The Effects of Social Media Sentiment on Financial Markets: A High-Frequency Study

Ni Yang

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Abstract

Social media has become one of the main communication channels over the last decade. It has reformed how investors acquire and exchange news and become their leading information source in the digital era. Social media platforms allow for the rapid dissemination of news, opinions, and sentiment to a vast number of market participants in real time. In line with the landscape change, recent studies have emphasised the significance of social media sentiment effects on financial markets. However, the majority of research focuses on the predictability of the sentiment derived from social media or assesses its impact on a specific type of financial asset. The mechanisms by which social media affects prices and investors are still not clear. In addition, whether social media sentiment captures information or noise is debatable. In this thesis, I examine the role of social media sentiment in financial markets from a market microstructure perspective and study its influence on various aspects of market dynamics.

I produce a social media sentiment index from millions of real-time Twitter (now called *X*) messages through textual analytics, and I demonstrate the price impact of social media sentiment and its effect on market informational efficiency at a high-frequency level. Furthermore, I explore the spillover effects between social media sentiment and market volatility across various financial assets by employing Refinitiv MarketPsych analytics sentiment indices. The analysis at intraday and daily granularity captures the nuances of real-time social media sentiment impacts on market dynamics, demonstrating the mechanism of social media sentiment influencing financial markets. Hence, this thesis

aims to contribute to the extant literature on how social media sentiment affects and interacts with financial markets in a high-frequency context.

The first study of the thesis examines the mechanism by which social media sentiment affects stock prices. I assess the impact of Twitter posts on stock returns at the minute level. I find that social media sentiment can affect stock prices via trades. Specifically, an increase in buyer- (seller-) initiated trades has a significantly positive (negative) price impact. The impact is stronger with an increase in the number of tweets and sentiment, and persists even after controlling for volatility, liquidity shock, and limit-order activity. Both bullish and bearish tweets amplify the impact of trades on returns. It shows that the effect of social media sentiment is transmitted to stock prices through trades. The impact of Twitter sentiment on prices causes a permanent price movement at intraday, indicating that Twitter sentiment contains information.

The second study investigates the impact of social media sentiment on the informational efficiency of financial markets. I examine the relationship between the aggregated tone of Twitter posts, i.e., the sentiment index used in the first study, and two commonly used market efficiency measures in empirical studies: return autocorrelation and variance ratio. The findings reveal that higher social media sentiment leads to higher intraday return autocorrelation and variance ratio the following day, indicating a decrease in market informational efficiency. I account for various influential factors, employ different sentiment analysis approaches, and consider different intervals for sentiment construction, all of which consistently support this relationship. Moreover, I demonstrate that social media sentiment impacts informational efficiency through the occurrence of herding behaviours among traders, with higher sentiment leading to heightened herding activity the following day. This study supports the notion that social media sentiment contributes to a decline in the quality of the information environment, resulting in informationally inefficient equity prices the following day.

The third study delves into the dynamics of spillover effects between social media sentiments and market-implied volatilities among stock, bond, foreign exchange, and commodity markets. I find that informational spillover comes mainly from volatility indices to sentiment indices, with stock market volatility (VIX) being the most significant net generator. Within each asset class, there is a stronger spillover from volatility to the sentiment, but a marginal effect for the opposite direction. The connectedness between sentiment and volatility increases in turbulent economic periods, such as the Global Financial Crisis, Brexit, the US-China trade war, and the COVID-19 pandemic. Moreover, sentiment indices can switch from being a net receiver to a net generator of shocks during turbulent periods. This study shows that social media repeats existing news media signals, but some investors interpret repeated signals as genuinely new information.

