	(1.30)	(1.20)	(-0.81)	(0.65)	(0.63)	(0.18)	(2.77)	(-0.20)	(-0.71)	(0.35)
$D_t^{-N} \times Sent_t^N$	0.0131	0.3833***	-0.1087***	0.0685	0.1336***	-0.0031	0.0885	0.1959	-0.0029	-0.1325	0.1025	0.1746	0.2424**	-0.0480
	(0.90)	(4.03)	(-2.96)	(0.41)	(3.37)	(-0.03)	(0.62)	(1.35)	(-0.04)	(-1.30)	(0.74)	(1.57)	(2.15)	(-0.73)
$D_t^{+N} \times Sent_t^N$	0.0178	-0.0351	0.0631	-0.1673*	-0.0582	-0.0973	0.0700	-0.0945	-0.0998	-0.0675	-0.5384***	-0.0141	0.0870	-0.0473
	(1.15)	(-0.33)	(1.28)	(-1.78)	(-1.41)	(-1.05)	(0.50)	(-0.69)	(-1.19)	(-0.42)	(-2.72)	(-0.08)	(0.70)	(-0.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.0116	0.0791	0.0526	0.0042	0.0302	0.0165	0.0418	0.0229	0.0268	0.0652	0.0714	0.103	0.0984	0.101
F-stat	3.27	17.6	11.7	1.81	7.01	4.24	9.43	5.52	6.31	14.5	15.8	23.2	22.1	22.8

Figure 4.4: Market sensitivities to overnight sentiment. The figure contrasts the global market sensitivities to the overnight news and social media sentiment. Considering the standardisation of country sentiment scores and the inclusion of controls, the coefficients of $Sent^N$ and $Sent^S$ from Eq.(4.4) - $\hat{\beta}_1^N$ and $\hat{\beta}_1^S$ - represent the magnitude of change in returns (in per cent) in response to a one-standard-deviation change in sentiment after controlling for other factors that are known to determine the rate of return. Each point on the graph represents an intersection of the estimated $Sent^N$ and $Sent^S$ from Eq.(4.4), while the sizes of plotted points are scaled to represent the absolute values of the larger t-statistic of the corresponding coefficients.

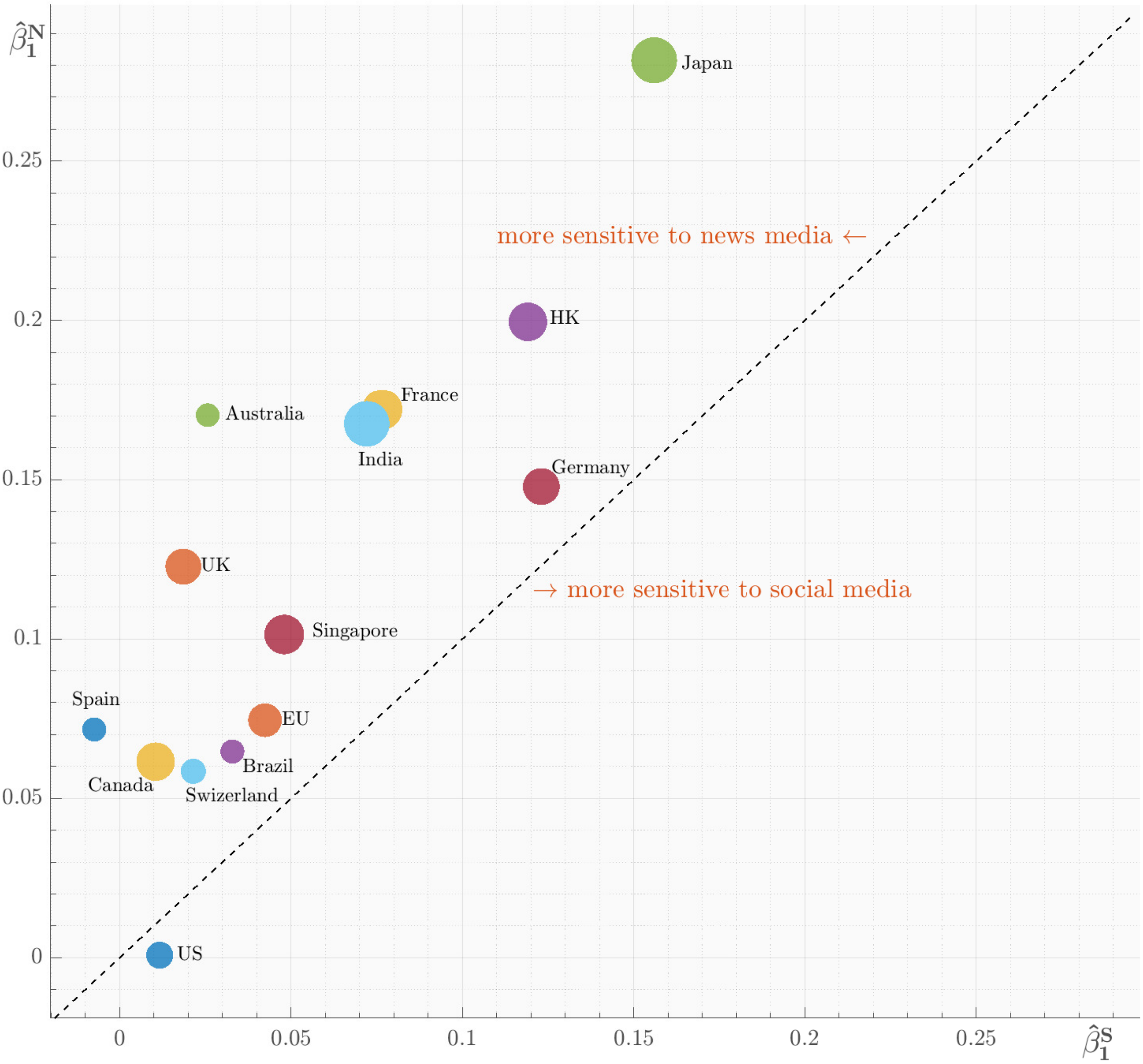
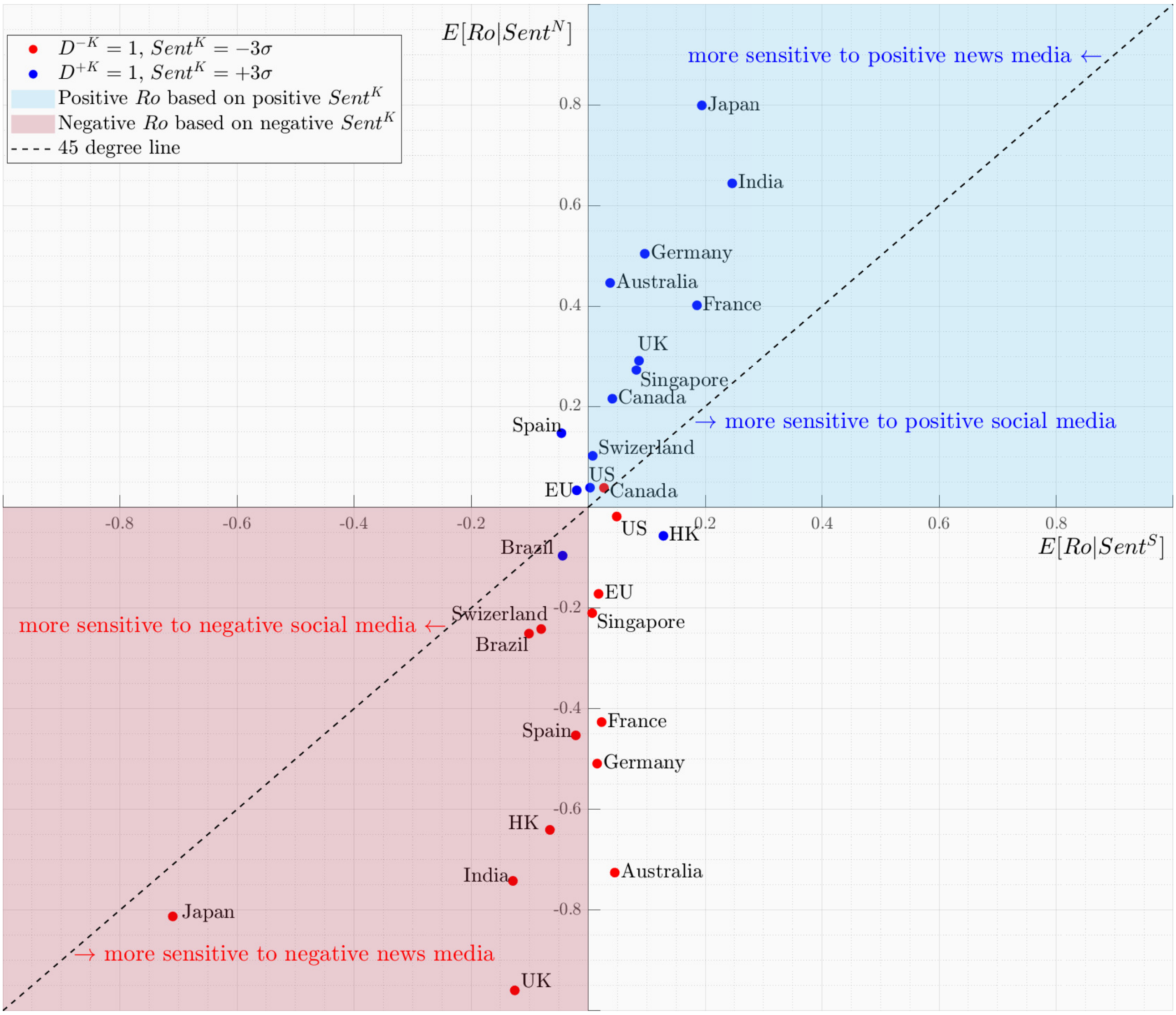


Figure 4.5: Market reactions to positive and negative sentiment. The figure contrasts market reactions to optimistic and pessimistic overnight news and social media sentiment. Considering the standardisation of country sentiment scores and the inclusion of controls, the horizontal axis represents expected overnight returns conditional on strong social media sentiment ($Sent^S = \pm 3\sigma$), and the vertical axis indicates expected overnight returns conditional on strong news media sentiment ($Sent^N = \pm 3\sigma$). Each point on the graph represents an intersection of the estimated responses from the model in Eq.(4.4) using 3σ change in sentiment based on social (x-axis) and news media (y-axis). The blue dots indicate responses to the positive sentiment, i.e., $E[Ro|D^{+S} = 1, D^{+N} = 0, Sent^S = 3\sigma]$ for the x-coordinate, and $E[Ro|D^{+S} = 0, D^{+N} = 1, Sent^N = 3\sigma]$ for the y-coordinate. The red dots indicate similar responces but for the negative sentiment, i.e., $E[Ro|D^{-S} = 1, D^{-N} = 0, Sent^S = -3\sigma]$ and $E[Ro|D^{-S} = 0, D^{-N} = 1, Sent^N = -3\sigma]$.



4.4 Robustness Checks

In the previous section, we reported the results of accumulating sentiment from the previous day closing to the next day market open. We check the robustness of our findings by varying the lengths of sentiment aggregation windows to explore the effectiveness of the return predictability from sentiment signals. Following the same format, we regress overnight returns on the standardised cumulative sentiment using Eq.(4.1) to Eq.(4.4) and report the results when social and news media sentiment are aggregated in the three hours before the market open. Our analysis of the optimal window to gauge the emotional scores indicates that windows spanning from 30 minutes to six hours before markets open forms the most "effective" signals in terms of the overall model fit and significance of estimated coefficients on sentiment variables. A duration of less than 30 minutes, e.g., 15 minutes before the opening time, suffers from a data sparsity problem that is detrimental to signal performance. Another negative aspect of shorter aggregation windows comes from the high volatility of sentiment scores, whereas aggregating sentiment over longer periods allows for a reduction of noise and an exposition of a more persistent trend. Unquestionably, the overall model fit for each of the countries in our sample varies slightly when the aggregation window is altered, but the best fit is achieved in the region between 30 minutes and six hours before the market opening. Furthermore, we observe an inverse relationship between the data availability in each market (proxied by the number of available 1-minute news and social media scores reported in Table A.6) and the optimal length of the aggregation window. For consistency, we use the three-hour window in our reported robustness tests in Tables 4.8 and 4.9. Results for alternative lengths of the aggregation windows are available upon request.

Tables 4.8 and 4.9 report sensitivities of the DJIA and FTSE100 overnight returns, respectively, to the social and news media sentiment three hours before market opens. These two tables contain results that are consistent with the ones reported in Section 4.3. Similarly, in these tables, Columns (2) to (4) measure social media impacts and Columns (5) to (7) evaluate news media sentiment influences.

When aggregating sentiment just three hours before the market open instead of using an entire overnight period, the social media sentiment in the case of the DJIA retains significant predictability, although at relatively lower economic magnitudes. A comparison between the restricted model (Column 2) in Tables 4.5 and 4.8 shows that the coefficient shrinks from 0.0053 to 0.0039 if we only consider the morning pre-opening sentiment (e.g., from 6:29 am to 9:29 am in the US market, and from 4:59 am to 7:59 am in the UK market). After including all the control variables and dummy variable terms (the unrestricted model), the coefficients on $Sent^S$ improved in both Tables 4.5 and 4.8 (Column 4), relative to their restricted models (Column 2). However, both the statistical and economic significance reduced in the shorter-period sentiment tests. Compared with Table 4.5, an increase of one standard deviation in social media sentiment three hours before the opening leads to only 0.76% increases in the opening prices (Table 4.8 Column (4)), a reduction of more than 35% from 1.17% reported in Column (4) of Table 4.5. Moreover, the negative tonality continues to display a stronger impact than the positive side, as both the D_t^{-S} and its interaction term maintain similar magnitudes at statistically significant levels, while D_t^{+S} and its interaction term both remain insignificant. Together, in Table 4.8, a one-standard-deviation spike in negative DJIA social media sentiment (a decline in sentiment) three hours before opening leads to a 2.23% decrease in opening returns $(0.0076 \times (-1) + (-0.049) + (-0.0343) \times (-1) = 0.0223)$. By contrast, this negative DJIA social media sentiment for the full overnight period (in Table 4.5) gives rise to only a 1.84% reduction in opening returns $(0.0117 \times (-1) + (-0.05) + (-0.0433) \times (-1) = -0.0184)$. On the other hand, the coefficients based on the news sentiment data are now insignificant in all three models (Columns (5) to (7) of Table 4.8).

Table 4.9 shows that the FTSE100 social media sentiment expounds similar effects whether sentiment is aggregated at shorter or full overnight period, while the FTSE100 news sentiment effect diminished remarkably if aggregating at only three hours before the opening. The estimated coefficients from models based on social media in Columns (2) and (3) are at similar magnitudes to those in Table 4.6 (a marginal decrease from 0.0391 to 0.0334, and from 0.0355 to 0.0327, respectively), with their t-statistics lower but still significant. An astonishing result is observed in Column (4) where after considering the tonality, the explanatory power of $Sent^S$ is largely improved from 0.0186 to 0.0518, with t-statistics significant at the 10% level. The result suggests that, for the FTSE100, aggregating the social media sentiment from the previous day close to the next day open might have generated an obscurely wider window that has dampened the precision of the signal. However, if we focus on just the three hours pre-opening, the signal from social media might be more useful in predicting opening prices. In contrast, Columns (5) to (7) in Table 4.6 show that focusing on news sentiment of the FTSE100 in just the pre-opening period might be less ideal compared with watching the entire overnight period, providing additional support for a more dynamic nature of social media compared to news. The coefficient of $Sent^N$ dropped sharply from 0.1447 to 0.0335 in the model in Column (5), and it dwindled from 0.1491 to 0.0301 after controlling for the market variables in Column (6). The t-statistics are also considerably smaller compared with the overnight sentiment group, while the key variable coefficients of the most flexible model in Column (7) are now all insignificant. For the FTSE100, these results suggest that news sentiment should be aggregated at wider window lengths.

Table 4.8: DJIA three-hour cumulative sentiment regressions. This table summarises the regression results of Eqs.(4.1) to (4.4) on the Dow Jones Industrial Average. The dependent variable Ro is the overnight return (close-to-open) of the DJIA in per cent. The main independent variables are the standardised average cumulative sentiment on social media ($Sent_t^S$) and news media ($Sent_t^N$) three hours before the market open (6:29 am to 9:29 am). D_t^{-k} and D_t^{+k} are dummy variables that indicate the bottom and top decile average cumulative sentiment days. Rc_{t-1} is the close-to-close return on the previous day in per cent. VLM_{t-1} is the de-meaned log number of trades on the previous day. RV_{t-1} is the de-meaned realised volatility on the previous day in per cent. VIX_{t-1} is the de-meaned log(VIX) on the previous day.

DJIA dependent = overnight return on day(t) in percent							
		Social Media ($k = S$)			**News Media** ($k = N$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	0.0037	0.0039*	0.0037	0.0055*	0.0039*	0.0037	0.0043
	(1.39)	(1.68)	(1.39)	(1.96)	(1.68)	(1.38)	(1.48)
$Sent_t^k$		0.0039*	0.0004	0.0076*	-0.0009	-0.001	0.0006
		(1.65)	(0.18)	(1.80)	(-0.37)	(-0.42)	(0.15)
D_t^{-k}				-0.049*			-0.0091
				(-1.89)			(-0.42)
D_t^{+k}				-0.0021			-0.0346
				(-0.07)			(-1.16)
$D_t^{-k} \times Sent_t^k$				-0.0343**			-0.0058
				(-2.21)			(-0.5)
$D_t^{+k} \times Sent_t^k$				-0.0119			0.0163
				(-0.78)			(0.9)
Rc_{t-1}	0.0056**		0.0056**	0.0056**		0.0057**	0.0058**
	(1.98)		(1.98)	(1.98)		(1.99)	(2.02)
VLM_{t-1}	0.0256***		0.0253***	0.0251***		0.0256***	0.0254***
	(4.13)		(3.98)	(3.94)		(4.12)	(4.08)
RV_{t-1}	-0.0046		-0.0057	-0.0257		-0.0041	-0.0058
	(-0.03)		(-0.04)	(-0.17)		(-0.0275)	(-0.04)
VIX_{t-1}	-0.0012		-0.0008	0.0026		-0.0013	-0.012
	(-0.12)		(-0.08)	(0.26)		(-0.13)	(-0.13)
adj.R^2	0.0114	0.0010	0.0108	0.0133	-0.0005	0.0102	0.0097
F-stat	6.00	2.73	4.80	3.61	0.14	4.83	2.89
p-value	0.00	0.099	0.0002	0.0002	0.711	0.0002	0.0022
Nobs.	1,738	1,739	1,738	1.738	1,739	1,738	1,738

Table 4.9: FTSE100 THREE-HOUR CUMULATIVE SENTIMENT REGRESSIONS. This table summarises the regression results of Eqs.(4.1) to (4.4) on the FTSE100 Index. The dependent variable Ro is the overnight return (close-to-open) of the FTSE100 in per cent. The main independent variables are the standardised average cumulative sentiment on social media ($Sent_t^S$) and news media ($Sent_t^N$) three hours before the market open (4:59 am to 7:59 am). D_t^{-k} and D_t^{+k} are dummy variables that indicate the bottom and top decile average cumulative sentiment days. Rc_{t-1} is the close-to-close return on the previous day in per cent. VLM_{t-1} is the de-meaned log number of trades on the previous day. RV_{t-1} is the de-meaned realised volatility on the previous day in per cent. VIX_{t-1} is the de-meaned log(VIX) on the previous day.

FTSE100 dependent = overnight return on day(t) in percent							
		Social Media ($k = S$)			**News Media** ($k = N$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	0.0227	0.2267	0.0227	0.0209	0.0227	0.0227	0.0317*
	(1.53)	(1.52)	(1.53)	(1.25)	(1.52)	(1.53)	(1.90)
$Sent_t^k$		0.0334**	0.0327**	0.0518*	0.0335**	0.0301**	0.0336
		(2.24)	(2.18)	(1.90)	(2.24)	(1.98)	(1.28)
D_t^{-k}				0.0263			0.0096
				(0.19)			(0.06)
D_t^{+k}				-0.0933			-0.14
				(-0.61)			(-0.82)
$D_t^{-k} \times Sent_t^k$				-0.0203			0.0216
				(-0.26)			(0.23)
$D_t^{+k} \times Sent_t^k$				0.0280			0.0433
				(0.32)			(0.46)
Rc_{t-1}	0.0008		0.0008	0.0010		0.0023	0.0027
	(0.05)		(0.05)	(0.06)		(0.14)	(0.17)
VLM_{t-1}	0.0825		0.0767	0.0796		0.0791	0.0787
	(1.52)		(1.42)	(1.46)		(1.46)	(1.45)
RV_{t-1}	10.834***		11.056***	10.941***		10.884***	10.884***
	(4.04)		(4.13)	(4.07)		(4.06)	(4.06)
VIX_{t-1}	-0.2453***		-0.2367***	-0.2383***		-0.2241***	-0.2229***
	(-3.79)		(-3.66)	(-3.66)		(-3.42)	(-3.40)
adj.R^2	0.0126	0.0023	0.0148	0.0132	0.0023	0.0143	0.0131
F-stat	6.56	5.00	6.21	3.58	5.02	6.04	3.56
p-value	0.00	0.03	0.00	0.00	0.03	0.00	0.00
Nobs.	1,738	1,739	1,738	1,738	1,739	1,738	1,738

4.5 Conclusion

We investigate the influence of overnight social and news media sentiment on the returns of 14 major stock markets at the opening. Controlling for known factors that impact the rate of return, we find that changes in the overnight return, that is, the opening price relative to the previous trading day close, can be attributed to the build-up of investor sentiment in the social and news media. And this effect is significant both statistically and economically. Our results suggest that the more optimistic the sentiment is, the higher the next day opening price, and that the more pessimistic the sentiment appears, the lower the next opening price. Polarised emotions, either positive or negative, such as the top and bottom decile sentiment, tend to be more influential than the moderate sentiment (within interior deciles). Our analysis shows that the overnight sentiment does not simply subsume previous day market activity, but in fact contains additional information signal that can improve the explanatory ability in return forecasting models.

We also find that only in the US does social media exert greater forces on the market, while news sentiment remains the strongest in influencing stock markets around the world. This finding cautiously highlights the issue of hastily applying US-based evidence to other markets. Furthermore, the economic magnitudes of return predictability induced from overnight social and news media sentiment in the US is much smaller than in other countries, reaffirming the fact that the US market is among one of the most liquid and efficient markets in the world.