Overall, this thesis sheds light on the interplay between social media sentiment and financial market dynamics. It shows the mechanisms underlying the influence of social media sentiment on financial markets within the context of high-frequency analysis, contributing to the fast-growing research on the impact of social media on financial markets. Hence, the above findings have important implications for investors and market officials seeking to understand and better regulate social media as an information dissemination channel in the fast-changing environment. It provides insights for investors on utilising social media sentiment in real-time investment strategy. This thesis also emphasises the importance of regulatory frameworks when it comes to social media activity for market quality and stability.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed: Ni Yang

Date: November 2023

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Chapter 1

Introduction

Over the last decade, the way people acquire information and communicate with each other has shifted remarkably. Technology changes and widespread networks have led to the gradual replacement of traditional news media by emerging new platforms---social media[1] as a more rapid source of information. Social media platforms enable news and information to spread instantaneously worldwide.

Following this landscape change, social media has reshaped how investors obtain and exchange information. For example, investors can receive updates on market-moving information in real time. With access to social media platforms, investors are able to spread news, opinions, and moods to a vast number of audiences swiftly. Subsequently, we can derive social media sentiment to reflect investors' prevalent tone or collective beliefs on social media. Specifically, social media sentiment incorporates investors' opinions, interactions and connections of sharing and responding to posted news and messages regarding a market or individual stocks.

[1] Social media users increased from 1.72 billion in 2013 to 4.76 billion in 2023, 92% internet users are social media users nowadays. See, the global overview report, https://datareportal.com/reports/digital-2023-global-overview-report

As an aggregated tone of underlying assets, social media sentiment has impacts on financial markets by influencing market participants and their transactions in implicit ways. Baker and Wurgler (2007) argue that investor sentiment is investor belief about future risks that are not justified by the fundamentals at hand, and investors' decisions can be affected by their mood or market sentiment. Price adjustments occur as investors revise their beliefs in response to new information coming from public media (De Long et al., 1990). As such, social media facilitates interactions among investors, connects them with financial markets actively and rapidly, and ultimately affects asset prices by impacting investor collective trading behaviours.

Extant research mainly focuses on the association between the predictive ability of sentiment extracted from traditional news media and stock market prices, documenting that sentiment can predict stock returns at various frequencies. Some studies document that prices converge to a new equilibrium or with partial reversal (Tetlock, 2007; 2011; Sprenger et al., 2014a; Gu and Kurov, 2020). This indicates that media sentiment is informative about financial markets. The faster information flow through social media platforms can impact trading decisions and change the supply and demand of buyers and sellers, leading to quick reactions in asset prices and changes in trading volumes even within minutes or hours. However, they do not explore how social media sentiment is transmitted to the movements in security prices. As such, I employ a market microstructure approach to assess the mechanism by which social media sentiment affects financial markets. This thesis explores how social media sentiment influences different aspects of financial markets. With the emerging of social media and its enhanced data granularity in capturing investor sentiment and anticipation of market movement intraday, we are able to investigate how investor sentiment influences financial market prices in a way that has not been previously explored.

Market microstructure studies the trading mechanism and process in which asset prices are formed. For instance, the incorporation of the information arrival is concerned with the price discovery process, revealing how new information is eventually reflected in market participants' orders and transactions. Rapid information dissemination via social media could significantly affect the price discovery process because investors obtain information faster and trade swiftly by placing corresponding orders, contributing to fast-changing price dynamics. In this thesis, I employ social media and market transaction data at a high-frequency to study price impacts from social media sentiment and investigate market quality.

From a market microstructure perspective, understanding the underlying mechanism is vital as it provides insights for various regimes. For example, how social media sentiment affects the market participants, their execution of orders, and its price impact of trades. Also, it helps to discover social media sentiment influences on market quality, such as informational efficiency and market stability. Specifically, such outcomes may benefit the development of more sophisticated and effective trading strategies that take advantage of the social media sentiment intraday, significantly improving asset pricing models and forecasting models for news-driven and high-frequency trading. More importantly, it assists market makers to understand market swings caused by social media sentiment. After assessing the comprehensive role of social media and its real-time impacts on different aspects of financial markets, market regulators can monitor collective trends on social media and provoke more effective rules to promote market stability and prevent systemic inefficiency in a timely manner.

Social media sentiment has many advantages if compared to the market-based investor sentiment proxy, such as trading volumes or option implied volatilities (Baker and Wurgler, 2007), survey-based methods (Brown and Cliff, 2004) or search-based proxies such as Google search volume (Vozlyublennaia, 2014). First, social media sentiment is a direct and instantaneous reflection of investor sentiment, rather than the equilibrium of economic forces, at real-time frequency with less delay or answering bias concerns. Furthermore, generated from millions of messages, the big data-based social media sentiment index ensures the precision of data quantification with the superiority of less information distortion, addressing heterogeneous issues such as fake news (Cepoi, 2020; Shi and Ho, 2021). This is crucial as it impacts sentiment data's reliability and predictive power (Renault, 2017).

In terms of data granularity for matching fast-changing market conditions, it is important to emphasise that textual-based social media sentiment offers high synchronicity. This research examines the role of social media sentiment in impacting financial markets in real time. For Chapters 3 and 4, I extract millions of Twitter feeds (known as tweets) for natural language processing and gauge a Twitter sentiment index regarding the overall market[2] for intraday and daily analyses. In Chapter 5, I employ Refinitiv MarketPsych analytics social sentiment indices. The Refinitiv MarketPsych sentiment analyses millions of real-time social media messages across platforms to provide comprehensive asset-specific sentiment data. It processes them with a high-speed AI-based machine learning algorithm for natural language processing, which ensures the precision of sentiment quantification with the superiority of less information distortion.

First, in Chapter 3, I delve into the relationship between social media sentiment and stock market prices from 2012 to 2018. Specifically, I explore the price impact of tweets on stock markets to uncover the mechanism by which social media sentiment impacts market prices. I focus on Twitter sentiment related to the SPDR S&P 500 ETF (Ticker: SPY) as a representation of the US stock market. Then, I modify Hasbrouck's

[2] Moreover, using natural language processing for messages textual analysis can depict a visualised map of investors' market interests in a word cloud (see., Appendix I), which capture the theme of the millions of messages and better facilitate the understanding of the collective trends and market sentiment among investors.

(1991) informativeness of trades model by interacting the sentiment measure with the trade variable in the vector autoregression (VAR) model. This is to measure the price impact of social media sentiment on prices through its impact on trades. I find that Twitter sentiment enhances the impact of trades on intraday returns. Trades have a greater price impact with an increase in the number of tweets or a higher degree of bullishness. This finding suggests that as there is more social media discussion related to the stock market, the price impact of trades becomes stronger. The impact of buyer- (seller-) initiated trades on stock prices is stronger when the market sentiment on social media is bullish (bearish). This price impact persists even after controlling for volatility, liquidity shocks. More importantly, a shock on Twitter sentiment causes a permanent price movement, showing that Twitter sentiment contains information.

The results highlight the importance of social media sentiment in stock market price movements at the intraday level. The above findings reveal a significant impact of social media sentiment on stock prices through its impact on trades at intraday, a mechanism that, to our best knowledge, has not previously been documented in the literature. Also, it contributes to the ongoing debate on the informativeness of social media (see, e.g., Sprenger et al., 2014b; Karagozoglu and Fabozzi, 2017; Schnaubelt et al., 2020), documenting that Twitter sentiment contains information about the stock market.

A different but equally important question I address in Chapter 4 is how social media sentiment affects financial market quality. In terms of market quality, I especially focus on market efficiency, which reflects how rapidly a market incorporates information and correctly prices the intrinsic value of the underlying assets. This is vital for traders because social media sentiment can cause variations of pricing friction, therefore, potentially influencing the efficiency of asset allocation (Smales, 2017). I examine the causal relation between social media sentiment and market efficiency, investigating whether sentiment influences market efficiency.