By incorporating the direction of tonality and allowing for the asymmetry in our modelling framework, we discover that negative news sentiment plays a greater role than positive sentiment in most international markets. Among others, Australia, India and Japan tend to be very easily affected by both positive and negative news sentiment. By contrast, Hong Kong is the only market that is highly prone to positive sentiment based on both social and news media. These mixed results pose difficulty in drawing a unified conclusion among all the economies, but nonetheless offering new directions for further research.

Overall, this study contributes to the behavioural finance literature on investor sentiment and its impact on stock markets. It assists in the understanding of the price discovery process in markets other than the US, with a novel dataset of high-frequency textual-based sentiment and an approach that helps to disentangle the return-sentiment feedback loop.

Chapter 5

Conclusion

Motivated by the ceaseless hype regarding social media that is seemingly challenging the relevance of the traditional news industry, I strive to compare the similarities and differences in their impacts on the stock markets. In a fast-evolving digital and mobile world that generates millions of pieces of information every day, knowing how to disentangle the two intertwined media channels and evaluate their influence on the efficient functioning of financial markets is vital and challenging work.

In this thesis, I addressed the following related questions in a series of three chapters of research: How has the rapidly evolving social and news media landscape changed in the past decade? How does the social and news media sentiment affect stock returns and volatility? Does the market move sentiment more than the sentiment influences the market? What if sentiment is measured for individual stocks rather than the aggregate stock market? How can the sentiment-and-return feedback loop be disentangled? How does overnight sentiment impact opening prices? Is this sentiment effect the same around the world? What similarities and differences do we find in comparison to the US?

My research benefits from having applied both daily and intraday sentiment scores that were based on the proprietary textual analysis algorithm from Thomson Reuters MarketPsych Indices (TRMI). This unique dataset provided me with the top 30% ranking social media sentiment and major newspaper sentiment targeting at specific entities (indices or stocks). Both aggregate market-level sentiment in the US and the sentiment of other major financial markets around the world as well as individual company-specific sentiment data were used to conduct this research.

Focusing on the US S&P500 index at a daily frequency, the first study examined the mutual influence of the social and news media and their interactions with returns and volatility. I documented three distinct regimes in this changing landscape using the sheer volume of social and news media activity, commonly known as *buzz*. I found that between 2011 and 2013 news media coverage stimulated activity in social media. This was followed by a transition period of two-way causality. From 2016, however, changes in the levels of social media activity led and generated news coverage volume. I uncovered a similar evolution of lead-lag patterns between sentiment measures constructed from the tonality contained in textual data from social and news media posts. I discovered that market fundamentals exerted stronger impact on investor sentiment than the other way around. I found that return responses to social media sentiment shocks almost doubled after the transition period, while return responses to news-based sentiment almost halved compared to their pre-transition level. More importantly, the linkage between volatility and sentiment was revealed to be much more persistent than that between returns and sentiment.

Tackling the question of how overnight sentiment impacted on the opening prices, in the second study, I concentrated on the DJIA constituent stocks to take advantage of their high media coverage in mitigating the detrimental issue of data sparsity. Using intraday sentiment scores, my analysis revealed that sentiment during non-trading hours was a strong predictor of opening returns. Specifically, sentiment from social media induced larger changes in opening prices than those from the news media. Negative sentiment impacts on opening returns were at higher economic magnitudes than positive sentiment. Nonetheless, these phenomena quickly diminished after the first minute of trading. Robustness tests showed that these effects were not driven by corporate earnings announcements. The chapter provides a new set of techniques and describes the development of a novel framework for high-frequency sentiment analysis to help shed light on the dynamics of stock markets in the fast-paced digital era.

Finally, in a quest to compare the similarities and differences of the US market with other markets, I continued contrasting the influence of social and news media to investigate how stock markets around the world react to changes in sentiment from these two media sources. Using data from 14 markets (Australia, Brazil, Canada, the EU, France, Germany, Hong Kong, India, Japan, Singapore, Spain, Switzerland, the UK and the US), I found that the amassed social and news media sentiment during non-trading periods led to changes in the next day opening returns in the same direction as the change in sentiment. I also discovered that only in the US stock market did social media exert a stronger impact on the opening prices, while the news media sentiment expounded a greater impact on stock prices in all the other major financial markets. Robustness tests showed that the aggregation of sentiment up to three hours prior to market opening helped generate effective signal for predicting the direction of the opening prices.

Overall, this thesis takes a time-series analysis at first to observe the lead-lag relationships of the social and news media, and uncovers that social media was becoming the dominant media source. Applying sentiment measures at a more granular intraday frequency allows for a more precise analysis of the information flow. The swift adjustment at market opening and the distinctions between the social and news media shed new light on the price dynamics. Differences between the US and other markets are highlighted as are the differences in price discovery in various markets around the globe; these results also suggest caution in applying US evidence naively to other contexts. This thesis contributes to the behavioural finance literature on investor sentiment and stock market reactions and brings about new insights to both investors and regulators in the digital economy age.

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Appendix A

Main Appendix

A.1 Appendix for Chapter 2

A.1.1 List of acronyms and notation

Table A.1: List of acronyms, data sources and variable names.

Acronym	Description
AAII	American Association of Individual Investors
ACF	Autocorrelation Function
AIC	Akaike Information Criterion
BIC	Schwartz's Bayesian Information Criterion
BW	Baker & Wurgler sentiment index
BW_O	The orthoganolized Baker & Wurgler sentiment index
CBOE	Chicago Board Options Exchange
CEFD	Closed-end fund discount
Datastream	Thomson Reuters Datastream
DJIA	Dow Jones Industrial Average
DJNS	Dow Jones Newswires
DW	Durbin-Watson test
GFC	Global Financial Crisis
GI	Harvard General Inquirer Dictionary
GSV	Google Search Volume
IQR	Interquartile Range
IRF	Impulse Response Function
LB	Ljung-Box test
MV	Market Variables
PACF	Partial Autocorrelation Function
PCA	Principal Component Analysis
RIC	Reuters Identification Code
S&P500	Standard & Poor's 500 Index
SEC	The US Securities and Exchange Commission
SIRCA	Securities Industry Research Centre of Asia-Pacific
VAR	Vector Autoregressive Model
TR	Thomson Reuters
TRMI	Thomson Reuters MarketPsych Indices
TRNA	Thomson Reuters News Analytics
TRNS	Thomson Reuters News Scope
TRTH	Thomson Reuters Tick History
VAR	Vector Autoregressive Model
WRDS	Wharton Research Data Services
WSJ	The Wall Street Journal
Code/Symbol	Description
.SPY	RIC for SPDR ETF
Datastream	Thomson Reuters Datastream
MPTRXUS500	TRMI company group code approximating S&P500 index constituents
$Buzz_{N,t}$	(N)ews media buzz at time t (report volume in news media)
$Buzz_{S,t}$	(S)ocial media buzz at time t (posting volume in social media)
$Sent_{N,t}$	(N)ews media net sentiment at time t (positive minus negative sentiment)
$Sent_{S,t}$	(S)ocial media net sentiment at time t (positive minus negative sentiment)
r_t	log return on day t
V_t	VIX (CBOE options volatility index) on day t

A.1.2 Testing for Unit Roots

Prior to fitting VAR models, we perform tests for unit root to ensure that all regressors are covariance stationary. Results in Table A.2 suggest rejection of the null hypothesis of unit root for all series.

Table A.2: Unit Root Test. The table displays Augmented Dickey-Fuller and Phillips-Perron unit root test statistics for 3 different model variants. ***, **, and * denote rejection of the null hypothesis of unit-root at 1%, 5%, and 10% significance levels, respectively. Critical values at 5% significance level are reported in the last column.

	Return	VIX	$Sent_S$	$Sent_N$	$Buzz_S$	$Buzz_N$	Crit.Val.
Panel A: Augmented Dickey-Fuller (ADF) test							
ADF	-44.76***	-1.83*	-11.12***	-17.11***	-3.02***	-3.03***	-1.94
ADF (with drift)	-44.85***	-5.45***	-13.93***	-19.63***	-11.46***	-15.04***	-2.86
ADF (with drift and trend)	-44.84***	-6.36***	-17.95***	-19.78***	-12.93***	-15.04***	-3.41
Panel B: Phillips-Perron (PP) test							
PP	-29.47***	-1.74*	-8.88***	-13.41***	-2.76***	-2.85***	-1.94
PP (with drift)	-29.56***	-5.16***	-10.92***	-15.36***	-10.28***	-14.17***	-2.86
PP (with drift and trend)	-29.56***	-6.03***	-13.82***	-15.47***	-11.61***	-14.17***	-3.41

A.1.3 ACF and PACF for main TRMI series

Figure A.1: Time-series Analysis of raw *Buzz* data. The left three panels show the sample distribution of the original social media posts volume measure: *Buzz*, as well as its autocorrelation function (ACF) and partial autocorrelation function (PACF) up to 40 days. The three panels on the right represent news-based *Buzz* series distribution, its ACF and PACF respectively. Sampling period: 2011/01/01-2017/11/30. The top two figures (blue series) verify descriptive statistics reported in Table 2.1, and highlight the fact that the original *Buzz* series contain several observations at the right tail (large outliers). Social (left) *Buzz* tends to be more volatile than news (right) counterpart. Both ACF and PACF indicate the presence of strong weekly seasonality for both $Buzz_S$ abd $Buzz_N$

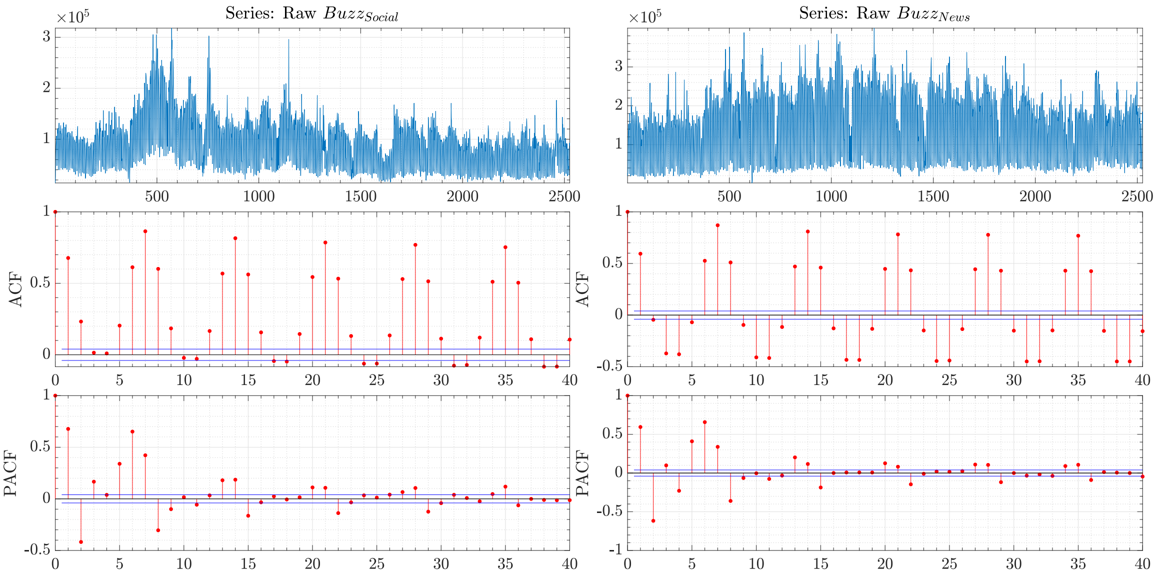


Figure A.2: Winsorized and De-Seasoned *Buzz* Time Series Check. The left three panels show the sample distribution of $Buzz_S$ after truncating the large value observations (asymmetric winsorizing the right tail outliers), its autocorrelation function (ACF) and partial autocorrelation function (PACF) up to 40 days. The right side three panels represent the winsorized and seasonality adjusted news-based *Buzz*, its ACF and PACF respectively. Sampling period: 2011/01/01-2017/11/30. Comparing with Figure A.1, the ACFs and PACFs of these two series indicate a diminished, yet not fully eliminated weekly seasonality. Since this research does not involve the association between *Buzz* and stock returns/volatility, the non-trading day adjusted *Buzz* distributions are not reported for brevity.

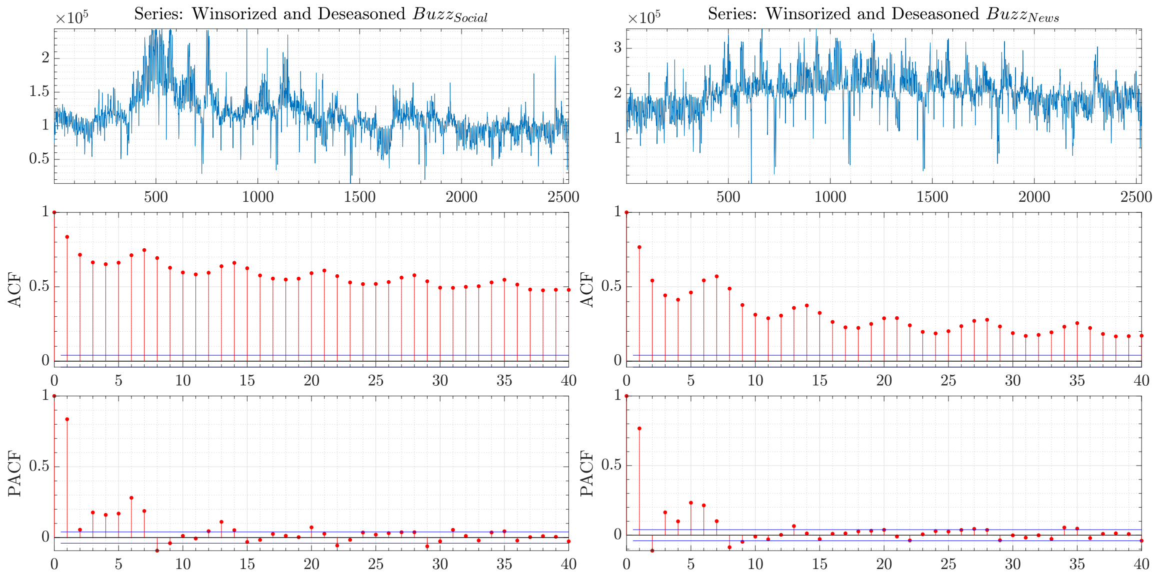


Figure A.3: Raw *Sentiment* Time Series Check. The left three panels show the sample distribution of the net positive and negative emotion scores from social media: $Sent_S$, as well as its autocorrelation function (ACF) and partial autocorrelation function (PACF) up to 40 days. The right side three panels represent news-based *Sentiment* series distribution, its ACF and PACF respectively. Sampling period: 2011/01/01-2017/11/30. The top two figures (blue series) illustrate that the original *Sentiment* series are normalised to zero mean, consistent with descriptive statistics from Table 2.1. Social (left) *Sentiment* exposes more negative observations than news-based (right) scores. Both ACF and PACF indicate the existence of weekly seasonality, and this property is more obvious in news-based sentiment scores.

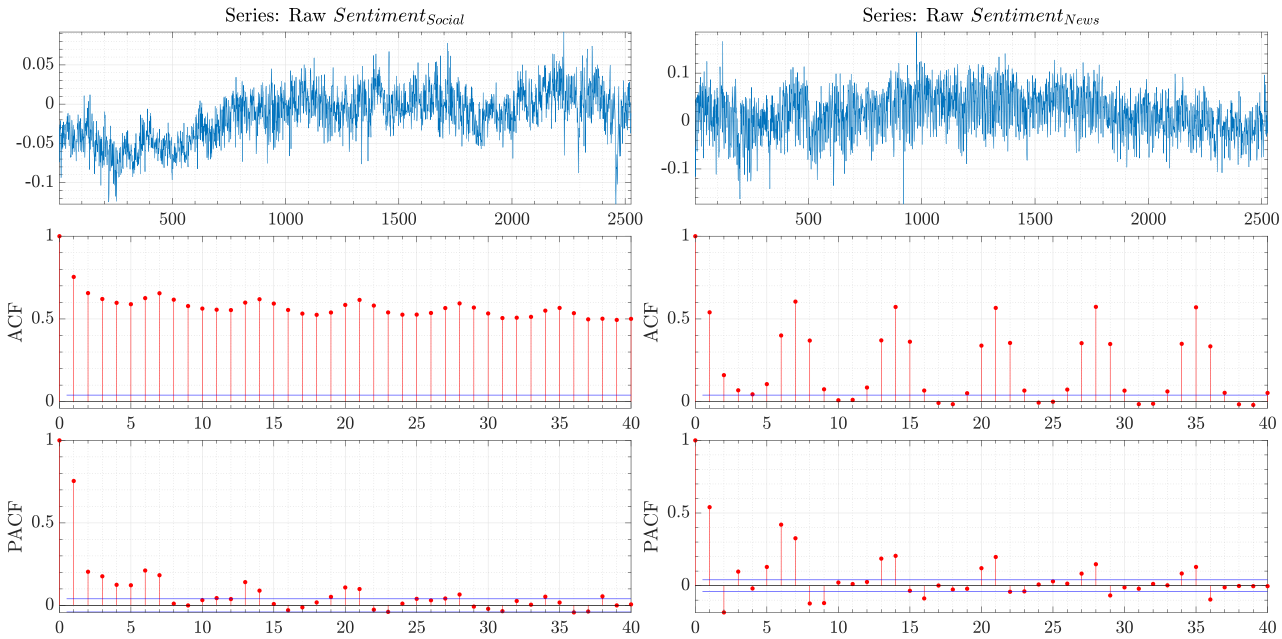


Figure A.4: De-Seasoned and Market Merged *Sentiment* Time Series Check. The left three panels show the sample distribution of the seasonality adjusted and non-trading day averaged value of $Sent_S$, as well as its autocorrelation function (ACF) and partial autocorrelation function (PACF) up to 40 days. The right side three panels represent news-based *Sentiment* series distribution after dealing with the weekly effects and merging with the trading-day only market variables. Its ACF and PACF are presented below respectively. Sampling period: 2011/01/01-2017/11/30. Since *Sentiment* are volume (*Buzz*) weighted and normalised, we do not winsorize *Sentiment* series. This research concentrates on the inter-relations between *Sentiment* and stock variables, we match the *Sentiment* scores with market variables by averaging the non-trading day values. Both ACF and PACF indicate that the weekly seasonality is properly tackled with after these procedures.

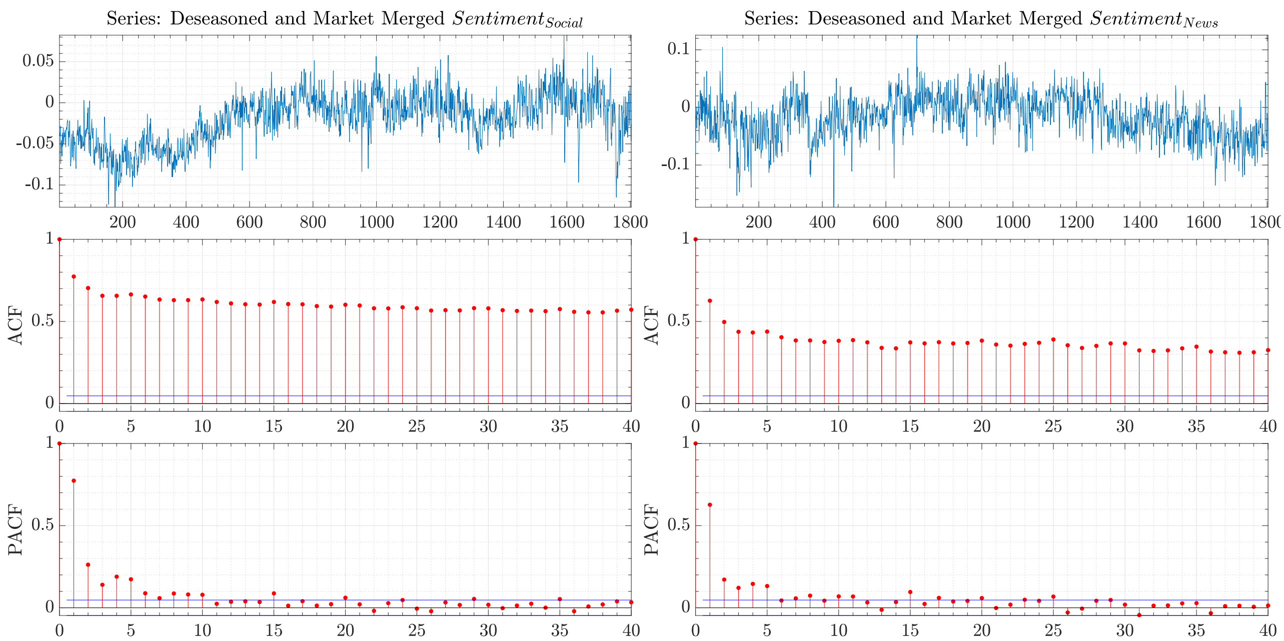
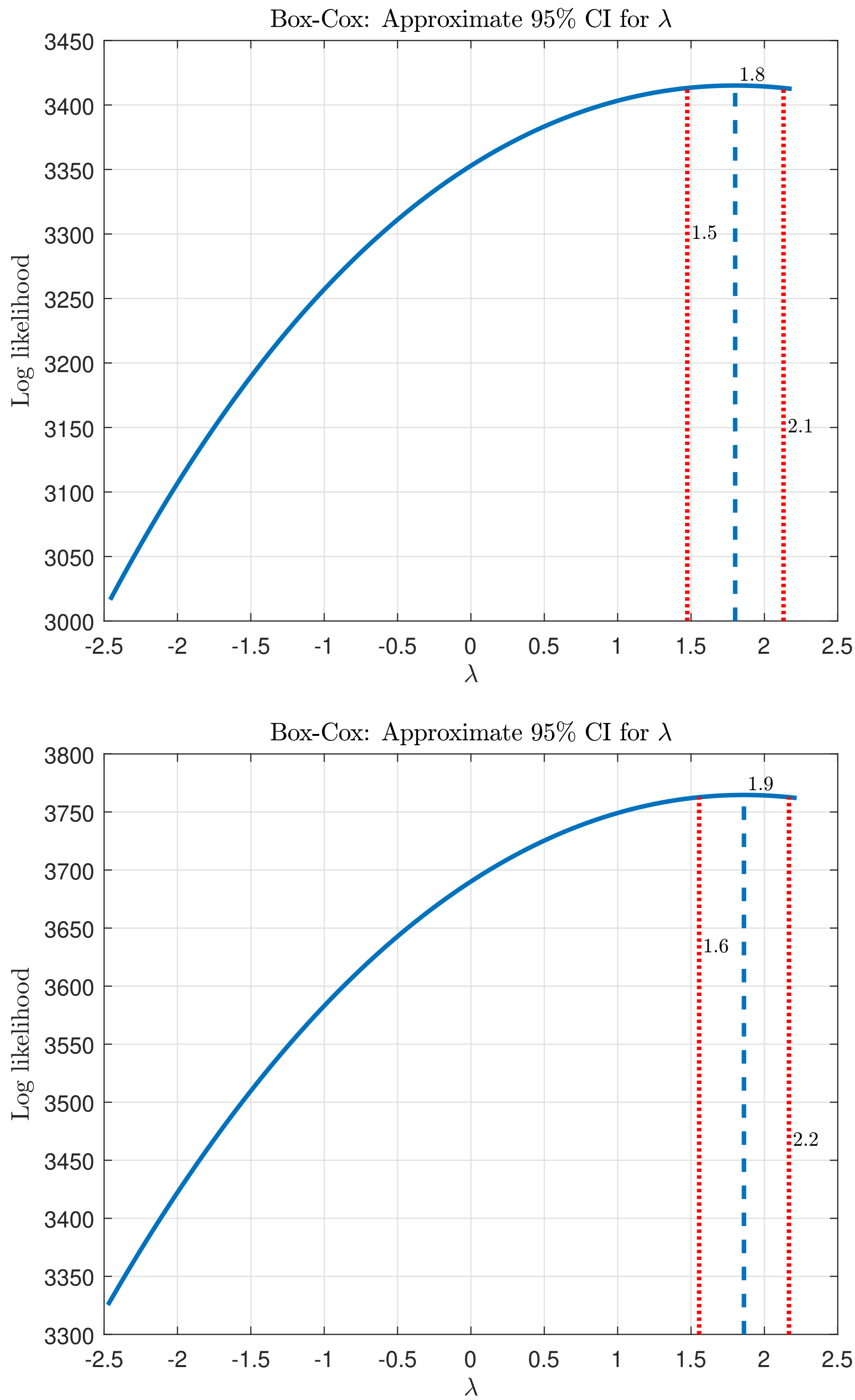


Figure A.5: Maximum likelihood estimate and the 95% confidence interval of the Box-Cox transformation parameter to a linear model of the form $Sent^{\lambda} = \alpha + \beta \times VIX$ (left panel: sentiment based on news media; right panel: sentiment based on social media). The purpose is find a good value for λ, transforming the dependent variable, through a Box-Cox power transformation. Based on G. E. P. Box, D. R. Cox, "An Analysis of Transformation", Journal of the Royal Statistical Society. Series B (Methodological), Vol. 26, No. 2 (1964) , pp. 211-252.



A.2 Appendix for Chapter 3

Table A.3: List of acronyms, data sources, and variable definitions

Acronym	Description
DJIA	Dow Jones Industrial Average
ETF	Exchange-traded Funds
LSE	London Stock Exchange
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. $P_{i,t,j} = \frac{1}{2}\left(Ask_{i,t,j} + Bid_{i,t,j}\right)$
$t = 1, ..., T$	Index of days in the sample
$j = 0, ..., J$	Each day is divided into one-minute intervals indexed by $j = 0, ..., J$
$i = 1, ..., N$	Asset indexation with $i = 0$ reserved for a broad market index or a benchmark
$r_{i,t,j}$	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., $CAR_{i,t}[\tau_1, \tau_2] = \sum_{j=\tau_1}^{\tau_2} AR_{i,j,t}$
$Sent_{i,j,t}^{S}$	one-minute **s**ocial media sentiment score for stock i on day t at time j
$Sent_{i,j,t}^{N}$	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
$\lvert\mathcal{D}_{i,x}\rvert$	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 A.4: Sentiment Data Availability. The total number of non-missing observations and average daily counts are presented for the social and news media for the Dow Jones Index and each of its constituents. Stocks delisted from the DJIA during the sample period are included. Calculations are based on the Thomson Reuters MarketPych Indices (TRMI) social and news media *Sentiment* scores at 1-minute frequency. The sample period is 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

Figure A.6: 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.(3.7) and (3.8), respectively, for the case of news media sentiment. It complements the results shown in Figure 3.6. Each scatter point represents an intersection of the two slope coefficients from Eq.(3.7) on the y-axis and Eq.(3.8) on the x-axis. For example, the scatter points for CSCO.OQ are constructed based on the regression output reported in Table 3.6. 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 ($\mathcal{D}_{i,1}$).

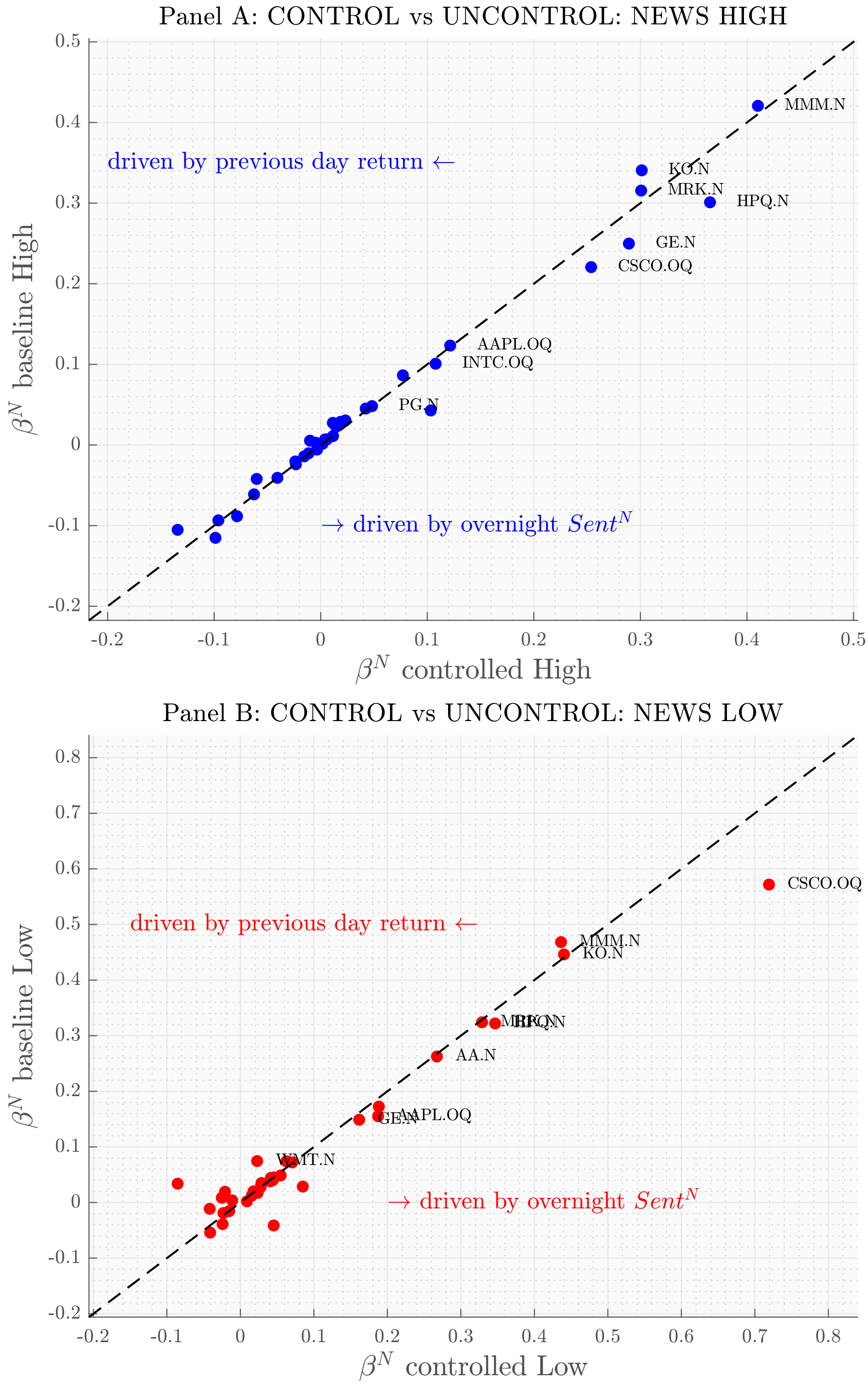
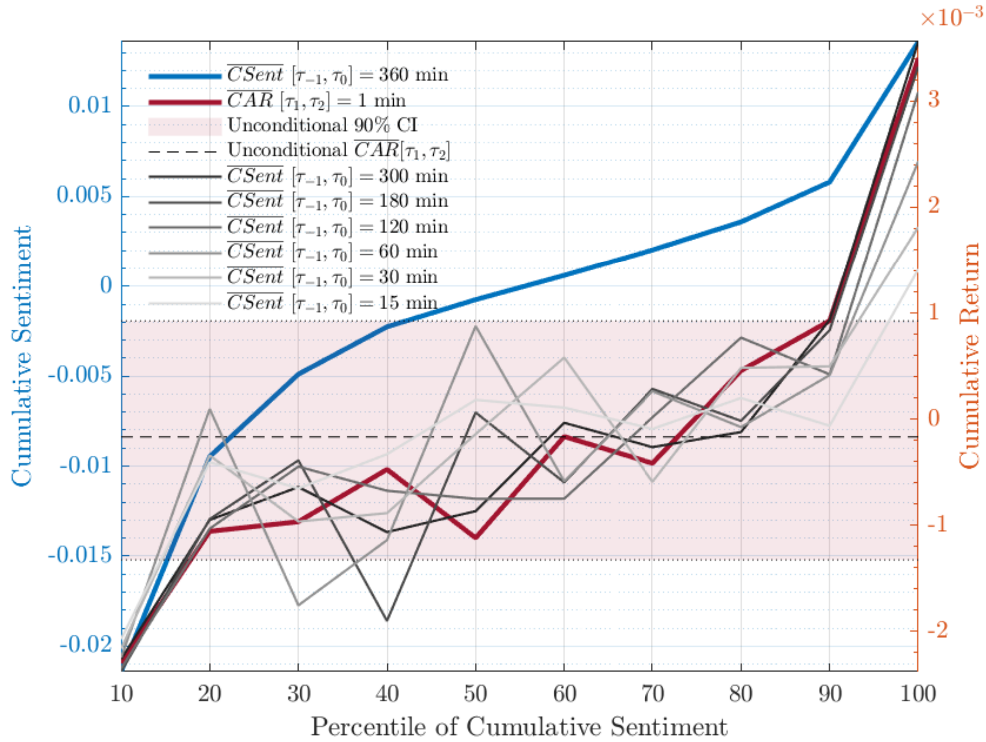
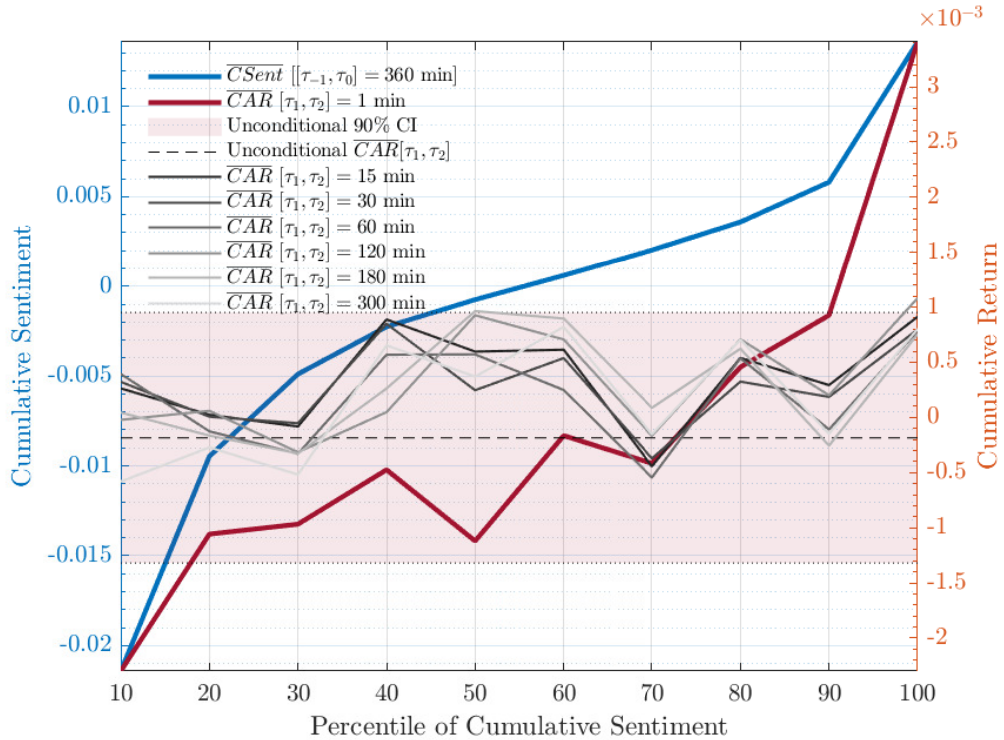


Figure A.7: Alternative Event Window lengths: the case of social media for CSCO.OQ. This figure demonstrates how we determine the optimal pre-event and post-event windows ($[\tau_{-1}, \tau_0]$ and $[\tau_1, \tau_2]$). The horizontal axis shows percentiles of the sorting variable, the cumulative sentiment 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, created by 1,000 bootstrap simulations.

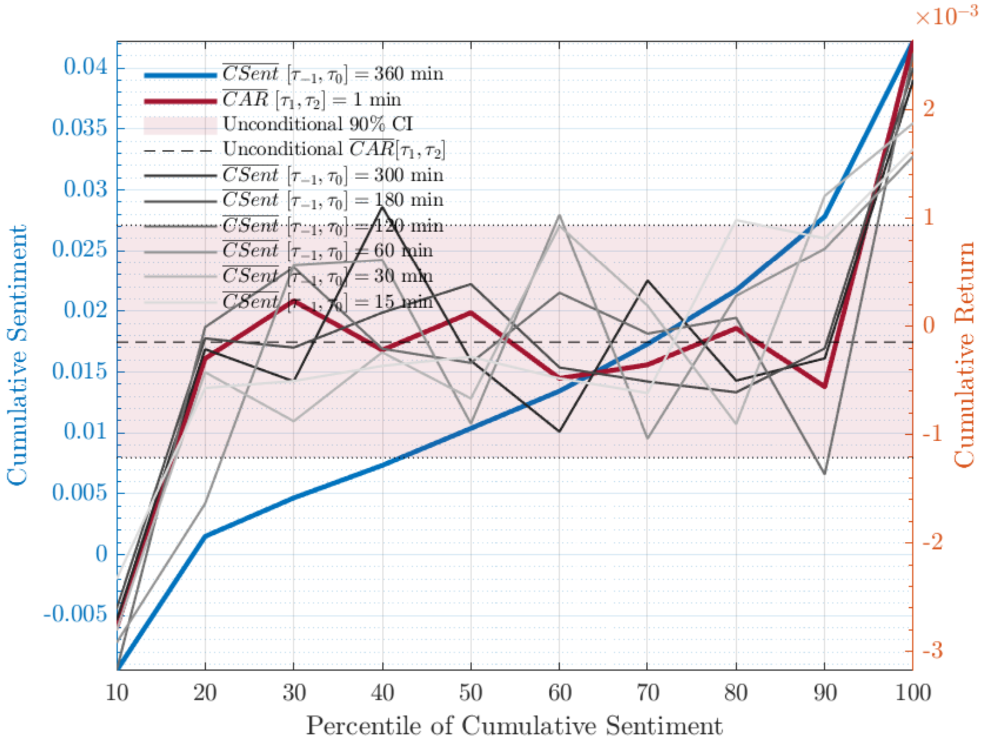


(a) Optimal $[\tau_{-1}, \tau_0]$

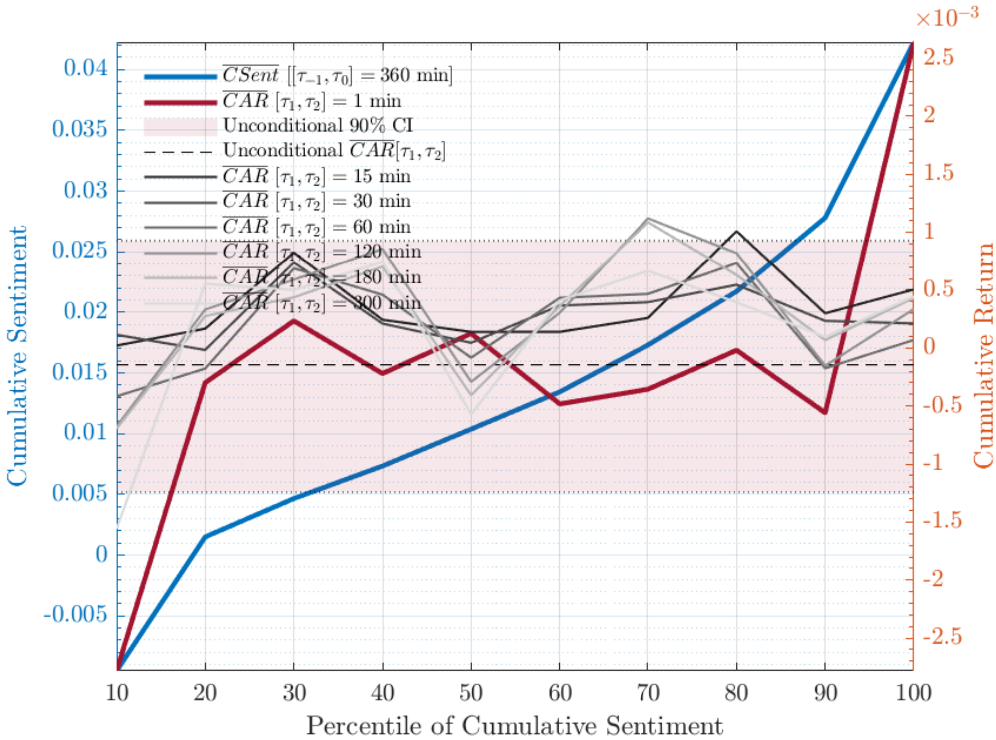


(b) Optimal $[\tau_1, \tau_2]$

Figure A.8: Alternative Event Window lengths: the case of news media for CSCO.OQ. This figure demonstrates how we determine the optimal pre-event 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, created by 1,000 bootstrap simulations.



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



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

A.3 Appendix for Chapter 4

Table A.5: ACRONYMS, VARIABLES AND THEIR DEFINITIONS. Sentiment variables are obtained from Thomson Reuters MarketPsych. Overnight returns, daily returns and daily average realised volatility are from Oxford-Man Institute of Quantitative Finance.

Acronym	Description
OLS	Ordinary least squares
OVB	Omitted variable bias
Oxford-Man	Oxford-Man Institute of Quantitative Finance Realised Library
TRMI	Thomson Reuters MarketPsych Indices
TRNA	Thomson Reuters News Analytics
TRTH	Thomson Reuters Tick History
VIF	Variance Inflation Factor
VIX	The Chicago Board Options Exchange (CBOE) Volatility Index
Variables	**Description**
k	Media type, where k take values S and N denoting social and news media, respectively
n_t^k	Number of non-missing observations of sentiment of media k across the overnight period
Ro	Overnight return, or close-to-open return
Rc	Daily return, or close-to-close return
RV	De-meaned daily average realised volatility
$Sent^k$	Standardised cumulative sentiment from media type k
VLM	De-meaned log daily trades
VIX	De-meaned log daily VIX index
$x_{t,j}^k$	Raw sentiment data from the k media type on day t at time j
X_t^k	Cumulative sentiment of media k averaged across the overnight period (divided by the cardinality)
$\overline{X}^k$	Mean score of the cumulative sentiment of media k across the sample period (days)
σ_{X^k}	Standard deviation of the cumulative sentiment of media k across the sample period (days)

In Table A.6 we provide the descriptive statistics for the 1-minute TRMI data from 1 January 2011 to 30 November 2017 for all country indices in our analysis. Based on the average sentiment scores over the entire sample period, Brazil is the only country netting overall negative tonality from both social and news media sources. Asian markets (Singapore, Hong Kong, India, and Japan) exhibit overall positive tonality from both media sources. The magnitudes of overall sentiment tonality for Australia, Spain, Switzerland, US, and UK only marginally deviate from zero. Overall sentiment tonalities for France, Germany, and, as a consequence, the EU's STOXX index, are positive but at lower magnitudes compared to Asian markets. The volatility of social media sentiment is higher compared to the sentiment volatility based on news media sources (with the exception of Singapore where the two volatilities are equal). The US and Canada are the only two markets where the number of 1-min sentiment observations based on social media are greater compared to traditional news media sources, pointing to heightened activity in the social media domain in these two markets.

Table A.6: TRMI Descriptive Statistics. This table summarises the descriptive statistics of all the TRMI sample company group indices. x^S and x^N are the net positive and negative emotions of a specific entity (the representative index) on the social and news media, respectively. The sample period is from 1 January 2011 to 30 November 2017 at one-minute frequency.

		TRMI				
		Mean	Std	Min	Max	Nobs.
ASX	x^S	0.01	0.49	-1	1	618,017
	x^N	-0.01	0.44	-1	1	1,033,660
Bovespa	x^S	-0.03	0.58	-1	1	121,920
	x^N	-0.08	0.47	-1	1	221,731
CAC	x^S	0.03	0.53	-1	1	167,340
	x^N	0.01	0.52	-1	1	557,285
DAX	x^S	0.02	0.54	-1	1	223,247
	x^N	0.01	0.47	-1	1	841,920
DJIA	x^S	-0.01	0.35	-1	1	2,753,605
	x^N	0.02	0.33	-1	1	2,536,911
EUSTOXX	x^S	0.03	0.51	-1	1	557,034
	x^N	0.01	0.44	-1	1	1,446,764
FTSE100	x^S	0.00	0.52	-1	1	450,888
	x^N	-0.02	0.43	-1	1	1,410,028
FTStraits	x^S	0.05	0.55	-1	1	83,053
	x^N	0.05	0.53	-1	1	150,955
HangSeng	x^S	0.06	0.53	-1	1	387,350
	x^N	0.05	0.53	-1	1	468,960
IBEX	x^S	-0.01	0.57	-1	1	46,791
	x^N	0.00	0.51	-1	1	214,968
Nifty	x^S	0.11	0.56	-1	1	332,530
	x^N	0.05	0.47	-1	1	566,467
Nikkei225	x^S	0.06	0.51	-1	1	412,601
	x^N	0.01	0.44	-1	1	1,311,914
Swiss	x^S	0.03	0.54	-1	1	213,296
	x^N	-0.01	0.50	-1	1	650,666
TSX	x^S	0.03	0.47	-1	1	1,038,727
	x^N	0.05	0.46	-1	1	859,937

Table A.7: Oxford-Man Descriptive Statistics. This table lists the deceptive statistics of the key market variables for all the sample markets. *Ro* indicates the close-to-open overnight return, *Rc* indicates the close-to-close daily return, *RV* represents the realised volatility and Trades represents the total number of daily trades in each market. The sample period is from 1 January 2011 to 30 November 2017 at daily frequency. The data source is from Oxford-Man Institute of Quantitative Finance.