I use a textual sentiment analysis approach similar to the previous chapter to investigate the impact of social media sentiment on market informational efficiency from 2012 to 2022. I employ two commonly used informational efficiency metrics: return autocorrelation and variance ratio, as used in previous studies (Hendershott and Jones, 2005; O'Hara and Ye, 2011; Comerton-Forde and Putniņš, 2015). Then, I regress these market efficiency metrics on the social media sentiment measure to explore whether increased sentiment leads to changes in market informational efficiency. The findings demonstrate that as social media sentiment becomes more positive or bullish, it leads to increased return autocorrelation and variance ratio the following day, indicating a decrease in informational efficiency. Furthermore, the results demonstrate that the impact of social media sentiment on informational efficiency stems from the emergence of herding behaviours among traders, with higher sentiment leading to heightened herding activity, but not vice versa. After accounting for various influential market factors, employing different sentiment analysis approaches, and considering different intervals for sentiment construction, all of which lend support to the robustness of the above finding.

In Chapter 4, I also empirically examine the underlying mechanism by investigating the relationship between social media sentiment and herding behaviour[3]. I demonstrate that social media sentiment impacts informational efficiency through the occurrence of herding behaviours among traders, with higher sentiment leading to heightened herding activity the following day, but not vice versa. For many participants, professionally curated and commercial databases may be inaccessible or come at a high cost, leading them to rely more heavily on information obtained through other sources,

[3] I particularly assess the "echo chamber" effect as a part of the next Chapter 5 and demonstrate robust evidence.

such as social media platforms (Bukovina, 2016). This high reliance on social media but lack of thorough understanding of it can result in investors' herding behaviour, negatively impacting informational efficiency. Therefore, this thesis benefits investors in understanding social media sentiment and improving market quality.

Social media sentiment plays such a vital and dynamic role in stock markets, influencing large-scale participants' trading behaviours and subsequent stock returns and market efficiency. I wonder if the impact of social media sentiment could be transmitted from one to other financial markets (such as bond, foreign exchange, and commodity markets), showing broader impacts. Despite the extant studies on social media and financial markets, whether sentiment from social media spillovers across different financial asset classes remains underexplored. Existing studies mainly focus on volatility spillover to interpret the linkage between two assets from the uncertainty transmission angle. I, however, explain the connectivity among different asset classes via a behavioural perspective.

More specifically, Chapter 5 investigates social media sentiment across various assets to assess its role in the financial system. I explore the spillover effect between market-specific sentiments and corresponding market-specific implied volatilities for five asset classes from 2008 to 2020. This chapter provides vital implications for investors seeking to hedge asset-specific uncertainty and is also helpful for market officials considering monitoring market stability.

I combine the Refinitiv MarketPsych Analytics (RMA) social media sentiment, and the Chicago Board Options Exchange (CBOE) implied volatility indices of stock, bond, foreign exchange, and commodity markets. Then, I utilise those asset-specific indices to disentangle spillover effects between sentiment and volatility across asset classes following Diebold and Yilmaz (2012, 2014) connectedness framework. This framework measures the shares of forecast-error variation in an asset due to shocks arising elsewhere, assisting the further detailed analysis of social media sentiment and market volatility spillover effects.

After the static and time-varying connectedness analyses, the findings of Chapter 5 suggest that sentiments and volatilities of the above five markets are mildly connected. There is a stronger spillover from volatility to the sentiment of the same market, but a marginal effect in the opposite direction. Informational spillover mainly originates from volatility indices to sentiment indices, and the stock market implied volatility VIX (also known as the 'fear gauge') is the major net spillover transmitter to other assets. However, sentiment indices can switch from being a net receiver to a net transmitter of shocks during turbulent economic periods, such as the Global Financial Crisis, Brexit, the US-China trade war, and the COVID-19 pandemic.

Beyond the linkages between sentiments and volatilities, I also explore the rationale behind the findings from social media being an "echo chamber" (Jiao et al., 2020). That is, social media posts reshare existing news signals, but some investors interpret repeated signals as genuinely new information. This channel explains why social media sentiment is, on average, a net receiver of shocks but turns into a net trigger in turbulent times when investors are actively seeking information. Furthermore, this complements the previous chapters showing that after social media sentiment is incorporated swiftly into financial markets within minutes or hours (Chapter 3), its effect reverses at daily level or lower frequencies (Chapter 4) demonstrating its noise characteristic. One of the key novelties of this work compared to the previous studies is that I consider investor sentiment specific to each asset class. This study significantly contributes to the social media sentiment spillover across financial markets and provides evidence for social media's echo chamber role.