Oxford-Man variables		Mean	Std	Min	Max	Nobs.
ASX	*Ro*	0.0000	0.0077	-0.0291	0.0370	1,807
	Rc	0.0002	0.0083	-0.0365	0.0356	1,806
	RV	0.0000	0.0000	0.0000	0.0008	1,807
	Trades	719	19	514	969	1,807
Bovespa						
	Ro	0.0004	0.0129	-0.0482	0.0831	1,807
	Rc	0.0001	0.0145	-0.0880	0.0660	1,806
	RV	0.0001	0.0002	0.0000	0.0034	1,807
	Trades	817	45	391	845	1,807
CAC						
	Ro	0.0001	0.0102	-0.0516	0.0750	1,807
	Rc	0.0003	0.0125	-0.0785	0.0630	1,806
	RV	0.0001	0.0001	0.0000	0.0023	1,807
	Trades	2,040	51	1,164	3,677	1,807
DAX						
	Ro	0.0001	0.0104	-0.0560	0.0772	1,807
	Rc	0.0005	0.0125	-0.0669	0.0560	1,806
	RV	0.0001	0.0002	0.0000	0.0024	1,807
	Trades	29,637	1,045	16,926	30,601	1,807
DJIA						
	Ro	-0.0003	0.0082	-0.0393	0.0563	1,807
	Rc	0.0004	0.0084	-0.0541	0.0410	1,806
	RV	0.0001	0.0002	0.0000	0.0059	1,807
	Trades	16,018	6,355	4,899	23,412	1,807
EUSTOXX						
	Ro	0.0001	0.0112	-0.0458	0.0904	1,807
	Rc	0.0002	0.0126	-0.0840	0.0601	1,806
	RV	0.0001	0.0002	0.0000	0.0054	1,807
	Trades	2,040	4	1,949	2,041	1,807
FTSE100						
	Ro	0.0001	0.0069	-0.0384	0.0462	1,807
	Rc	0.0002	0.0092	-0.0483	0.0380	1,806
	RV	0.0000	0.0001	0.0000	0.0016	1,807
	Trades	68,130	21,228	11,899	314,308	1,807
FTStraits						
	Ro	0.0001	0.0050	-0.0338	0.0258	1,807
	Rc	-0.0001	0.0076	-0.0412	0.0283	1,806
	RV	0.0000	0.0000	0.0000	0.0005	1,807
	Trades	15,618	7,337	2,941	46,690	1,807
HangSeng						
	Ro	0.0008	0.0076	-0.0405	0.0492	1,807
	Rc	0.0003	0.0103	-0.0654	0.0498	1,806
	RV	0.0001	0.0001	0.0000	0.0010	1,807
	Trades	6,911	3,914	602	9,661	1,807
IBEX						
	Ro	0.0005	0.0120	-0.0569	0.0788	1,807
	Rc	0.0002	0.0141	-0.1194	0.0559	1,806
	RV	0.0002	0.0002	0.0000	0.0055	1,807
	Trades	6,022	255	2,540	6,214	1,807
Nifty						
	Ro	0.0003	0.0053	-0.0524	0.0396	1,807
	Rc	0.0002	0.0098	-0.0592	0.0437	1,806
	RV	0.0001	0.0001	0.0000	0.0015	1,807
	Trades	16,788	1,889	4,311	21,322	1,807
Nikkei225						
	Ro	0.0001	0.0100	-0.0539	0.0972	1,807
	Rc	0.0006	0.0135	-0.1055	0.0771	1,806
	RV	0.0001	0.0002	0.0000	0.0030	1,807
	Trades	1,318	552	1,071	3,602	1,807
Swiss						
	Ro	0.0000	0.0080	-0.0412	0.1022	1,807
	Rc	0.0003	0.0097	-0.0867	0.0502	1,806
	RV	0.0001	0.0001	0.0000	0.0042	1,807
	Trades	12,318	2,615	6,183	27,156	1,807
TSX						
	Ro	0.0002	0.0071	-0.0329	0.0455	1,807
	Rc	0.0001	0.0079	-0.0431	0.0395	1,806
	RV	0.0000	0.0001	0.0000	0.0032	1,807
	Trades	1,574	65	721	2,855	1,807

Table A.8: Variance Inflation Factors. This table summarises the five different variance inflation factors (VIFs) for each independent variables in Eq.(4.3) for the DJIA and FTSE100 indices and social media versus news media, respectively. To help quantify the severity of multicollinearity in an ordinary least squares (OLS) regression analysis, VIF provides an index that measures how much the variance of an estimated regression coefficient is increased because of collinearity. If $VIF(\hat{\beta}_i) > 10$ then multicollinearity is high, and if $5 < VIF(\hat{\beta}_i) \leq 10$ then multicollinearity has certain influences to the model. The square root of the variance inflation factor indicates how much larger the standard error increases compared to if that variable had zero correlation to other predictor variables in the model. For example, If the variance inflation factor of a predictor variable were 5.27 ($\sqrt{5.27} = 2.3$), this means that the standard error for the coefficient of that predictor variable is 2.3 times larger than if that predictor variable had zero correlation with the other predictor variables. This table shows that all of the DJIA and FTSE100 variables' VIFs are between 1 and 2, less than 5—the commonly used cutoff, indicating our models are not suffer from the multicolliearity problem.

	DJIA		FTSE100	
	Social	News	Social	News
$Sent_t^k$	1.1605	1.0055	1.0385	1.1918
Rc_{t-1}	1.0377	1.0390	1.0313	1.1124
VLM_{t-1}	1.1671	1.1051	1.2183	1.2206
RV_{t-1}	1.3629	1.3570	2.0364	2.0358
VIX_{t-1}	1.5501	1.4787	1.8056	1.8522

Appendix B

Supplementary Appendix

B.1 Tried-and-true vs Bold-and-New: on commonality between Baker & Wurgler and MarketPsych Indices

Recently launched 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 do this, we aggregate the daily 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 B.1. The results in Table B.1 demonstrate commonalities between TRMI sentiment indicators and the BW index, yet, the magnitude of correlation coefficients are indicative of divergence of these two measures. This suggests that 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 allowing us to study the dynamics in temporal displacement within sentiment scores (news vs social) and between sentiment and market variables (sentiment vs returns and/or volatility).

Table B.1: Correlation Between BW and TRMI Sentiment Indices. Sample period Jan/2011-Sep/2015. TRMI daily 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. BW and BW_O denote the investor sentiment from equation (2) and the orthogonalized sentiment index from equation (3) of Baker and Wurgler (2006) respectively. ***, **, 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

B.2 Robustness check: model selection

Model selection is an integral part of the statistical analysis of VAR models. For VAR models, model selection consists of two parts:

1. determining the lag order, and
2. determining the substructures of the VAR model.

Much of the existing literature on VAR model selection focus only on the first part, i.e., the lag order determination part, presumably because that misspecification of the lag order often has undesirable implications for subsequent analysis.

When the selected lag order is underfitted, there can be significant residual autocorrelations. Simulations of Ivanov and Kilian (2005) revealed that lag order selection is practically important for impulse response analysis. A number of approaches have been proposed for lag order selection, including the information criterion based approaches such as AIC (Akaike, 1998), BIC (Schwarz, 1978) and HQC (Hannan and Quinn, 1979), the hypothesis testing based approaches such as the sequential likelihood ratio test.

Recently, with the development of penalty-based variable selection techniques such as the Lasso (Tibshirani, 1996) and the adaptive Lasso (Zou, 2006), researchers have begun to consider both parts of VAR model selection simultaneously. Hsu et al. (2008) applied the idea of the Lasso to VAR models to select the lag order and determine the substructures of the coefficient matrices all together. Ren and Zhang (2010) proposed a model selection method using the adaptive Lasso. Although most of the above-mentioned methods have solid theoretical justifications, simulation study results are mixed and usually conflicting, and a universally acceptable method is still unavailable.

In what follows, we present our results from AIC and BIC estimation in Subsection B.2.1. We detail and contrast estimates of bivariate VAR(1) and VAR(7) systems and discuss why we prefer a more parsimonious VAR(1) system in Subsection B.2.2. We perform a formal likelihood ratio test by sequentially contrasting VAR($p-1$) vs VAR(p) models. We present our most conservative test results when comparing the most restrictive VAR(1) model to the least restrictive VAR(7) in Subsection B.2.3. Faced with potential omitted variable bias in our estimation of off-diagonal elements in bivariate VARs, we check the robustness of these coefficients by estimating VAR systems with expanded set of variables. Subsection B.2.4 details our findings.

B.2.1 Optimal Lag Length: Information Criterion

One of most frequent approach to specification is the use of information criteria. The logic behind is the following: we want to minimize the sum of squared error, but in the meantime we want to penalize the dimension of the model (and so the loss of degrees of freedom). Note that the BIC criterion puts a stronger penalty on the number of regressors. Choose the model with the smallest BIC.

Table B.2: Optimal Lag Selection using Information Criteria. Panel A tabulates AIC and BIC criteria from lag 1 to lag 12 for the VAR systems between social media *Buzz* and news *Buzz*. Similarly, Panel B lists AIC and BIC values for the VAR with social media *Sentiment* and news *Sentiment*. Optimal lag is denoted with * and boldface. BIC selects more parsimonious models by imposing heavier penalties for number of lags. AIC is included to facilitate judgment and for completeness. BICs of Panels A and B suggest that the optimal lag for investigating social media and news dynamics are 7. Likewise, Panels C and D test optimal lags for the VAR systems between *Sentiment* and *Return* for social and news media respectively, 5 lags is detected to be most suitable. Panels E and F list the AIC and BIC of VARs between $Sentiment^2$ and VIX for social and news media respectively, BIC indicates that 2 lags are most appropriate for the model specification.

Panel A: $Buzz_S$ **vs** $Buzz_N$

	Lag 1	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lag 6**	**Lag 7**	**Lag 8**	**Lag 9**	**Lag 10**	**Lag 11**	**Lag 12**
AIC	3.189	3.153	3.092	3.055	2.988	2.847	2.787	2.773	**2.772***	2.776	2.777	2.776
BIC	3.203	3.176	3.125	3.097	3.039	2.907	2.856	**2.852***	2.861	2.873	2.884	2.892

Panel B: $Sent_S$ **vs** $Sent_N$

	Lag 1	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lag 6**	**Lag 7**	**Lag 8**	**Lag 9**	**Lag 10**	**Lag 11**	**Lag 12**
AIC	4.165	4.079	4.031	4.005	3.982	3.941	3.911	**3.909***	3.911	3.912	3.913	3.911
BIC	4.179	4.102	4.064	4.047	4.033	4.001	**3.981***	3.988	3.999	4.01	4.019	4.027

Panel C: $Sent_S$ **vs** $Return$

	Lag 1	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lag 6**	**Lag 7**	**Lag 8**	**Lag 9**	**Lag 10**	**Lag 11**	**Lag 12**
AIC	4.735	4.655	4.624	4.588	4.549	4.545	4.543	4.541	4.536	**4.534***	4.537	4.541
BIC	4.754	4.686	4.667	4.643	**4.616***	4.625	4.635	4.645	4.653	4.663	4.679	4.695

Panel D: $Sent_N$ **vs** $Return$

	Lag 1	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lag 6**	**Lag 7**	**Lag 8**	**Lag 9**	**Lag 10**	**Lag 11**	**Lag 12**
AIC	5.159	5.122	5.098	5.082	**5.06***	5.063	5.064	5.065	5.067	5.063	5.062	5.063
BIC	5.177	5.153	5.141	5.138	**5.128***	5.143	5.156	5.169	5.183	5.193	5.204	5.217

Panel E: $Sent_S^2$ **vs** VIX

	Lag 1	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lag 6**	**Lag 7**	**Lag 8**	**Lag 9**	**Lag 10**	**Lag 11**	**Lag 12**
AIC	3.229	3.203	3.197	3.176	3.169	3.159	3.160	**3.148***	3.148	3.149	3.152	3.152
BIC	3.248	**3.234***	3.240	3.231	3.236	3.238	3.252	3.252	3.264	3.278	3.293	3.305

Panel F: $Sent_N^2$ **vs** VIX

	Lag 1	**Lag 2**	**Lag 3**	**Lag 4**	**Lag 5**	**Lag 6**	**Lag 7**	**Lag 8**	**Lag 9**	**Lag 10**	**Lag 11**	**Lag 12**
AIC	3.706	3.688	3.693	3.680	3.681	3.678	3.682	**3.674***	3.677	3.679	3.683	3.686
BIC	3.724	**3.719***	3.735	3.735	3.748	3.758	3.774	3.779	3.794	3.808	3.825	3.840

B.2.2 Optimal Lag Length: Why VAR(1) is Parsimonious Form of VAR (7)

Table B.3: VAR(7) Parsimonious Form Examination (A). Sample A: 2011/01/01-2011/12/31 (the **first year** of our sampling period); p-values smaller than 0.1, 0.05 and 0.01 are denoted as *, **, and *** respectively. Left panel shows VAR model coefficients estimated as in the General Setup when $\mathbf{x} = (Buzz_S, Buzz_N)'$ and $p = 7$; right panel indicates coefficients estimated when $\mathbf{x} = (Sent_S, Sent_N)'$ and $p = 7$. The p-value columns show that the innner lags' (lag 2 to lag 6's) coefficients are insignificant in both models, and most of the significant coefficients are concentrated on lag 1 and lag 7. This indicates that VAR(1) might be a parsimonious form representation of VAR(7).

Sample A: First 365 days							
VAR(7): $Buzz_S$ vs $Buzz_N$				**VAR(7): $Sent_S$ vs $Sent_N$**			
	Coef.	*s.e.*	p-value		Coef.	*s.e.*	p-value
Constant1	-0.0742	0.0460	0.11	Constant1	-0.2109	0.0724	0.00***
Constant2	-0.2417	0.0694	0.00***	Constant2	0.0884	0.1284	0.49
AR1(1,1)	0.6312	0.0683	0.00***	AR1(1,1)	0.5072	0.0589	0.00***
AR1(2,1)	0.0198	0.1030	0.85	AR1(2,1)	0.2718	0.1044	0.01***
AR1(1,2)	-0.0202	0.0452	0.65	AR1(1,2)	-0.0283	0.0337	0.40
AR1(2,2)	0.6084	0.0681	0.00***	AR1(2,2)	0.3482	0.0597	0.00***
AR2(1,1)	-0.0046	0.0802	0.95	AR2(1,1)	-0.0243	0.0648	0.71
AR2(2,1)	0.0954	0.1209	0.43	AR2(2,1)	-0.0939	0.1149	0.41
AR2(1,2)	-0.0687	0.0525	0.19	AR2(1,2)	-0.0028	0.0361	0.94
AR2(2,2)	-0.2647	0.0792	0.00***	AR2(2,2)	0.0487	0.0639	0.45
AR3(1,1)	0.0336	0.0803	0.68	AR3(1,1)	0.1230	0.0645	0.06
AR3(2,1)	-0.0353	0.1210	0.77	AR3(2,1)	-0.0374	0.1143	0.74
AR3(1,2)	0.0228	0.0534	0.67	AR3(1,2)	-0.0387	0.0361	0.28
AR3(2,2)	0.0878	0.0806	0.28	AR3(2,2)	0.0748	0.0640	0.24
AR4(1,1)	-0.0306	0.0804	0.70	AR4(1,1)	0.0238	0.0650	0.71
AR4(2,1)	-0.0955	0.1212	0.43	AR4(2,1)	-0.0425	0.1151	0.71
AR4(1,2)	-0.0153	0.0535	0.78	AR4(1,2)	0.0245	0.0362	0.50
AR4(2,2)	-0.0257	0.0806	0.75	AR4(2,2)	0.0891	0.0642	0.17
AR5(1,1)	0.0810	0.0805	0.31	AR5(1,1)	0.1037	0.0642	0.11
AR5(2,1)	0.1523	0.1213	0.21	AR5(2,1)	-0.0070	0.1138	0.95
AR5(1,2)	-0.0537	0.0534	0.31	AR5(1,2)	0.0042	0.0361	0.91
AR5(2,2)	-0.1052	0.0805	0.19	AR5(2,2)	0.0134	0.0640	0.83
AR6(1,1)	0.0876	0.0812	0.28	AR6(1,1)	0.0558	0.0643	0.38
AR6(2,1)	-0.0882	0.1223	0.47	AR6(2,1)	0.0662	0.1139	0.56
AR6(1,2)	0.0189	0.0527	0.72	AR6(1,2)	-0.0299	0.0360	0.41
AR6(2,2)	0.2426	0.0795	0.00***	AR6(2,2)	-0.0062	0.0638	0.92
AR7(1,1)	0.0142	0.0686	0.84	AR7(1,1)	0.0390	0.0591	0.51
AR7(2,1)	-0.1398	0.1034	0.18	AR7(2,1)	0.0783	0.1047	0.45
AR7(1,2)	0.0876	0.0455	0.05**	AR7(1,2)	0.0725	0.0334	0.03**
AR7(2,2)	0.2093	0.0686	0.00***	AR7(2,2)	0.0230	0.0592	0.70

[continue table next page]

Table B.4: VAR(7) Parsimonious Form Examination (B). Sample B: 2016/11/30-2017/11/30 (the **last year** of our sampling period); p-values smaller than 0.1, 0.05 and 0.01 are denoted as *, **, and *** respectively. Left panel shows VAR model coefficients estimated as in the General Setup when $\mathbf{x} = (Buzz_S, Buzz_N)'$ and $p = 7$; right panel expresses coefficients estimated when $\mathbf{x} = (Sent_S, Sent_N)'$ and $p = 7$. The results indicate that the inner lags' (lag 2 to lag 6's) coefficients are insignificant in both models, and most of the significant coefficients are concentrated on lag 1 and lag 7. This indicates that VAR(1) might be a parsimonious form representation of VAR(7).

Sample B: Last 365 days							
VAR(7): $Buzz_S$ **vs** $Buzz_N$				**VAR(7):** $Sent_S$ **vs** $Sent_N$			
	Coef.	*s.e.*	p-value		Coef.	*s.e.*	p-value
Constant1	-0.1695	0.0451	0.00***	Constant1	-0.0039	0.0959	0.97
Constant2	-0.0429	0.0563	0.45	Constant2	-0.3800	0.0916	0.00***
AR1(1,1)	0.6037	0.0680	0.00***	AR1(1,1)	0.6260	0.0560	0.00***
AR1(2,1)	-0.0516	0.0848	0.54	AR1(2,1)	0.1098	0.0535	0.04**
AR1(1,2)	0.0462	0.0549	0.40	AR1(1,2)	-0.0809	0.0595	0.17
AR1(2,2)	0.7532	0.0686	0.00***	AR1(2,2)	0.4117	0.0568	0.00***
AR2(1,1)	0.0029	0.0804	0.97	AR2(1,1)	0.0107	0.0654	0.87
AR2(2,1)	-0.0422	0.1004	0.67	AR2(2,1)	-0.0727	0.0624	0.24
AR2(1,2)	-0.1293	0.0675	0.06	AR2(1,2)	0.0049	0.0651	0.94
AR2(2,2)	-0.2267	0.0842	0.01***	AR2(2,2)	0.0646	0.0622	0.30
AR3(1,1)	-0.0200	0.0802	0.80	AR3(1,1)	-0.0844	0.0655	0.20
AR3(2,1)	-0.0205	0.1002	0.84	AR3(2,1)	0.0203	0.0625	0.75
AR3(1,2)	0.0768	0.0679	0.26	AR3(1,2)	0.0177	0.0651	0.79
AR3(2,2)	0.1312	0.0848	0.12	AR3(2,2)	-0.0547	0.0621	0.38
AR4(1,1)	-0.0323	0.0802	0.69	AR4(1,1)	0.0705	0.0653	0.28
AR4(2,1)	-0.0059	0.1001	0.95	AR4(2,1)	-0.0980	0.0623	0.12
AR4(1,2)	-0.0253	0.0681	0.71	AR4(1,2)	-0.0206	0.0649	0.75
AR4(2,2)	-0.0499	0.0851	0.56	AR4(2,2)	0.0144	0.0620	0.82
AR5(1,1)	-0.0071	0.0802	0.93	AR5(1,1)	0.0625	0.0654	0.34
AR5(2,1)	0.0427	0.1002	0.67	AR5(2,1)	0.0984	0.0624	0.12
AR5(1,2)	-0.0319	0.0681	0.64	AR5(1,2)	-0.0065	0.0648	0.92
AR5(2,2)	-0.0019	0.0850	0.98	AR5(2,2)	-0.0354	0.0619	0.57
AR6(1,1)	0.1152	0.0802	0.15	AR6(1,1)	-0.0596	0.0658	0.36
AR6(2,1)	0.0482	0.1001	0.63	AR6(2,1)	-0.0121	0.0628	0.85
AR6(1,2)	0.0334	0.0673	0.62	AR6(1,2)	-0.0223	0.0649	0.73
AR6(2,2)	0.1582	0.0840	0.06	AR6(2,2)	0.0382	0.0620	0.54
AR7(1,1)	0.0404	0.0685	0.55	AR7(1,1)	0.2191	0.0568	0.00***
AR7(2,1)	0.0800	0.0855	0.35	AR7(2,1)	0.0262	0.0542	0.63
AR7(1,2)	0.0742	0.0543	0.17	AR7(1,2)	-0.0091	0.0596	0.88
AR7(2,2)	0.0512	0.0678	0.45	AR7(2,2)	0.1243	0.0569	0.03**

B.2.3 Optimal Lag Length: Likelihood Ratio test

Appropriate lag length selection can be critical. In this section, we investigate the appropriateness of our lag choice. If the number of lags in VAR system is too small, the model is misspecified; if the number of lags is too large, degrees of freedom are wasted. The likelihood ratio test, which evaluates the statistical significance of the difference in log-likelihoods at the unrestricted and restricted parameter estimates, is generally considered to be the most reliable of the three classical tests of model specification (namely, Likelihood Ratio test, Wald test, and Lagrange Multiplier test).

We reconfirm our selection of VAR(1) over VAR(7) with likelihood ratio test. Our results are presented in Figure B.1. Our goal is to determine whether bivariate VAR systems, $Buzz_S$ and $Buzz_N$ (top panel) and $Sent_S$ and $Sent_N$ (bottom panel), containing only one lag are indeed appropriate. The proper test for this cross-equation restriction is a likelihood ratio test.[1] Given the sample size restriction in our rolling window analysis, we follow recommendations in Sims (1980) and compute the likelihood ratio statistic as

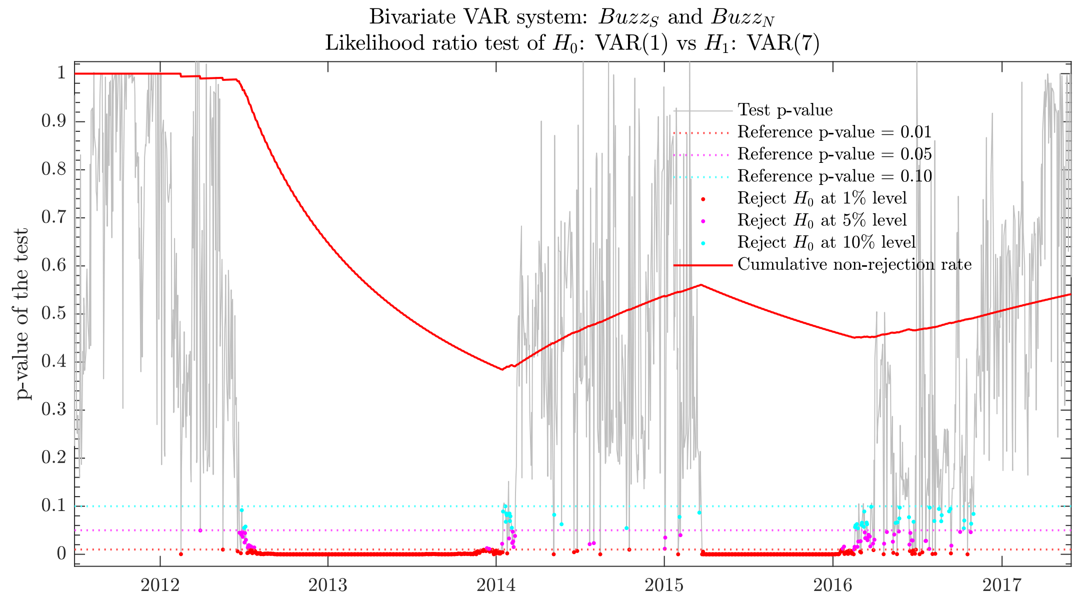
$$(T - c)\left(\ln|\Sigma_1| - \ln|\Sigma_7|\right),$$

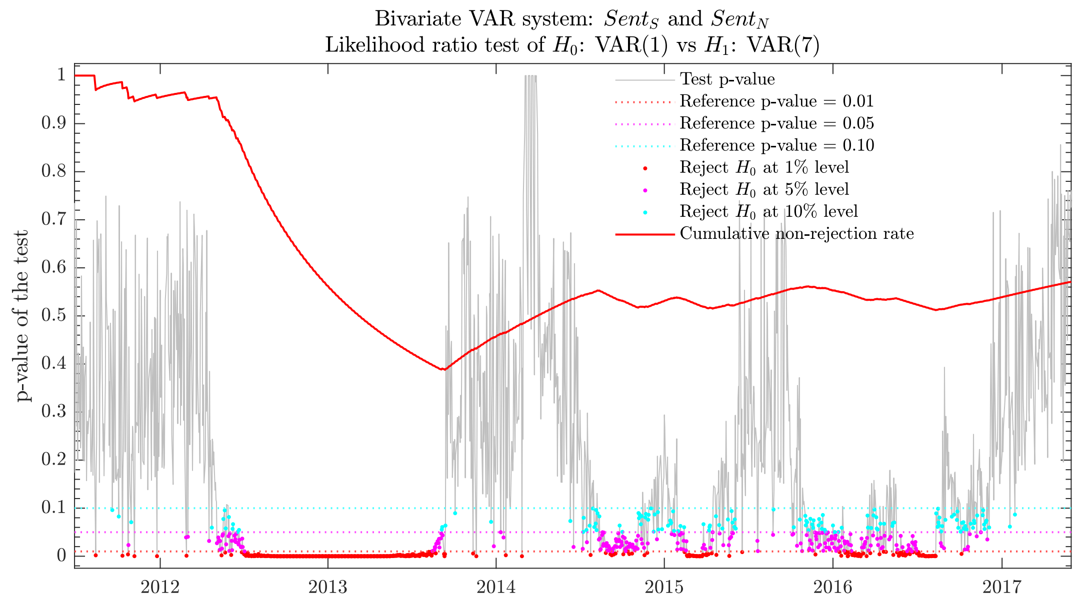
where T is number of observations, c the number of parameters estimated in each equation of the unrestricted system, Σ_n the covariance matrix of residuals from VAR(n) system, and $\ln|\Sigma_n|$ the natural logarithm of the determinant of Σ_n. This statistic has an asymptotic χ^2_k distribution with degrees of freedom, k, equal to the number of restrictions in the system.

Using estimation window of 252 days (for consistency with our main analysis), we perform a rolling window VAR estimation on each day in our sample. The number of estimated VAR systems is 1,546 for each series set for each lag length. p-values of the likelihood ratio test along time using the equation above are plotted in Figure B.1. At the beginning, mid-sample, and at the end of our sample period, VAR(1) systems are appropriate. There are two sub-periods, namely 2013 - 2014 and 2016, where estimation would have benefited from VAR systems allowing for larger number of lags. Since our objective is to contrast the earlier period to the later period, our decision in selecting VAR(1) model is justified for both *Buzz* and *Sentiment* series.

[1] We followed the procedure outlined in Enders (2014, pp.303-305).

Figure B.1: Likelihood ratio test results The figure displays p-values overtime from the likelihood ratio test by contrasting the test statistic, $(T-c)(\ln|\Sigma_1| - \ln|\Sigma_7|)$ to critical values of χ^2 distribution.





B.2.4 Model specification: VAR subsystems and omitted variable bias

As pointed out in Stock and Watson (2001), the VAR shocks, like those in conventional regression, reflect factors omitted from the model. If these factors are correlated with the included variables, then the VAR estimates will contain omitted variable bias ensuing undesirable implications for subsequent analysis.

In contrast to Figure 2.1, where results are depicted for the bivariate system, $\mathbf{x}_t = (Buzz_S, Buzz_N)'$, in Figure B.2 we present results from the four-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Buzz_S, Buzz_N)'$ in the top panel and a six-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Buzz_S, Sent_S, Buzz_N, Sent_N)'$ in the bottom panel. The pattern in the lead-lag dynamics between social media buzz and news media buzz is strikingly similar. Even with inclusion of 4 additional variables, the change in estimated coefficients is minimal. More importantly, the sign and significance of the estimates is still in accordance with the bivariate VAR(1) system in Figure 2.1. Given the sample size restrictions and the degrees-of-freedom constraints, we allude to the simpler bivariate form VAR(1) model as the best fit.

Similarly, to contrast Figure 2.2, where results are depicted for the bivariate system, $\mathbf{x}_t = (Sent_S, Sent_N)'$, in Figure B.3 we present results from the four-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Sent_S, Sent_N)'$ in the top panel and a six-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Buzz_S, Sent_S, Buzz_N, Sent_N)'$ in the bottom panel. The pattern in the lead-lag dynamics has larger deviations compared to *Buzz*-focused systems as discussed in previous paragraph. Nevertheless, similarity among lead-lag patterns in Figures 2.2 and B.3 is evident.

Figure B.2: Rolling Window VAR(1) Off-Diagonal Elements - daily *Buzz*. This plot depicts the inter-relationships between $Buzz_S$ and $Buzz_N$ series from 2011/01/01 to 2017/11/30. In contrast to Figure 2.1, where results are depicted for the bivariate system, $\mathbf{x}_t = (Buzz_S, Buzz_N)'$, in the current figure we present results from the four-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Buzz_S, Buzz_N)'$ in the top panel and a six-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Buzz_S, Sent_S, Buzz_N, Sent_N)'$ in the bottom panel. Sample contains 2,526 observations for each series, with the first 365 observations used as pre-estimation window. The shaded area indicates a transition period. The red line represents the leading effect from news media to social media, and the blue line indicates the leading effect from social media to news. Coefficients that are significant at the 90% level are shown with bold dots.

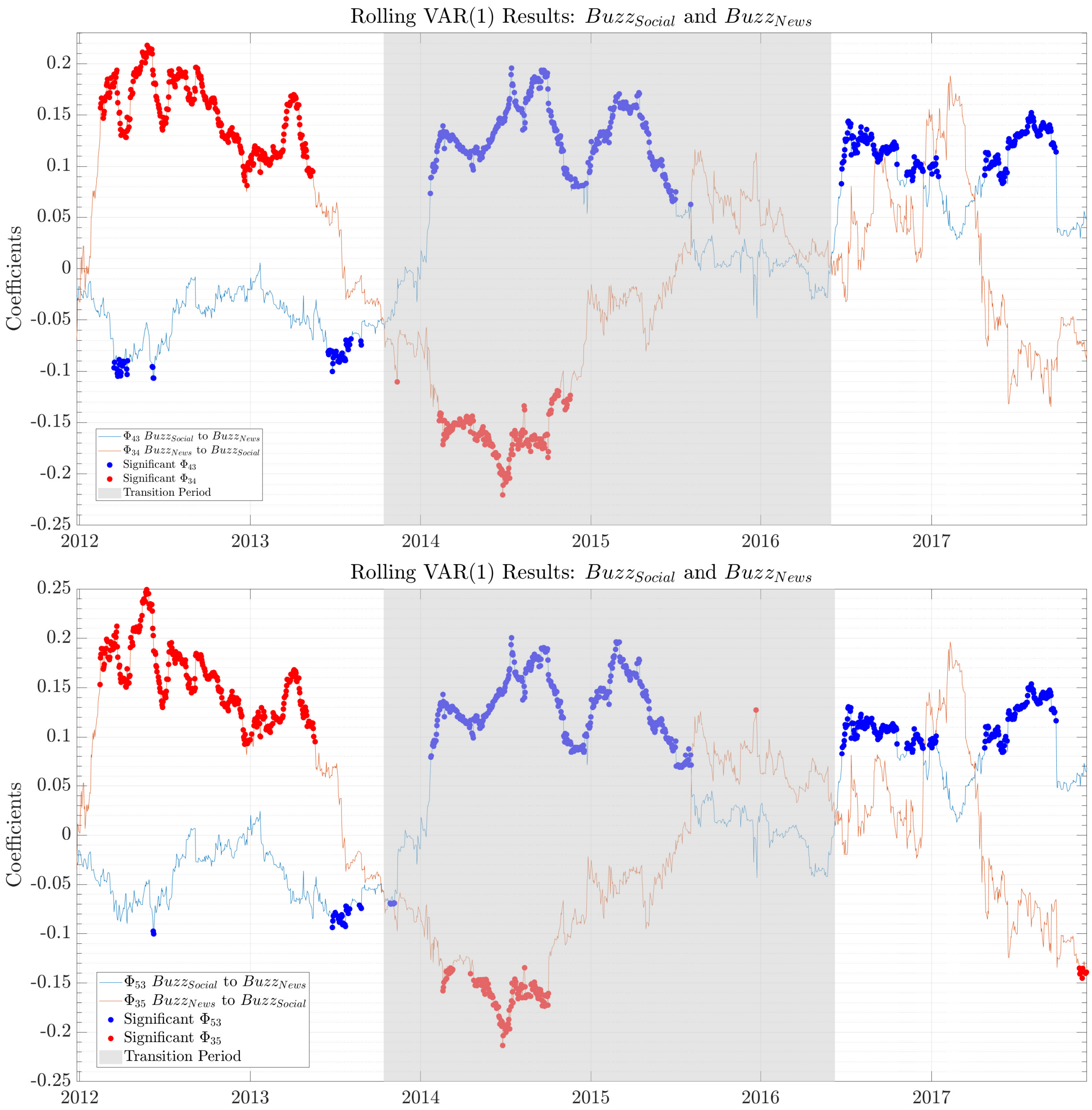
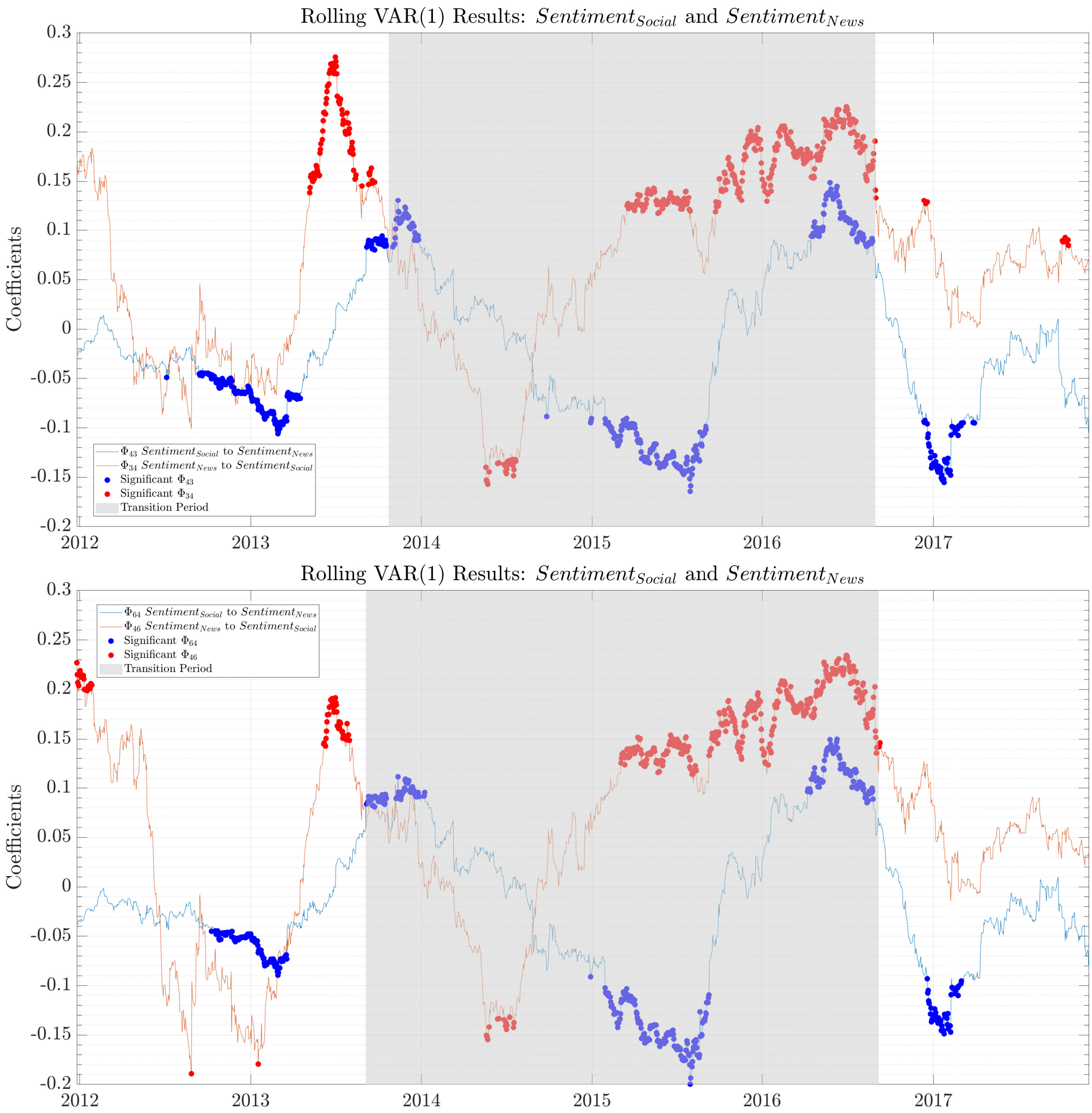


Figure B.3: Rolling Window VAR(1) Off-Diagonal Elements - daily *Sentiment*. This plot depicts the inter-relationships between $Sent_S$ and $Sent_N$ series from 2011/01/01 to 2017/11/30. In contrast to Figure 2.2, where results are depicted for the bivariate system, $\mathbf{x}_t = (Sent_S, Sent_N)'$, in the current figure we present results from the four-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Sent_S, Sent_N)'$ in the top panel and a six-variable VAR(1) system with $\mathbf{x}_t = (Return, VIX, Sent_S, Buzz_S, Sent_N, Buzz_N)'$ in the bottom panel. Sample contains 2,526 observations for each series, with the first 365 observations used as pre-estimation window. The shaded area indicates a transition period. The red line represents the leading effect from news media to social media, and the blue line indicates the leading effect from social media to news. Coefficients that are significant at the 90% level are shown with bold dots.



B.3 TRMI data and variables

Thomson Reuters MarketPsych Indices (TRMI) are derived from an unparalleled collection of prime news, global Internet news coverage, and a broad and reliable range of social media. The TRMI social media feed consists of both MarketPsych and Moreover social media content. Moreover Technologies' aggregated social media feed is derived from tens of thousands of social media sites and is incorporated into the TRMI from 2009 to the present. MarketPsych social media content was downloaded from public social media sites from 1998 to the present. After the social media posts or news articles are published in the TRMI content sources, a linguistic software abstracts the new content feed, parses and scores the content and attributes the score to global indices, companies, bonds, countries, commodities, currencies, and cryptocurrencies.

TRMI scores are composed of a combination of variables. The absolute values of all TRMI-contributing variables, for all asset constituents, over the past 24 hours are determined. These absolute values are then summed for all constituents. This sum is call the "Buzz".

Thomson Reuters MarketPsych computes 35 emotional scores which are divided into three types of sentiment indicators for a specific company or company group: 1) **Emotional** indicators including *Anger*, *Fear* and *Joy*; 2) **Fundamental** perceptions such as *Long vs Short*, *Earnings Forecast*, and *Interest Rate Forecast*; and 3) **Buzz** metric, a measure indicative of how much market-moving topics, such as *Litigation*, *Mergers*, and *Volatility* are being generated and discussed.

Thomson Reuters MarketPsych Indices (TRMI) analyse news and social media to convert the volume and variety of professional news and the internet into manageable information flows. The indicators are updated every minute for companies, sectors, regions, countries, commodities and energy topics, indices and currencies. TRMIs are based on relevant text collected over a window of content. If over that window there was no relevant text identified, then the correct value is "NA", not zero.[2] The indices are marked as ranging from either -1 to 1 (polarized indices) or 0 to 1 (unidirectional indices). TRMIs are evaluated on three different content sets: news, social media, and the combined content. History on all content dates back to the beginning of 1998. Only English-language text is used.

Collection of News media. Reuters news is present in the entire historical news dataset, as are a host of mainstream news sources collected by MarketPsych Data. During 2005, the archive began including Internet news content collected by Moreover Technologies. The Moreover content is restricted to those from top international and business news sources, top regional news sources, and leading industry sources.

Collection of Social media. The social media collection process is less diverse. It starts in 1998 with content collected by MarketPsych Data. Internet forums and finance-specific tweets compose this space. Starting in late 2008, Moreover Technologies social media content is included. Using popularity ranks measured by incoming links, this includes generally the top 30% of blogs, microblogs, and other social media content. Note that selected Moreover social media is included in the company groups social media dataset. The company groups data is composed of a subset of finance-specific Moreover content and the MarketPsych-based social media collection.

[2]An NA differs in meaning from true zero in that true zero represents the presence of text corresponding to positive and negative values that add up to zero. In other words, a zero value reflects that relevant text was found and its sentiment implications net to zero. In contrast, NA represents the absence of any relevant text and of any resultant measurement. Note that when the Buzz is zero, this means that no values were detected for any of the indices and thus all index values necessarily will be NA.

Tables B.5 and B.6 present descriptive statistics for the 35 sentiment indices based on social media and news respectively. We group **polarized ([-1,1])** and **unidirectional ([0,1])** emotional scores into Panels (A) and (B) respectively. The media activity measure, ***Buzz*** **($[0,\infty)$)**, is summarised in Panel (C). All polarized sentiment scores are buzz-weighted, averaging any positive references net of negative references in the last 24 hours. Upon examination of the descriptive statistics, we observe the following facts:

- First, *Buzz*, a sheer media coverage volume metric for both social and news media, has a much larger absolute value than other emotional proxies (average *Buzz* value of 116,484.46 for social media and 202,401.31 for news, while other emotional scores contains mean value close to zero). Social media *Buzz* is highly positively skewed with the third moment equals to 1.37, and contains several large outliers. The kurtosis of 6.32 indicates a leptokurtic distribution (the last line in Table B.5). In contrast, news media buzz is more symmetric and contains less outliers than social media, with skewness equal to -0.01 and kurtosis 3.91 - slightly higher than 3 (the last line in Table B.6).

- Second, we observe fewer missing values among social emotional scores than among news in Panel (A) and (B), probably resulting from the fact that news reports require more stringent censorship procedures than social media. Peterson (2016, p.54) argues that "...Professional news sources include those with third-party editors and a journalistic responsibility to avoid slanderous or libelous commentary. Editors and fact-checkers ensure not only that news journalists uphold the brand's journalistic standards, but also that they do not commit libel or publish inaccurate information."

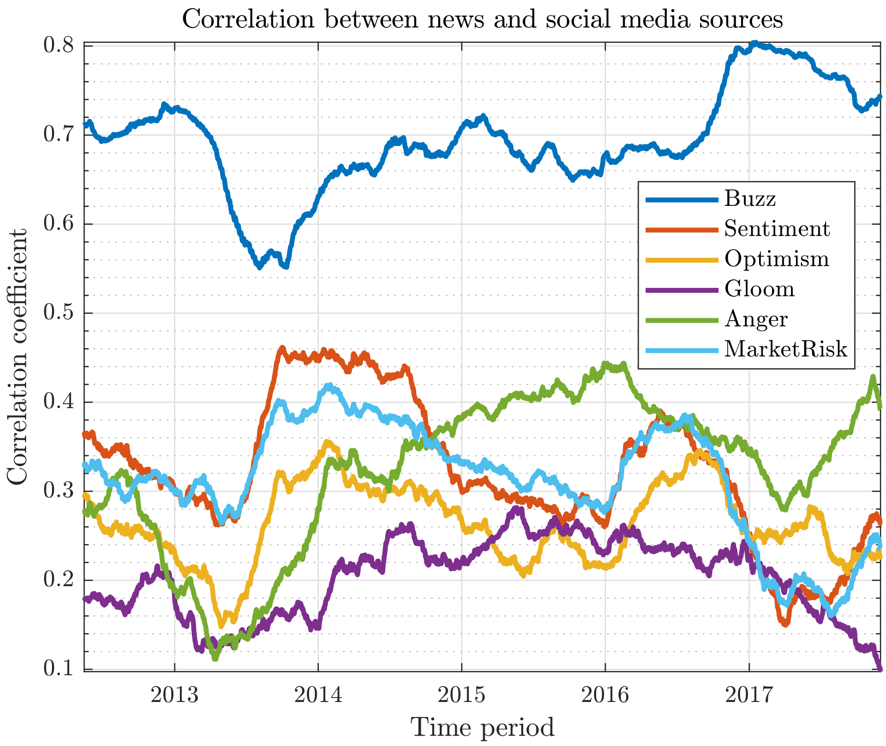
- Third, the [-1,1] polarized group scores from social media tend to be more extreme than the news. Buzz-weighted and normalised around zero mean, the polarized group emotional scores exhibit close mean and median values. However, the presence of large kurtosis values in the social media polarized group (Panel (A) of Table B.5) capture the large swings in emotional scores of social media posts. Similarly, although both social and news media unidirectional group indices suggest fat tail characteristics, extremely strong words are less frequent in news media than social media (Panel (B) of Table B.5 and Table B.6).