Overall, this thesis develops a better understanding of the effect of social media sentiment on financial markets. The chapters in this thesis elucidate the mechanism of social media sentiment in impacting market returns at high-frequency level, depicting its role in affecting market informational efficiency and demonstrating its spillover influence across various financial markets. Chapter 6 synthesises the above findings and emphasises the contributions and implications of this thesis.

Chapter 2

A Primer on Investor Sentiment, Social Media Effects and Market Dynamics

2.1 Introduction

This chapter presents a primer on the main themes related to this thesis, including investor sentiment, social media impacts and market dynamics, market microstructure and market volatility. As groundwork for the thesis, we first discuss investor sentiment, its impacts on financial decisions and measurements for it. We then explain social media and rationalise the concept and advantages of social media sentiment. We then review the significant effects of social media sentiment in financial markets. To develop a general framework for the three following chapters of this thesis, we discuss the price discovery process and how information contained in social media sentiment is incorporated into prices from a market microstructure perspective, which relates to Chapter 3. Subsequently, we discuss market quality and pricing efficiency and their linkages with social media sentiment for Chapter 4. Finally, we model spillover effect of different markets' sentiments and their relations to market volatilities, which is necessary for comprehending Chapter 5. In summary, this chapter aims to lay a foundation for understanding the thesis and the following chapters.

2.2 Investor Sentiment and Social Media Effects

2.2.1 Investor sentiment and its impacts

De Long et al. (1990) argue that investor sentiment reflects investors' expectations about future asset returns that are not warranted by the fundamentals. To an extent, such sentiment can alter investors' perception of risk and attention (Brown and Cliff, 2004), affecting their decisions making and deviating asset prices from its intrinsic values.

Prior studies have documented that investment decision-making is a complex and mixed process of cognitive evaluation and sentimental consequences (Dowling and Lucey, 2005; Loewenstein et al., 2001). According to Forgas (1995) and Slovic et al. (2004), risk and uncertainty are factors by which sentiment affects an investor's decision. The higher the complexity and uncertainty of a situation, the more emotions could influence investment decisions (Birru and Young, 2022). For example, one could be more (less) likely to be optimistic in valuing an asset when having a good (bad) mood, increasing (decreasing) the likelihood of investing in risky assets, even though the mood is irrelevant to an investment environment (Nofsinger, 2005). Thus, investors' sentiment influences their risk perception and financial decision-making processes, leading to movements in asset prices.

Additionally, investor's decision is not only formed uniquely by her independent analysis but also shaped by the shared public opinions and beliefs, such as the media sentiment trend (Barber and Odean, 2008). The interactions occur when investors update their information set to assist their investment decisions by accessing public media. Tetlock (2011) argues that public news disseminates information and influences investor sentiment, accelerating the convergence of the crowd's belief. If there are biases, it can create corresponding anomalies in financial markets. For instance, using an incomplete information model, Merton (1987) shows that many investors are unaware of a subset of securities, and the visibility on media increases investor mood or attention, increasing market value and lower expected returns of assets.

Asset prices represent average beliefs among investors about valuation in financial markets (Millller, 1977; Banerjee and Kremer, 2010; Goutte, 2019). Investors' belief in a firm's value is a vital impactor of trading prices besides genuine information (Scheinkman and Xiong, 2003). The media effect reflects public expectations and disseminates information to broader audiences, promptly sculpting investors' beliefs. It changes investors' decisions regarding a news-relevant asset, significantly impacting the supply and demand of that asset, resulting in a series of price adjustments and a new market equilibrium.

Media affects financial markets by influencing investors' beliefs. Dolan (2002) explains that investors' trading behaviours are linked to investment-related content in media because their decisions are reactions to new information. Faster and better information dissemination enhances awareness among investors, mitigating information asymmetry and increasing the relevant company's market value. However, investors cannot process overwhelming amounts of new information efficiently due to limited attention and cognitive processing ability. Therefore, investors pay more attention to market-level indexes than specific stocks. As such, prices overreact to general (or uninformative) information and underreact to detailed (or informative) information.