- Lastly, all of the TRMI indices are significantly autocorrelated with potential long memories. Our findings are based on Durbin-Watson (DW) test and Ljung-Box test with up to 5 lags (LB-5).

The availability of 35 emotional scores poses a dilemma: which emotional score is the most prominent one? In order to determine which emotional score(s) we should focus on, we report the **within group** pairwise contemporaneous correlations among all available sentiment indices in Figure B.6 on page 161 of the appendix. To aid interpretation and comparison of a large number of coefficients, we depict correlations in a schema ball instead of a large correlation table. Panels (a) and (b) depict associations among social and news indices, respectively. Yellow curves show positive correlations, and purple lines represent negative correlations. The thickness and brightness indicate the strength of correlation relationship, i.e. the thicker the curve, the closer the correlation coefficient is to ± 1. We find that, among both social and news based series, *sentiment* and *optimism* are strongly positive correlated with *marketRisk* - a measure defined by TRMI as "bubble-o-meter": the speculative extent relative to rationality. We also notice that *gloom* and *anger* embody the strongest negative correlations with *sentiment* and *optimism*. Therefore, we will pay closer attention to the following TRMI indices among the 35 available measures, namely: *buzz, sentiment, optimism, marketRisk, gloom*, and *anger*.

To measure the strength of dependence between social media and news based emotional scores, we employ Kendall rank correlation. Since emotional indices tend to sway from the normal distribution, the Pearson correlation is not appropriate. Using 500-day rolling window, Figure B.4 displays estimated correlation coefficients across time for the six indices mentioned above. Each line in the figure represents a correlation between an index based on social media and its news-based counterpart. The series are positively correlated, indicating that social media and news-based scores are in concordance. The correlations, however, are far from perfect, validating our objective to contrast these two sources of investor sentiment. In addition, these concordance estimates exhibit strong heterogeneity across time, requiring analysis over several sub-samples.

Figure B.4: Contemporaneous Correlation Dynamics between Key Social and News Indices. All six sentiment indices represent company group for the period from 2011/01/01 to 2017/11/30. Kendall correlation coefficients are calculated using rolling 500-day estimation window. For example, Buzz (blue line) depicts correlation dynamics between *buzz* from social media and *buzz* from news media. The correlation coefficients between social and news are positive for all six indices, however, they display time-varying heterogeneity over the sample period.

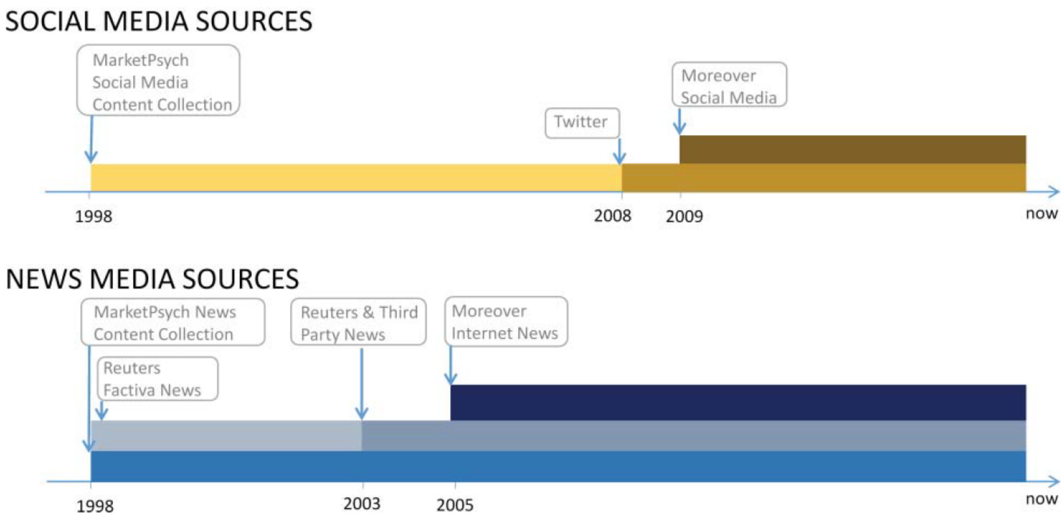


Based on these findings, we draw two conclusions that help us select the appropriate model specification. First, relatively low correlations suggest that social media and news do contain idiosyncratic components and that emotional scores based on these two types of media could be gainfully exploited either jointly or contrasted with each other in predictive regressions. Second, the time-varying relationship between social media and news-based indicators suggest that analysis should not be done over the entire sample period but rather with multiple sub-periods, e.g. a rolling window with a shortened span. In our quest to explore the lead-lag relationship between social media and news based sentiment, we further examine lagged cross-correlation (see graphs in Figure B.7 on page 162 of the appendix). Panel (a) displays the correlations between the previous day social media based indices and current day news indices, while panel (b) illustrates the correlation between the previous day news-based indices and the present day social indices. The findings are analogous to contemporaneous case: positively correlated social and news based series (although with lower magnitudes) and the time varying nature of lagged dependencies. Overall, Figure B.4 in conjunction with Figure B.7, indicate that the causal relationship between social and news media indices is dynamic, and causal modeling should be done in sub-samples rather than over the entire period.

We decide to focus on *Sentiment* and *Buzz* among all 35 indices as a result of both the above analysis and the Principal Component Analysis (PCA). We perform PCA separately on the polarized and unidirectional index groups (the list of all indices can be found in Tables B.5 or Table B.6). Since *Buzz* metric is conceptually different from other emotional scores, we do not incorporate *Buzz* in the PCA analysis. To figure out how many principal components should be considered, we generate scree plots for social and news groups respectively in Figure B.8. Panels (a) and (b) depict the number of most influential components for the 18 polarized and 16 unidirectional social media group indices. The first principal component of polarized social sentiment indices explains 28.32% of total variances, and the second component explains an additional 10.76% of total variation (Panel (a) of B.8). The "elbow" appears at the second component, indicating that after the second principal component, incremental explanatory power of other components is greatly diminished. Likewise, the first principal component describes 22.19% of total group indices variances, and the second component constitutes an additional 10.71% of total variability. After the second primary component, the remaining components account for a very small incremental proportion of the variability and are probably unimportant (Panel (b) of B.8). Panel (c) and (d) illustrate the number of most influential components for TRMI news polarized and unidirectional emotional scores. For the polarized group ([-1,1]), the first component explains 29.51% of total variance, and the second component explains additional 12.70% (panel (c)). With respect to the unidirectional group [0,1], the first component accounts for 20.79% of total variance, and the second component facilitate to construe extra 11.77% of total variation (panel (d)). We observe that the "elbow" point also appear at the second component for news groups, indicating that after the second primary component, incremental explanatory power of other components decreases, thus they are less essential to our analysis.

Based on the findings above, we abstract the first two principal components and investigate each variable's contribution to these two principal components. To determine the most crucial variables among all TRMI indices available, we create biplots (see Figure B.9 on page 164) to assess the magnitude and sign of each variable's contribution to the first two principal components, and how each observation is represented in terms of those components. The axes in the biplot represent the principal components and the observed variables are represented as vectors. Figure B.9 in the appendix illustrates the results for both polarized (left panels) and unidirectional (right panels) sentiment scores based on social media (top panels) and news (bottom panels). Among the indices in the polarized groups, *Sentiment* and $emotionVsFact$ have the highest contribution to variation in both social media and news-based scores (Panel (a) and (c)). For unidirectional group, *violence* is the most prominent variable among the news-based scores (panel (d)), while for social media indices, there is no clear dominant component, instead a mix of *violence*, *stress*, *anger*, *gloom* and *joy* all playing incremental part in contributing to variation in unidirectional emotions from social media posts (panel (d)). We do not consider *violence* since we are focusing on the US market in this paper, although *violence* could be an important consideration for textual analysis research that investigates emerging markets

Figure B.5: Timeline of textual content analysed for the social and news media TRMI. Source: Peterson (2016) *Trading on Sentiment: The Power of Minds Over Markets*, Wiley. p.303.



or markets domiciled in geo-political and social unrest regions. Since involving multiple polarized emotional scores will hinder parsimony of our models, we decide to focus on *sentiment* and avoid entailing *emotionVsFacts* in our current framework.

Change in TRMI data source does not appear to be the cause of the time-vaying relationship found. As shown in Figure B.5, the major change in social media sources used by MarketPsych was in 2009, when Thomson Reuters added Moreover Technology into the aggregated news feed, while news media source had its last revamp in 2005. Our sample begins in 2011 in this research, which is not interfered by this change of data source.

Table B.5: Descriptive Statistics for TRMI MPTRXUS500 Company Groups based Social Media. Sample period 01/Jan/2011 - 30/Nov/2017; sentiment indices are grouped into polarized scores with [-1,1] range and scores that are unidirectionally bounded on [0,1]. *Buzz*, representing the volume of information flow, differs from other indices and is only bounded from below at 0. Data in *laborDispute* were too sparse over our sample period, but is included here for completeness. Results of Durbin-Watson and Ljung-Box (5 lags) tests indicates presence of autocorrelation in all indices.

				Panel (A): Polarized Groups [-1,1]						
	Mean	**Std**	**Max**	**Min**	**Skew**	**Kurt**	**25th**	**Median**	**75th**	**IQR**
sentiment	-0.020	0.030	0.082	-0.127	-0.32	2.80	-0.040	-0.016	0.001	0.042
optimism	0.000	0.008	0.020	-0.034	-0.40	3.11	-0.005	0.001	0.005	0.010
loveHate	0.006	0.002	0.023	0.000	3.17	21.58	0.005	0.006	0.006	0.001
trust	-0.001	0.002	0.016	-0.021	-0.97	15.12	-0.003	-0.001	0.000	0.002
conflict	0.020	0.005	0.081	-0.002	2.70	21.92	0.017	0.020	0.023	0.005
timeUrgency	0.019	0.004	0.049	0.004	0.70	5.76	0.016	0.019	0.021	0.005
emotionVsFact	0.531	0.023	0.627	0.407	-0.20	4.54	0.518	0.532	0.546	0.029
marketRisk	-0.008	0.004	0.023	-0.027	-0.19	5.03	-0.011	-0.008	-0.005	0.005
longShort	0.004	0.004	0.090	-0.039	7.08	163.95	0.002	0.004	0.005	0.004
longShortForecast	0.001	0.001	0.003	-0.008	-1.87	24.97	0.000	0.001	0.001	0.001
priceDirection	0.003	0.002	0.014	-0.007	-0.04	4.33	0.002	0.003	0.004	0.003
priceForecast	0.001	0.000	0.003	-0.001	0.14	5.35	0.000	0.001	0.001	0.001
analystRating	0.001	0.001	0.008	-0.006	0.56	12.05	0.000	0.001	0.001	0.001
dividends	0.001	0.001	0.008	-0.004	2.12	25.00	0.001	0.001	0.001	0.001
earningsForecast	0.002	0.001	0.007	-0.003	0.86	6.03	0.001	0.002	0.002	0.001
fundamentalStrength	0.005	0.003	0.018	-0.004	0.86	4.73	0.004	0.005	0.007	0.003
managementChange	0.002	0.002	0.064	0.000	21.32	667.17	0.001	0.002	0.002	0.001
managementTrust	-0.001	0.002	0.016	-0.047	-7.58	114.09	-0.001	0.000	0.000	0.002
				Panel (B): Unidirectional Groups [0,1]						
	Mean	**Std**	**Max**	**Min**	**Skew**	**Kurt**	**25th**	**Median**	**75th**	**IQR**
anger	0.014	0.003	0.041	0.007	1.61	11.83	0.012	0.013	0.016	0.004
fear	0.005	0.001	0.010	0.003	0.98	6.86	0.005	0.005	0.005	0.001
joy	0.015	0.002	0.028	0.008	1.02	5.01	0.013	0.015	0.016	0.003
gloom	0.028	0.004	0.056	0.018	0.80	5.10	0.026	0.028	0.031	0.005
stress	0.056	0.004	0.099	0.044	1.35	15.43	0.054	0.056	0.058	0.004
surprise	0.008	0.001	0.026	0.005	2.23	21.96	0.007	0.008	0.009	0.002
uncertainty	0.023	0.003	0.035	0.012	-0.02	3.65	0.021	0.023	0.024	0.003
violence	0.029	0.005	0.063	0.021	1.90	8.72	0.026	0.028	0.031	0.005
volatility	0.026	0.003	0.055	0.019	1.47	10.56	0.024	0.026	0.028	0.004
debtDefault	0.004	0.001	0.018	0.002	2.07	15.73	0.003	0.004	0.005	0.001
innovation	0.003	0.001	0.011	0.001	1.02	6.48	0.002	0.003	0.003	0.001
laborDispute	-	-	-	-	-	-	-	-	-	-
layoffs	0.001	0.001	0.010	0.000	5.63	55.47	0.001	0.001	0.001	0.000
litigation	0.006	0.002	0.024	0.003	2.28	14.89	0.005	0.006	0.007	0.002
mergers	0.004	0.002	0.024	0.001	3.14	22.86	0.003	0.003	0.004	0.002
cyberCrime	0.001	0.001	0.015	0.000	5.53	47.44	0.000	0.001	0.001	0.001
				Panel (C): Buzz						
	Mean	**Std**	**Max**	**Min**	**Skew**	**Kurt**	**25th**	**Median**	**75th**	**IQR**
buzz	116,484.46	35,769.47	311,543.00	14,179.10	1.37	6.32	94,587.05	110,860.86	130,317.27	35,730.22

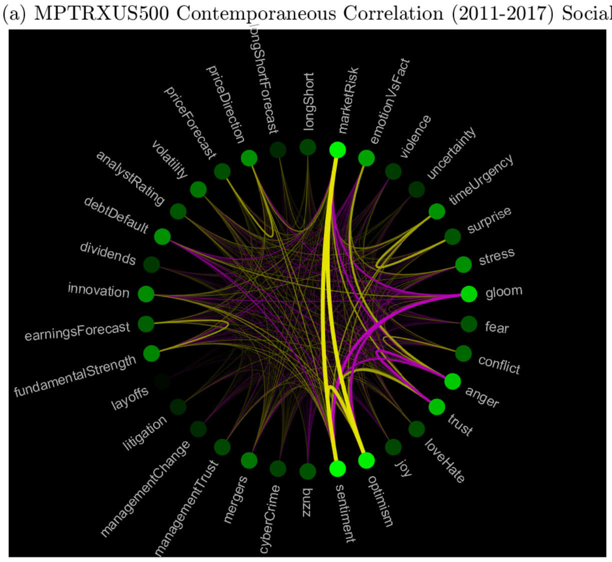
Table B.6: Descriptive Statistics for TRMI MPTRXUS500 Company Groups based News Media. Sample period 01/Jan/2011 - 30/Nov/2017; sentiment indices are grouped into polarized scores with [-1,1] range and scores that are unidirectionally bounded on [0,1]. *Buzz*, representing the volume of information flow, differs from other indices and is only bounded from below at 0. Data in *priceForecast, dividends, managementChange, laborDispute, layoffs* and *cyberCrime* were too sparse over our sample period, but is included here for completeness. Results of Durbin-Watson and Ljung-Box (5 lags) tests indicates presence of autocorrelation in all indices.

	Mean	Std	Max	Min	Skew	Kurt	25th	Median	75th	IQR
Panel (A): Polarized Groups [-1,1]										
sentiment	-0.017	0.037	0.126	-0.173	-0.29	3.22	-0.042	-0.015	0.009	0.051
optimism	0.006	0.007	0.038	-0.037	-0.35	4.39	0.001	0.006	0.010	0.009
loveHate	0.005	0.001	0.013	0.000	0.69	7.18	0.004	0.005	0.005	0.001
trust	-0.001	0.002	0.006	-0.012	-0.86	5.49	-0.002	-0.001	0.000	0.002
conflict	0.032	0.006	0.056	0.017	0.87	4.07	0.028	0.031	0.035	0.007
timeUrgency	0.024	0.004	0.046	0.000	0.06	4.88	0.021	0.024	0.026	0.005
emotionVsFact	0.537	0.028	0.612	0.346	-0.68	4.40	0.521	0.539	0.557	0.036
marketRisk	-0.007	0.004	0.010	-0.031	-0.43	3.84	-0.010	-0.007	-0.004	0.005
longShort	0.002	0.003	0.014	-0.009	0.01	5.17	0.001	0.002	0.004	0.003
longShortForecast	0.000	0.001	0.003	-0.003	0.09	5.67	0.000	0.000	0.001	0.001
priceDirection	0.004	0.003	0.016	-0.012	-0.20	4.28	0.003	0.004	0.006	0.003
priceForecast	-	-	-	-	-	-	-	-	-	-
analystRating	0.001	0.001	0.007	-0.009	-2.16	21.26	0.000	0.001	0.001	0.001
dividends	-	-	-	-	-	-	-	-	-	-
earningsForecast	0.002	0.001	0.008	-0.004	0.60	4.56	0.001	0.002	0.003	0.002
fundamentalStrength	0.008	0.005	0.038	-0.005	1.48	7.35	0.005	0.007	0.010	0.005
managementChange	-	-	-	-	-	-	-	-	-	-
managementTrust	0.001	0.003	0.019	-0.017	-1.11	9.60	0.000	0.001	0.003	0.003
Panel (B): Unidirectional Groups [0,1]										
	Mean	**Std**	**Max**	**Min**	**Skew**	**Kurt**	**25th**	**Median**	**75th**	**IQR**
anger	0.009	0.002	0.022	0.006	1.87	8.82	0.008	0.008	0.009	0.002
fear	0.007	0.001	0.014	0.004	1.19	6.56	0.006	0.006	0.007	0.001
joy	0.008	0.001	0.015	0.003	0.41	4.21	0.007	0.008	0.009	0.002
gloom	0.023	0.003	0.044	0.016	1.17	7.08	0.021	0.023	0.024	0.003
stress	0.056	0.005	0.078	0.042	0.58	4.09	0.053	0.055	0.059	0.006
surprise	0.007	0.001	0.020	0.004	2.15	17.83	0.006	0.006	0.007	0.001
uncertainty	0.019	0.002	0.030	0.012	0.43	3.52	0.017	0.019	0.021	0.003
violence	0.043	0.010	0.176	0.024	3.10	28.76	0.037	0.041	0.046	0.010
volatility	0.032	0.003	0.060	0.024	1.18	9.66	0.030	0.032	0.034	0.003
debtDefault	0.004	0.001	0.013	0.002	1.76	8.82	0.003	0.004	0.005	0.001
innovation	0.006	0.001	0.021	0.001	1.28	13.98	0.005	0.006	0.007	0.002
laborDispute	-	-	-	-	-	-	-	-	-	-
layoffs	-	-	-	-	-	-	-	-	-	-
litigation	0.011	0.003	0.038	0.005	1.60	9.33	0.009	0.010	0.013	0.004
mergers	0.005	0.002	0.022	0.001	1.68	9.49	0.004	0.005	0.006	0.002
cyberCrime	-	-	-	-	-	-	-	-	-	-
Panel (C): Buzz										
	Mean	**Std**	**Max**	**Min**	**Skew**	**Kurt**	**25th**	**Median**	**75th**	**IQR**
buzz	202,401.31	47,847.27	387,635.55	1,468.90	-0.01	3.91	172,081.500	202,994.290	231,451.110	59,369.610

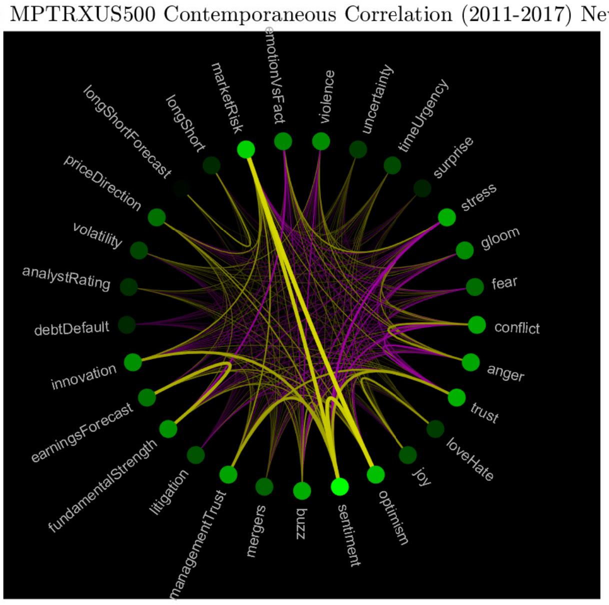
B.4 Correlation Schema-Balls

Figure B.6: Correlation coefficients between various emotional scores for the Company Group. The two panels are a visual representation of the pairwise contemporaneous correlations between all 35 scores for the company group (in place of 35-by-35 correlation matrices). Correlations for social media and news media based scores are highlighted in Panels (a) and (b) respectively. Yellow curves represent positive correlation coefficients, purple curves indicate negative correlations, the thickness and brightness of curves represent strength of correlation coefficients: the higher the absolute value of a correlation coefficient, the thicker and brighter is the curve that represents it. As indicated in Tables B.5 and B.6, there are more missing values among news-based scores. Concerned with the effect of data sparsity, we excluded a small number of emotional scores from our calculations. As a result, the number of variables in Panels (a) than (b) differ. Sample period: 01/Jan/2011 to 30/Nov/2017 at daily frequency.

(a) MPTRXUS500 Contemporaneous Correlation (2011-2017) Social

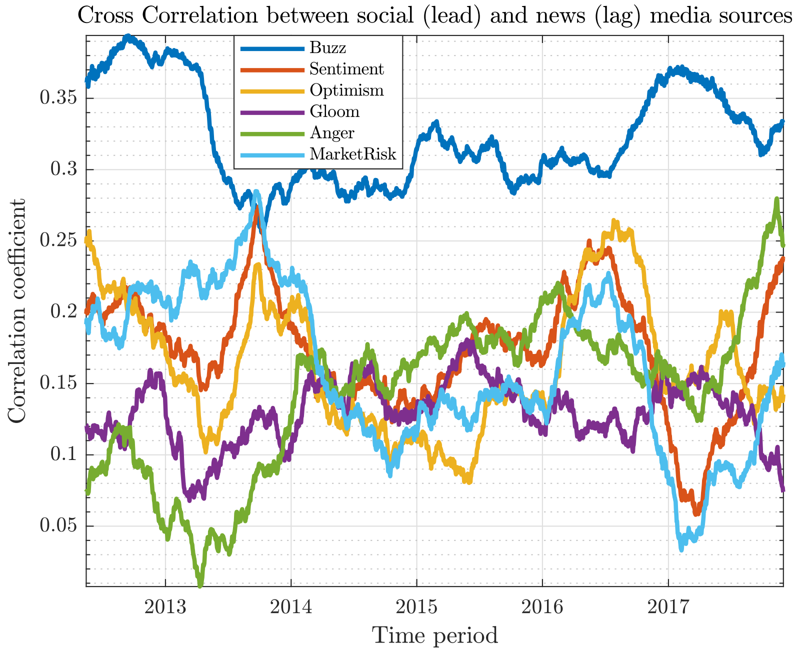


(b) MPTRXUS500 Contemporaneous Correlation (2011-2017) News

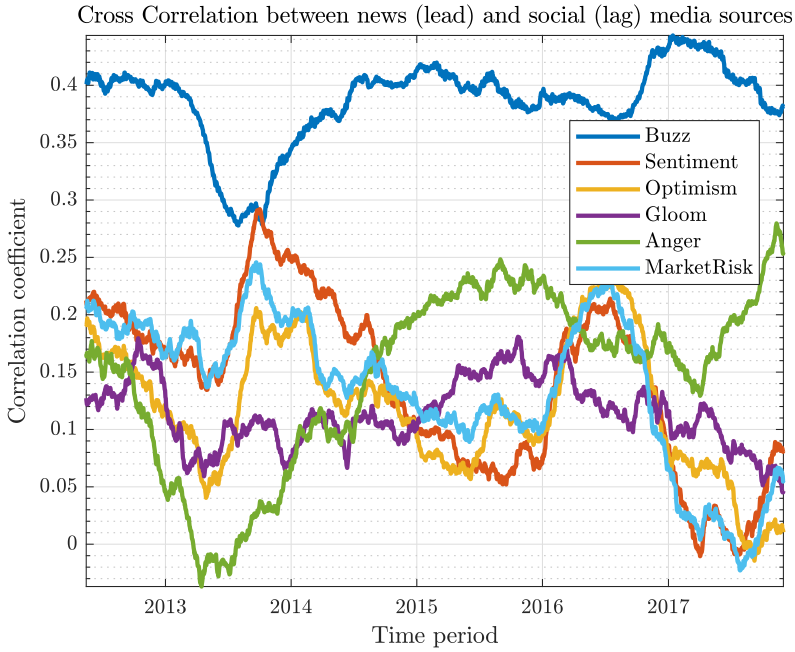


B.5 One day lag cross correlations between social and news.

Figure B.7: One Day Lag Cross-Correlation between Key Social and News scores. Panel (a) shows Kendal correlation between key social and news scores for the Company Group based on daily data, i.e. the cross-correlation between $Social_t$ and $News_{t-1}$; Similarly, Panel (b) shows Kendal correlation between $News_t$ and $Social_{t-1}$. Both figures present similar patterns to Figure B.4 where the correlation between social and news based indices varies over time, suggesting an approach capable of capturing time-variability in the dynamics between social and news based emotional scores.



(a) *Social* leads *News* one day

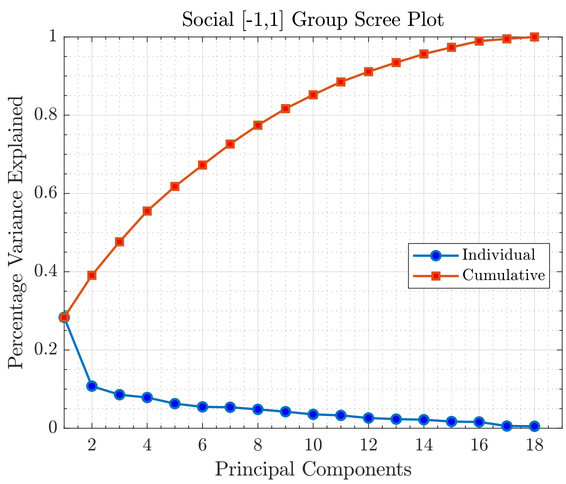


(b) *News* leads *Social* one day

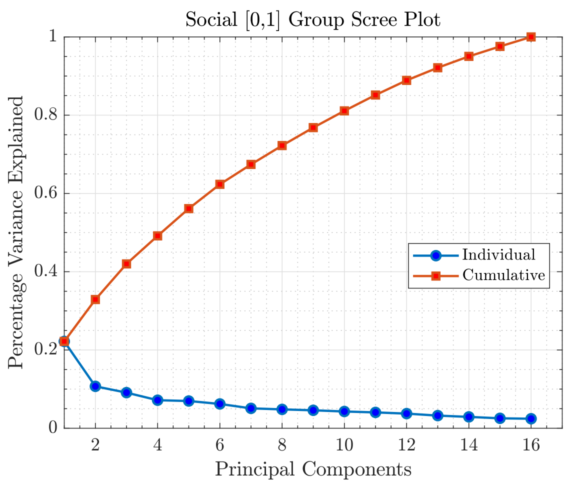
B.6 Principal Component Analysis

B.6.1 Scree Plots for Social and News Series

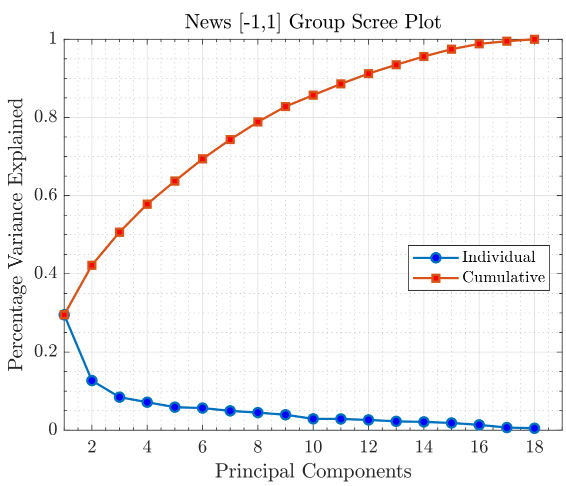
Figure B.8: Scree Plots from Principal Component Analysis of emotional scores for the Company Group. Panel (a) and (b) show individual (blue curve) as well as cumulative (red curve) contributions of each of the components considered based on PCA for the polarized group ([-1,1]) and unidirectional group ([0,1]) for **social** sentiment indices. For the polarized social sentiment indices (Panel (a)), the first component explains 28.32% of total variance, and the second component explains an additional 10.76% of total variation. For the unidirectional social sentiment indices (Panel (b)), the first component explains 22.19% of total variance, and the second component explains an additional 10.71% of total variation. After the second primary component, the remaining components account for a small incremental proportion of the variability and are probably unimportant. Panels (c) and (d) is constructed in a similar manner but based on **news** sentiment indices for the [-1,1] and [0,1] groups respectively. For the polarized news media group ([-1,1]), the first component explains 29.51% total variance, and the second component explains additional 12.70% (Panel (c)). With respect to the unidirectional news group [0,1], the first component accounts for 20.79% of total variance, and the second component facilitate to construe extra 11.77% of total variation (Panel (d)). Similar to social groups, after the second primary component, the remaining principal components account for a very small incremental fraction of the variability and are probably unimportant.



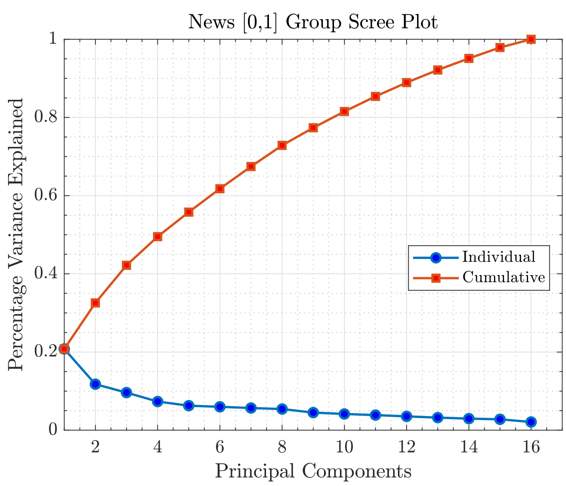
(a)



(b)



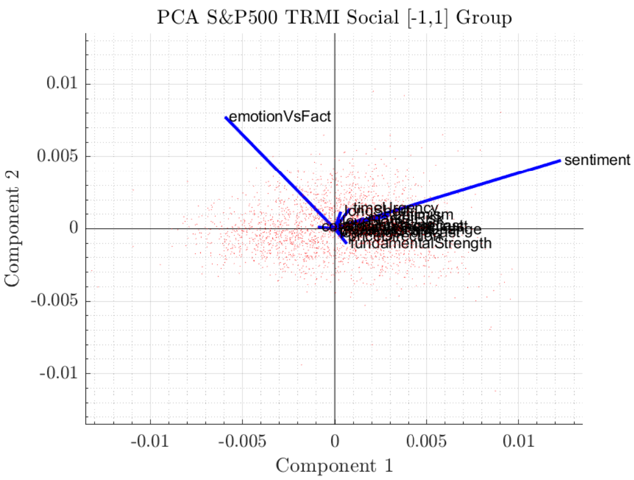
(c)



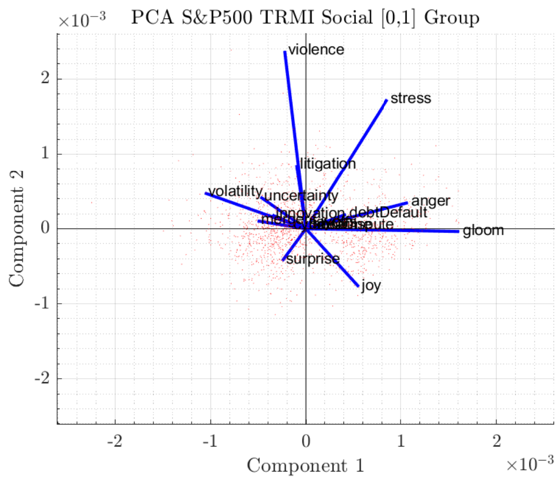
(d)

B.6.2 Biplots of the first two principal component coefficients

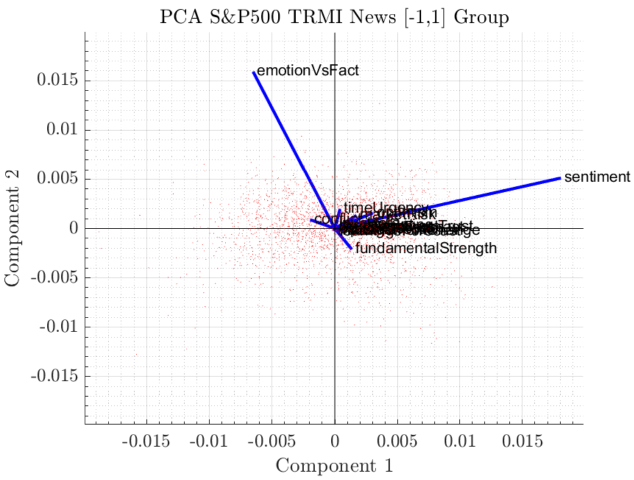
Figure B.9: Principal Component Analysis of the Sentiment Indices. Panel (a) is a biplot of the first two principal components for the [-1,1] sentiment score group in social sentiment indices; Panel (b) is a biplot of the first two principal components for the [0,1] sentiment score group in the social sentiment indices. Panels (c) and (d) are biplots constructed in a similar manner but using news sentiment data instead of social media. Panels (a) and (c) demonstrate that for both social and news media polarized groups ([-1,1]), *sentiment* and *emotionVsFacts* are the most crucial indices based on the variability they are able to explain in the data represented by the first two principal components. While Panel (d) indicates that *violence* is the most crucial emotional score in the news media [0,1] group, this conclusion is less obvious for the social media unidirectional group (Panel (b)). As *violence* is more relevant to research that focuses on emerging markets or markets that domicile in geopolitical unrest regions, we do not consider it in this paper. Since involving multiple polarized emotional scores will largely complicate the current research, we decide to focus on *sentiment* and avoid entailing *emotionVsFacts* in our models.



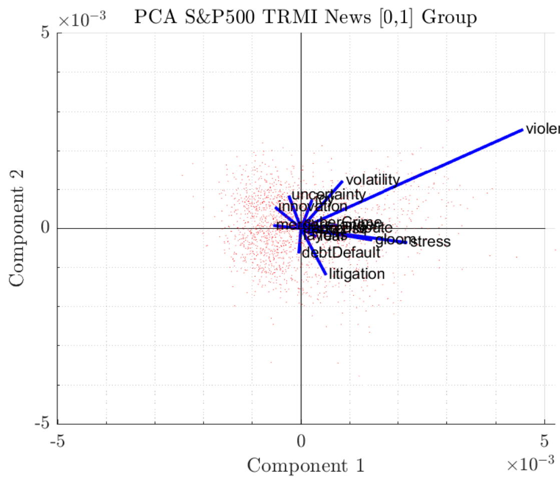
(a)



(b)



(c)



(d)

B.7 Number of TRMI Observations: Raw

Table B.7: TRMI DJIA Constituents Sample Number of Observations. This table lists the TRMI sample sizes for the social and news media activity volume, the emotions for each individual stock and the overall Dow Jones company groups. These observations are irregular before being dealt with by the re-time procedure. $Buzz^S$ and $Buzz^N$ are measures that capture the total volumes of the social or news media activities. $Sent^S$ and $Sent^N$ are the net positive and negative emotional scores for each entity from the social and news media, respectively. The sample period is 2011/01/01–2017/11/30 at 1-minute frequency.

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

Figure B.10: ***Buzz* Data Availability. News vs Social media**. The figure compares the average daily counts of non-missing observations from social (blue bars) and news (orange bars) media. The calculations are based on Thomson Reuters MarketPych Indices (TRMI) social and news media *Buzz* scores at 1-minute frequency. 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 buzz scores from social media.

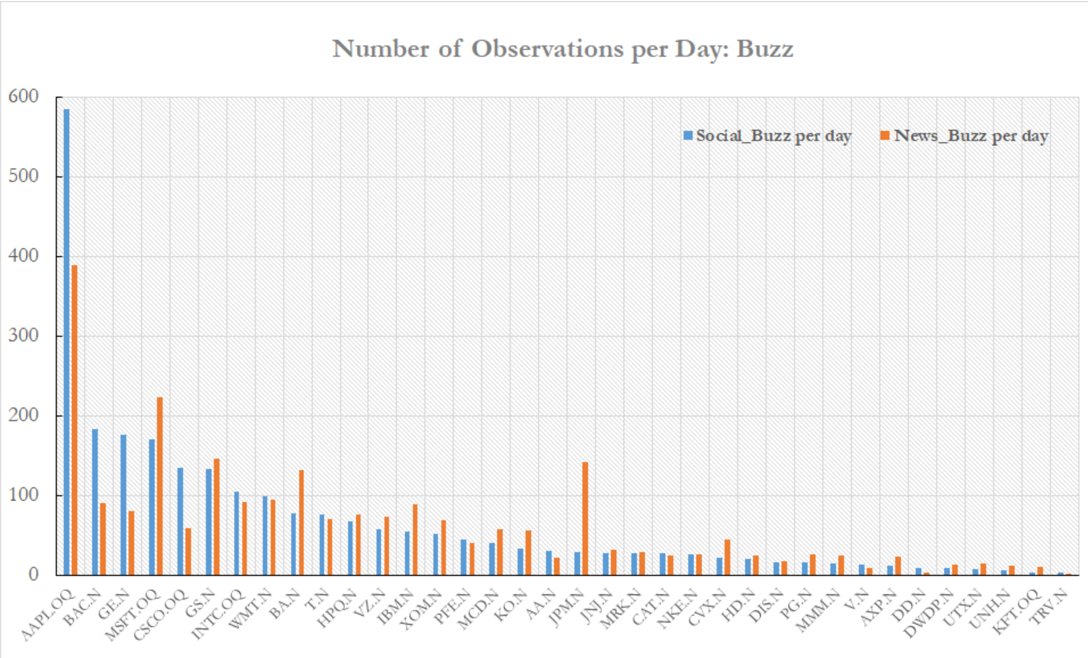
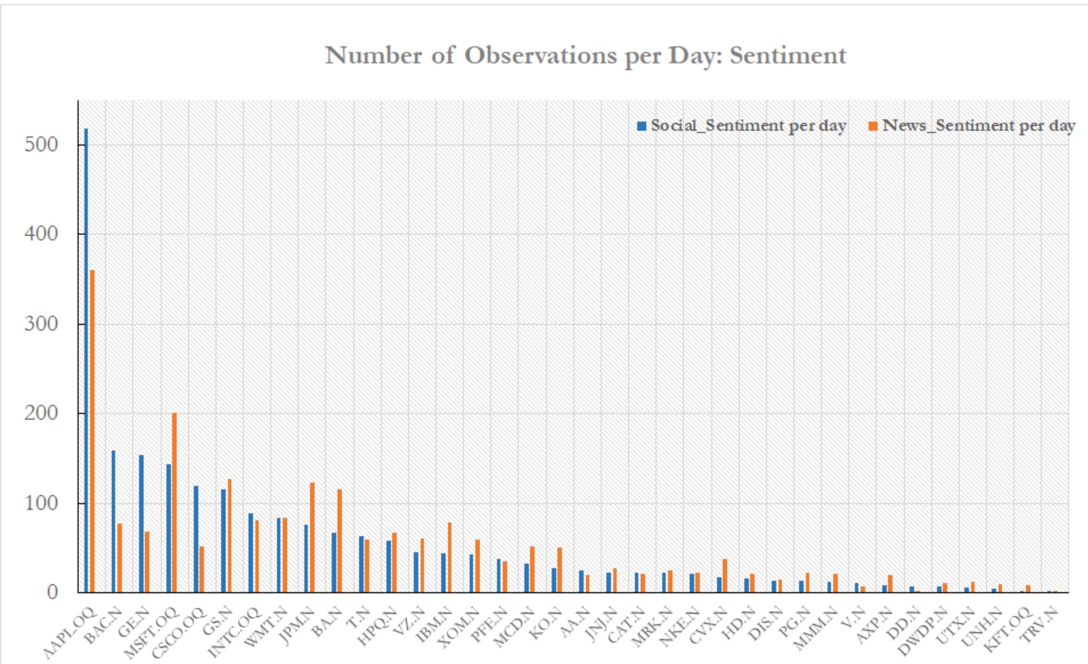


Figure B.11: ***Sentiment* Data Availability. News vs Social media**. The figure compares the average daily counts of non-missing observations from social (blue bars) and news (orange bars) media. The calculations are based on Thomson Reuters MarketPych Indices (TRMI) social and news media *Sentiment* scores at 1-minute frequency. 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.



B.8 Data pre-processing and Distribution of Event-days

We focus on the *sentiment* measure rather than the measure of coverage quantity (*buzz*) or other emotional scores provided by TRMI (such as *joy*, *fear*, or *gloom*). Firstly, *sentiment* synthesizes all 34 TRMI emotion indices for an entity, i.e. a stock or an index, providing more observations than any individual emotion score.[3] Secondly, we find that the salience in *sentiment* series is consistent with *buzz* series. Interested readers are referred to supplementary online appendix, specifically Table B.7 and Figures B.10-B.11. 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 combined measure of both the quantity of coverage and the attitudes expressed in articles or posts.[4]

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 index: $Sent^S_{i,t,j}$, $Sent^N_{i,t,j}$, and $r_{i,t,j}$. Our sample of 35 securities and the index covers the period from January 1, 2011 to November 30, 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 days-by-row and minutes-by-column mesh:

$$\underbrace{\mathbf{Sent}_i^S}_{(2{,}526\times 1{,}440)}, \quad \underbrace{\mathbf{Sent}_i^N}_{(2{,}526\times 1{,}440)} \quad \text{and} \quad \underbrace{\mathbf{r}_i}_{(2{,}526\times 1{,}440)}$$

We remove days that contain more than 95% of zero 1-minute returns. That is, 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. Table B.8 summarises total numbers of events for each stock in our sample for each cumulative overnight sentiment decile. Social and news media sentiment figures are presented in Panel A and Panel B, respectively. Considering the sparsity of these 'event-day' data, we removed Kraft from our sample as the number of events is deficient for a meaningful modeling. On average, a typical stock in the sample contains 1,741 event-days. Whereas most stocks have cumulative overnight sentiment evenly distributed across the 1,741 event days (e.g., AAPL.OQ, IBM.N and JPM.N), other stocks (e.g., TRV.N and UNH.N) exhibit uneven distribution of 'events' across deciles due to either highly polarized emotion days or particularly large number of thin trading days (at least at 1-minute frequency).

A particularly interesting observation from Table B.8 is that the number of event-days in mid-deciles for KFT, TRV, UNH, UTX, AXP, DD, and DIS is lower than at the extreme deciles. The event-days were removed due to unusually low number of bid/ask quotes on days with neutral overnight sentiment (around 5th and 6th deciles), providing additional evidence in support of our hypothesis that overnight sentiment influences the markets.

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

[4] For convenience, Table A.3 in the appendix lists all variable definitions, data sources and acronyms. Variables based on social or news media are denoted with (S) or (N) superscripts, respectively. Thus, $Sent^{(S)}$ and $Sent^{(N)}$ represent sentiment data from (S)ocial and (N)ews media, respectively.

B.9 Days with Excessive Sentiment and the Overlap with Earnings Announcements

It stands to reason that days with excessive sentiment from social or news media are the days where important announcements could have been made. We analyse the concurrence of earnings announcement release dates with the set of days where the cumulative sentiment is in the top or bottom 10% of the entire sample. To assist with understanding of how we compute the overlapping rate, we demonstrate our method in Figure B.12 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 increased probability of coincidental overlap with earnings announcements. The upper (lower) panel in Figure B.12 shows strong social (news) media sentiment days for the period from January 1, 2011 to November 30, 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 - days with strong sentiment. We observe no obvious clustering in days with strong sentiment. Earnings announcement dates are represented by vertical black solid lines. When a strong sentiment day coincides with an earnings announcement, 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.

Figure B.12: Event Clustering and Earnings Announcements Overlap (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, 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.