Empirical evidence shows that media coverage, such as newspapers, articles, and online forums, are prevalent sources that can affect investor sentiment and price movements in financial markets. For example, Tetlock (2007) finds that strong pessimism from the Wall Street Journal (WSJ) can forecast market price declines but with a subsequent price correction at a daily frequency. Mangee (2018) documents that investor sentiment based on contextualised information from news media explains medium- to longer-term swings in aggregate stock prices. Likewise, media sentiment is also found to impact the return of the gold futures market (Smales, 2014).

Investors' sentiment extracted from media coverage is often expressed qualitatively in language. An empirical priority is the measurements of investor sentiment, and extracting and converting the qualitative sentiment to quantitative values is vital for finance research. Regarding quantifying sentiment, literature shows multiple channels. There are four commonly used investor sentiment proxies: market-based indicators, survey-based indices, search-based measurements and media content-based methods[4]. Market-based indices often employ indicators such as grey market prices (Cornelli et al., 2006), trading volume, IPO-day returns, or option implied volatilities as proxies of sentiment values[5]. Nevertheless, Baker and Wurgler (2007) argue that the method represents an equilibrium of economic forces more than investors' sentiment.

Survey-based indices are often calculated on survey results (Brown and Cliff, 2004) or consumer confidence (e.g., the Michigan Consumer Sentiment Index). However, surveys are often released with lagged information due to long data collection process and low update frequency, for example, on a weekly or monthly basis (*the Investor Intelligence* used by Brown and Cliff, 2004), which is not suitable for studies at a higher frequency, such as daily or intraday. This difference in data frequency creates a non-synchronicity issue between the sentiment measure and fast-moving market dynamics. In addition, in term of revealing people's attitudes, sentiment measure based on survey data

[4] Alternatively, other approaches are also employed by previous studies, such as weather (Hirshleifer and Shumway, 2003), sporting events (Edmans et al., 2007), aviation disasters (Kaplanski and Levy, 2010) and music (Edmans et al., 2022).

[5] See, the extensive discussion and construction of the widely used Baker and Wurgler (2006) investor sentiment index based on the principal component analysis of six proxies, such as the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium.

is prone to answering bias, information distortion, and unavoidable "cross-validation" limitations (see, e.g., Vosen and Schmidt, 2011; Schober et al., 2016; Conrad et al., 2021).

Vozlyublennaia (2014) and Da et al. (2015) use a search-based measurement alternatively to overcome the issues of the above methods. Specifically, they employ the aggregated volume of Google search queries to proxy public investor sentiment. Google queries serve as investor attention proxy for information demand but differ from sentiment (indirect measurement). In comparison, investor sentiment extracted from media content is the market's prevalent and collective mood or opinions. The content-based method combines the effectiveness of search-based methods with more advantages because it can overcome the indirect proxy issue and confounding problems of search-based measurement. Thus, the content-based method is frequently used to extract investor sentiment in recent literature and is the choice for obtaining investor sentiment in this thesis.

The method for quantitatively gauging content-based investor sentiment follows an identification, categorisation and quantification procedure, namely, textual analysis[6]. Starting from identifying and grouping, one selects keywords from media contents (such as newspapers, magazines or reports mentioned above) and categorises them into different sentiment groups, which are defined by a sentiment dictionary (e.g., Harvard IV-4, Loughran-McDonald) or a natural language processing algorithm, or the combination of two. For example, Tetlock (2007) counts the number of words based on the Harvard IV-4 dictionary to have categorised and quantified sentiment outcomes. Finally, all the individual sentiment values are gauged quantitatively and aggregated to a specific frequency.

[6] Kearney and Liu (2014) provide a detailed survey of investor sentiment extracted from textual analysis.

2.2.2 Social media: an innovative source and approach

According to an investigation by the Federal Reserve Board (2023), investors' habit of updating their investment sets and decisions changes fundamentally along with the evolution of technology. Specifically, the rise of social media networks enables instant spreads of information and sentiment. In recent years, online sources such as social media platforms have been the main communication channels among individuals (Gan et al., 2020), and this has shifted the ways of communication for investors and how they obtain information.