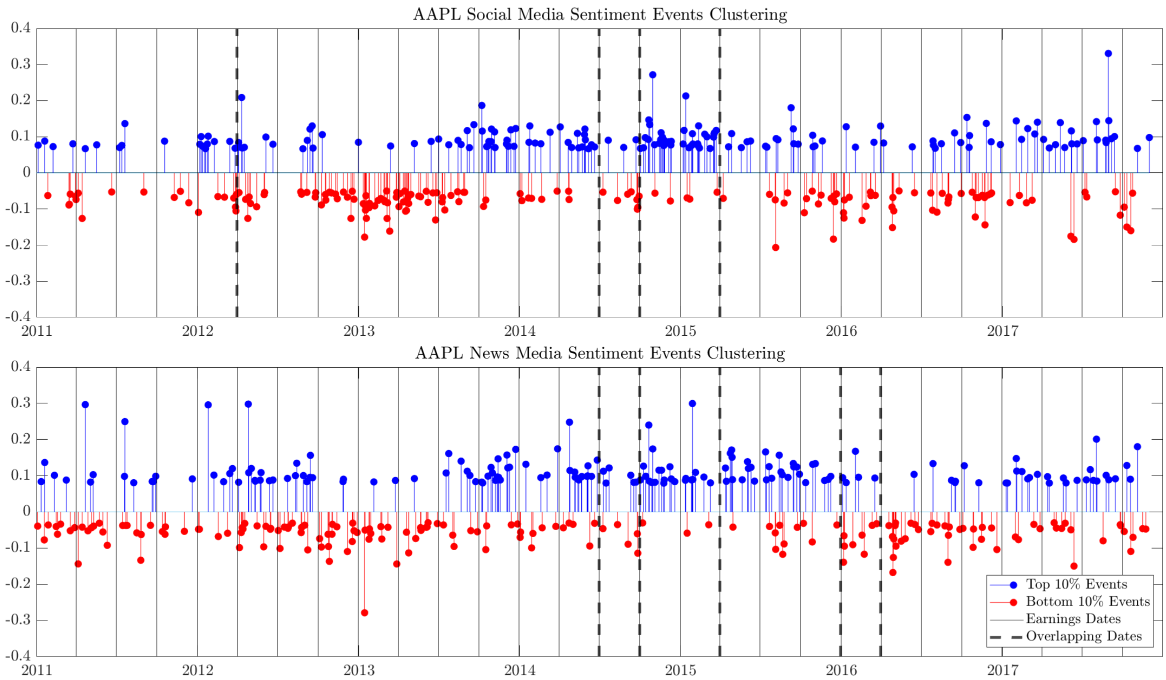


Table B.8: Overnight Sentiment Events Sample Distribution. This table shows the distribution of overnight sentiment 'events' for each sample stock. The sentiment series are aggregated from 4:01 pm to 09:29 am each day. Days of over 95% zero-returns are excluded, and the number of such days are summarised in the column 'Removed'. The column 'Events' is the total number of events for each sample stock we obtained after the data pre-processing procedure. Panel A shows the distribution of the aggregated social media sentiment events, and Panel B is a description of the aggregated news media sentiment events.

Panel A : Summary and Distribution of Sample Events - Social Media

RIC	Removed	Events	Negative				Neutral		Positive			
			10th	20th	30th	40th	50th	60th	70th	80th	90th	100th
AA.N	905	1,622	162	162	163	162	227	97	166	159	162	162
AAPL.OQ	786	1,741	174	174	174	174	174	175	174	174	174	174
AXP.N	786	1,741	174	174	622	0	0	35	178	170	175	173
BA.N	786	1,741	174	174	174	174	174	175	174	174	174	174
BAC.N	823	1,705	170	171	170	171	170	171	171	170	171	170
CAT.N	785	1,741	174	174	174	178	282	63	197	151	174	174
CSCO.OQ	786	1,741	174	174	174	174	174	175	174	174	174	174
CVX.N	786	1,741	174	174	174	174	236	119	168	174	174	174
DD.N	849	1,678	168	168	167	168	513	0	0	159	167	168
DIS.N	786	1,741	178	170	174	397	0	130	203	144	171	174
GE.N	791	1,736	174	173	174	173	174	174	173	174	173	174
GS.N	786	1,741	174	174	174	174	175	174	174	174	174	174
HD.N	785	1,741	174	174	175	310	38	174	174	174	174	174
HPQ.N	791	1,736	174	173	174	173	174	174	173	174	173	174
IBM.N	785	1,741	174	174	174	174	175	174	175	173	174	174
INTC.OQ	786	1,741	174	174	174	174	175	174	174	174	174	174
JNJ.N	785	1,741	174	174	174	174	189	160	174	174	174	174
JPM.N	786	1,741	174	174	174	174	175	174	174	174	174	174
KFT.OQ	2,457	68	7	7	40	0	0	0	0	0	7	7
KO.N	786	1,741	174	174	174	174	175	174	174	174	174	174
MCD.N	785	1,741	174	174	174	174	175	174	174	174	174	174
MMM.N	786	1,741	181	178	172	286	54	174	174	174	175	173
MRK.N	786	1,741	174	182	168	268	80	173	174	174	174	174
MSFT.OQ	786	1,741	174	174	174	174	175	174	174	174	174	174
NKE.N	785	1,741	174	196	152	301	48	174	174	174	174	174
PFE.N	786	1,741	174	174	174	174	175	174	174	174	174	174
PG.N	785	1,741	174	174	175	239	113	170	174	174	174	174
T.N	786	1,741	174	174	174	174	175	174	174	174	174	174
TRV.N	785	1,739	179	1281	0	0	0	0	0	0	112	167
UNH.N	784	1,741	174	1043	0	0	0	0	2	203	210	109
UTX.N	784	1,741	190	159	802	0	0	0	68	182	208	132
V.N	786	1,741	174	177	601	0	0	94	187	215	119	174
VZ.N	786	1,741	174	174	174	174	175	174	174	174	174	174
WMT.N	786	1,741	174	174	174	174	175	174	174	174	174	174
XOM.N	786	1,741	174	174	174	174	175	178	173	171	174	174
Total Events		**59,032**										

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Panel B : Summary and Distribution of Sample Events - News Media

RIC	Removed	Events	Negative				Neutral		Positive			
			10th	20th	30th	40th	50th	60th	70th	80th	90th	100th
AA.N	905	1,622	162	185	140	688	0	0	0	123	162	162
AAPL.OQ	786	1,741	174	174	174	174	174	175	174	174	174	174
AXP.N	786	1,741	174	174	354	0	178	165	174	174	174	174
BA.N	786	1,741	174	174	174	174	174	175	174	174	174	174
BAC.N	823	1,705	170	171	170	171	170	171	171	170	171	170
CAT.N	785	1,741	174	174	180	332	11	174	174	174	174	174
CSCO.OQ	786	1,741	174	174	174	174	174	175	174	174	174	174
CVX.N	786	1,741	174	174	174	174	176	173	174	174	174	174
DD.N	849	1,677	172	1,308	0	0	0	0	0	0	29	168
DIS.N	786	1,741	192	159	177	601	0	0	90	174	174	174
GE.N	791	1,736	174	173	174	173	174	174	173	174	173	174
GS.N	786	1,736	174	174	174	174	175	174	174	174	174	174
HD.N	786	1,741	174	174	176	359	0	162	175	173	174	174
HPQ.N	791	1,736	174	173	174	173	174	174	173	174	173	174
IBM.N	785	1,741	174	174	174	174	175	174	174	174	174	174
INTC.OQ	786	1,741	174	174	174	174	175	174	174	174	174	174
JNJ.N	786	1,741	174	174	174	284	65	174	174	180	168	174
JPM.N	786	1,741	174	174	174	174	175	174	174	174	174	174
KFT.OQ	2,458	68	8	6	6	21	0	0	7	6	7	7
KO.N	786	1,741	174	174	174	174	175	174	174	174	174	174
MCD.N	786	1,741	174	174	174	174	175	174	174	174	174	174
MMM.N	786	1,741	174	174	175	173	179	182	163	173	174	174
MRK.N	786	1,741	174	174	174	298	51	174	175	174	173	174
MSFT.OQ	786	1,741	174	174	174	174	175	174	174	174	174	174
NKE.N	786	1,741	174	174	175	258	90	174	177	171	174	174
PFE.N	786	1,741	174	174	174	174	226	123	174	174	174	174
PG.N	786	1,741	174	174	174	216	133	174	174	174	174	174
T.N	786	1,741	174	174	174	174	175	174	174	174	174	174
TRV.N	784	1,738	1648	0	0	0	0	0	0	0	0	90
UNH.N	786	1,741	175	1057	0	0	0	0	0	161	211	137
UTX.N	785	1,741	192	161	766	0	0	0	100	174	174	174
V.N	784	1,741	174	174	882	0	0	0	0	163	174	174
VZ.N	786	1,741	174	174	174	174	175	174	174	174	174	174
WMT.N	786	1,741	174	174	174	174	175	174	174	174	174	174
XOM.N	786	1,741	174	174	174	174	175	174	174	174	174	174
Total Events		**59,025**										

B.10 Examples of other stocks

In the main body of the paper, we presented exemplars based on CSCO.OQ. We provide a detailed account of the results for AAPL.OQ below. We follow the same steps in analysis the rest of the stocks in our sample, while providing only the summary of the results. The detailed account of our findings available upon request.

Figure B.13: Distribution of TRMI Social and News Media Sentiment by Time of Day for AAPL.OQ. The boxplots display the distribution of social media and news sentiment scores by time of day for Apple Inc (AAPL.OQ). Social media activity and sentiment scores are concentrated during trading hours, whereas this pattern is less obvious in the news-based sentiment. The sample period is from 1 January 2011 to 30 November 2017 at 1-minute frequency.

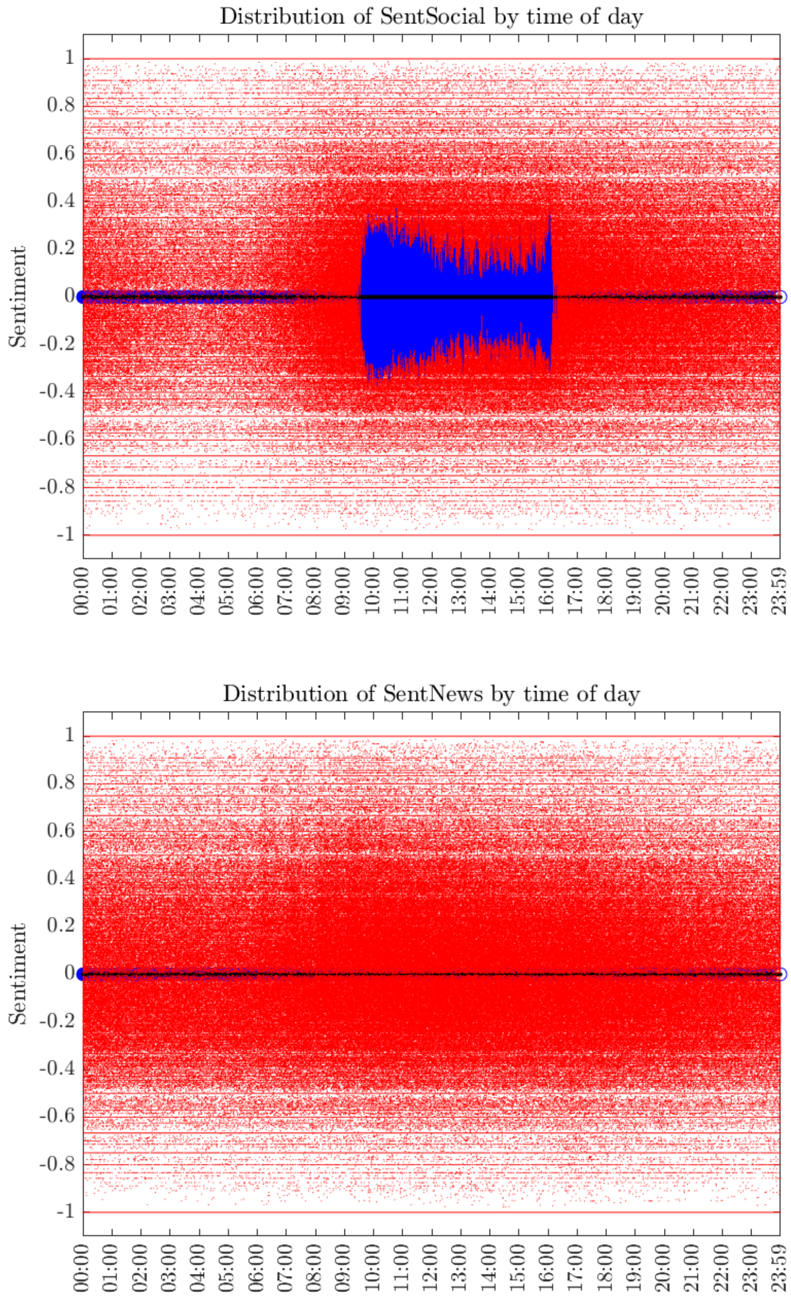
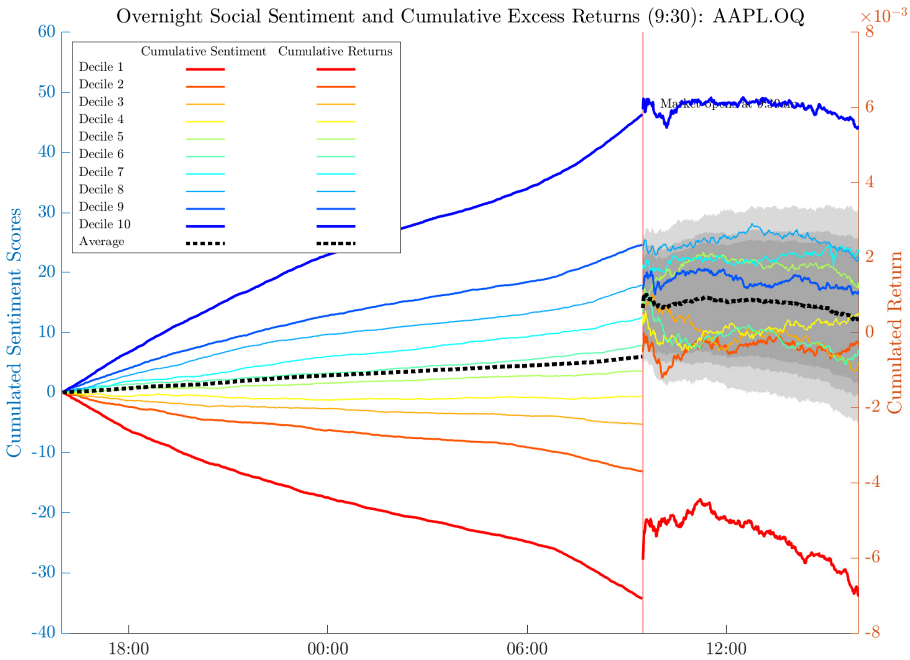


Figure B.14: Social Media: Overnight Sentiment and Opening Returns (AAPL.OQ) Sentiment and returns data are at 1-minute frequency from 1 January 2011 to 30 November 2017. Overnight sentiment is cumulated daily from previous day close to current day open (i.e., from 4:01 pm to 9:29 am). Cumulative sentiment 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 9:30 am, while in the bottom panel, it starts from 9:31 am, skipping 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 $M = 2,000$.



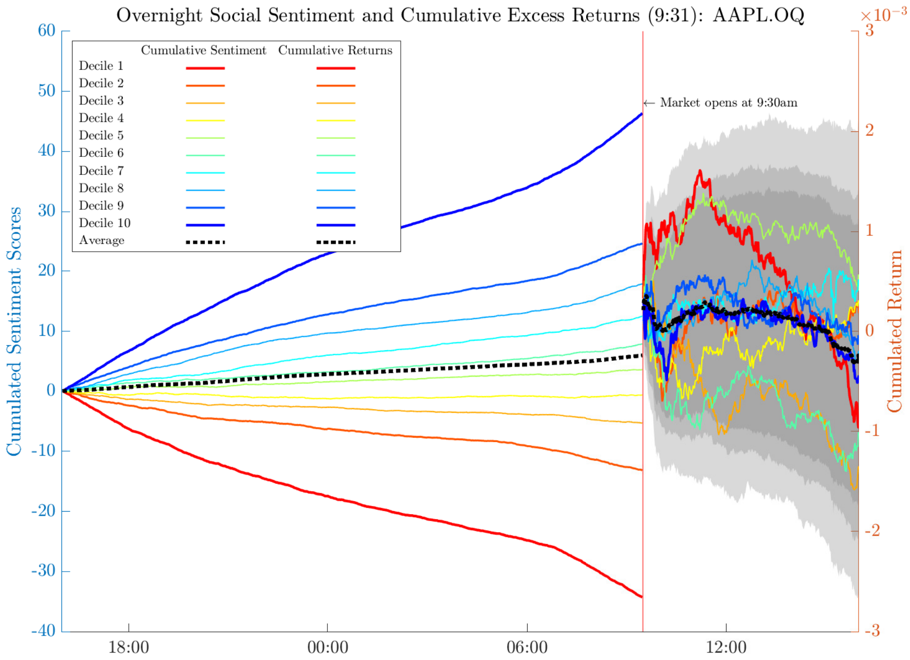
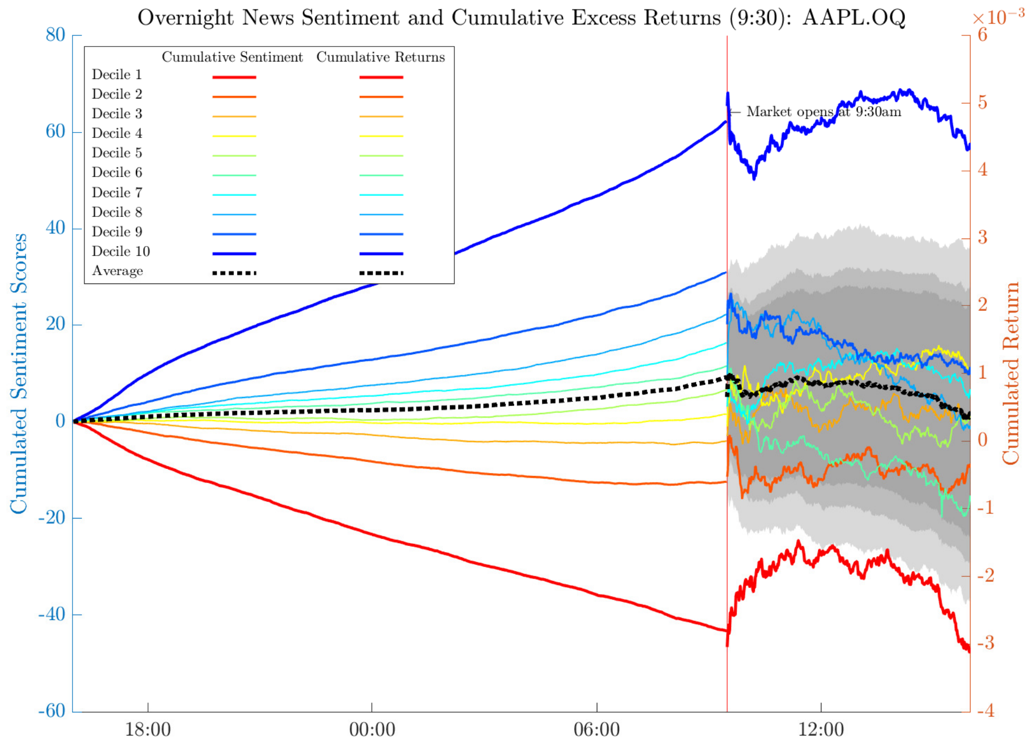


Figure B.15: News Media: Overnight Sentiment and Opening Returns (AAPL.OQ) Sentiment and returns data are at 1-minute frequency from 1 January 2011 to 30 November 2017. Overnight sentiment is cumulated daily from previous day close to current day open (i.e., from 4:01 pm to 9:29 am). Cumulative sentiment 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 9:30 am, while in the bottom panel, it starts from 9:31 am, skipping 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 $M = 2,000$.



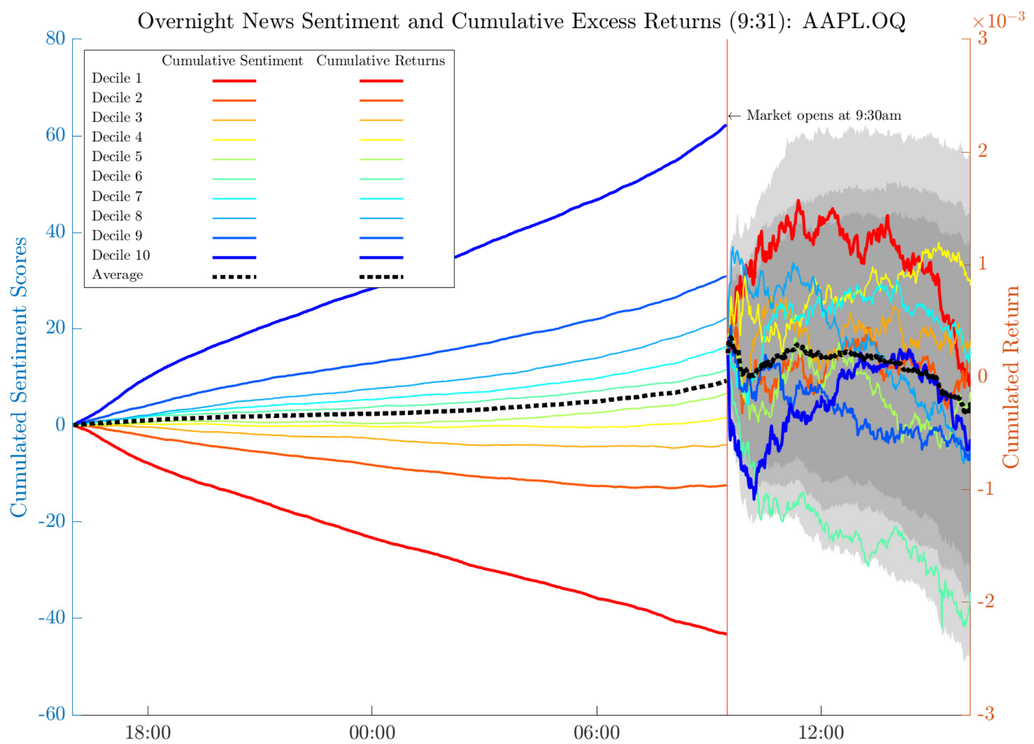


Figure B.16: Cumulative Returns and Ensuing Sentiment (AAPL.OQ) Sentiment and returns data are at 1-minute frequency from 1 January 2011 to 30 November 2017. Abnormal returns are cumulated daily from market open to close (from 9:30 am to 4:00 pm on each trading day). The cumulative abnormal returns (CARs) 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 4:00 pm to 9:29 am 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 $M = 2,000$.