Changes in regulations, moreover, have prompted companies to adapt to investors' new behaviour (SEC, 2008). In 2012, the US Securities Exchange Commission (SEC) reported that "social media is landscape-shifting". With greater Internet access, there are numerous channels for news to be disseminated in a timely way, including firms' official websites, internet message boards and social media. In addition, social media also provides global coverage unmatched by other media tools and the richest information for online research. From the regulator's standpoint, the SEC officially permitted companies to use social media outlets, such as Twitter, for vital information announcements (SEC, 2013). As social media platforms have the advantage of disseminating information at a higher speed to a broader range of audiences than traditional mass media outlets, the SEC also oversights the social media pages under the policy of fair disclosure to ensure investor protection (SEC, 2023). The features of social media and the policies make the platforms popular centres of investment information exchange among market participants.

Social media platforms are one of the premier rich sources of market sentiment because linguistic media content captures hard-to-quantify aspects of assets' fundamentals. Many recent studies document that social media platforms, such as Seeking Alpha, Facebook, Twitter and Reddit, significantly impact financial markets.

Among the first, Antweiler and Frank (2004) show the market predictability of messages on Yahoo! Finance and Raging Bull on Dow Jones Industrial Average volatility and trading volume after controlling the widely used traditional WSJ news. In the same vein, Chen et al. (2014) document that the opinions on Seeking Alpha (e.g., articles and comments) show prediction power for future securities returns and earnings surprises.

Apart from being a new and rich public information source, social media offers several technical advantages for research. Using Twitter as an example, we explain why social media is the optimal choice for this thesis. First, Twitter specialises in instant messages called "tweets". By analysing the tone of these tweets, the extraction and interpretation of news are now viable (Sprenger et al., 2014a). Second, historical tweets data is publicly available as a reliable source[7] and is manageable for analyses given the character limit on Twitter. Indeed, several studies document that tweets volume is related to the daily movement and trading volume of the Dow Jones Industrial Average Index (Bollen et al., 2011). Furthermore, Mao et al. (2011) show that jumps in Twitter feed and volume have a one- to two-day ahead predictive power of stock return. Third, the granularity of Twitter data allows us to study the effect of market sentiment in real-time (Bukovina, 2016; Renault, 2017; Cookson and Niessner, 2023). Twitter information is a reflection of instantaneously synchronous investors' sentiment in a direct way (Schnaubelt et al., 2020).

Finally, regarding effectiveness in capturing sentiment, social media sentiment from Twitter posts is more pronounced than other data, such as investor attention measured by Google search volumes. For instance, Mao et al. (2011) document that Twitter volume of financial term search queries outperforms Google queries in daily market return prediction. Thus, with more researchers being able to collect and manage

[7] They are searchable via webpages or via Twitter's official research API (at the time this thesis was being conducted).

millions of contents from social media platforms, social media sentiment is more frequently used to precisely represent investor sentiment as an innovative and informational source for research (Danbolt et al., 2015; Azar and Lo, 2016; Audrino et al., 2020; Rakowski et al., 2021, Long et al., 2023).

2.2.3 Twitter sentiment effects on financial markets

After the recognition of Twitter as an information platform for listed companies to release critical information (SEC, 2013), Twitter's relevant research has boomed for the last decade. Scholars are generally more interested in the relationship between Twitter sentiment and stock market predictability. For example, Mao et al. (2011) find that Twitter sentiment is a prediction signal that can be three to four days earlier with an 86.7% accuracy. Similarly, Bartov et al. (2018) document that opinions from aggregated Twitter messages can predict a company's both returns and forthcoming quarterly earnings.

Except for the predictability, Sprenger et al. (2014a) focus on extracted sentiment bullishness from Twitter messages and show increased bullishness moves along with the rising stock price. Similarly, Giannini et al. (2019) find that increased disagreement is associated with higher trading volume and volatility. The above shreds of evidence prove that Twitter sentiment affects financial markets in various ways by influencing the opinions and sentiments of users.

There are two extensive debates regarding social media sentiment and financial markets. One is the causality between social media sentiment and market movements. By showing the significant relationship between Sunday's Facebook Gross National Happiness index and subsequent Monday financial market movements, Siganos et al. (2014) argue that the causality is from sentiment to stock markets. Long et al. (2023) employ Reddit posts and uncover a similar transmission channel from social media sentiment to GameStop rallies at 5-, 10- and 30-minute intervals, but the reverse at a 1-minute interval.

Except for the discussion on causality, whether social media sentiment is noise or contains information also attracts much attention. On one hand, some studies show that sentiment may induce a temporary price pressure that moves prices away from the fundamentals (Sun et al., 2016; Behrendt and Schmidt, 2018). On the other hand, studies also show that such social media posts may contain information that moves prices permanently toward a new equilibrium (Azar and Lo, 2016; Gu and Kurov, 2020).

Although many aspects of social media sentiment and financial markets have been discovered, limited research has shed light on how social media sentiment drives price properties. However, the role of social media has not been comprehensively and systematically investigated at high frequency. Renault (2017) uses social media information to test the intraday sentiment effect. He studies the first 30-minute of the trading session sentiment effect on last 30-minute sentiment-driven trading anomaly. He argues that this "very short-lived" anomaly is due to the price pressure created by those sentiment-driven optimistic or pessimistic “irrational investors”. Similarly, Sun et al. (2016) also find that the sentiment effect can persist during the last two hours of a trading session. These studies show that social media sentiment not only has an influence on a weekly or daily frequency but also at intraday level, which is worth further exploring in this thesis.

Besides the impacts on stock return forecasting, social media sentiment is associated with volatility in the financial markets (Siganos et al., 2014; Da et al., 2015). Intuitively, Twitter sentiment induces divergence in people's opinions, increasing trading volume and uncertainty (Goutte, 2019). Behrendt and Schmidt (2018) find that stock market social media sentiment has a pronounced impact on both individual stock level and market level volatility. Studies also document the social media sentiment and volatility relationship in other markets, such as foreign exchange (Sibande et al., 2023) and commodities markets (Han et al., 2017).

2.3 Market Microstructure and Market Dynamics

In this sub-section, I provide an overview of the market microstructure research and market dynamics, which are closely related to the topics from Chapter 3 to Chapter 5.

2.3.1 Price discovery and trades

Market microstructure studies the process by which the trading behaviours of investors are incorporated into the trades and prices eventually, revealing trading mechanisms and the price discovery process (O'Hara, 1998). As one of the main concerns in informational microstructure research, price discovery analyses how information influences the evolution of the underlying value of an asset (Madhavan, 2000).

Literature highlights the significance of information in financial decision-making among investors, assessing the critical role of information flow in affecting orders and price formation. Madhavan and Smidt (1991) argue that information asymmetry is a factor that significantly affects price dynamics at intraday. While various market frictions influence prices[8], Tetlock (2011) documents that information flow can affect the status of frictions (e.g., alleviate information asymmetry) and lead to the revision of market

[8] There are typical fractions such as sunk cost (Benston and Hagerman, 1974), inventory cost (Amihud and Mendelson, 1980) and information asymmetry (Bagehot, 1971), however, studies show that information asymmetry effect dominates the others such as inventory effect. See., Hasbrouck (1988, 1991) and Jones et al., (1994).

participants' and dealers' expectations of the fundamental value of an asset. Therefore, it can ultimately change the supply and demand of securities and result in a new equilibrium.

The price discovery process evolves as trading outcomes of informed traders and market liquidity providers (such as dealers). Informed traders deliver and incorporate information into prices via trading, and they trade as much as possible until the information advantage is fully priced to maximize their profits. This incentive is in line with Grossman and Stiglitz (1980) who argue that profits are fair rewards for information assimilation. With a large number of orders placed in the market, liquidity providers will translate it as information-based trading and quickly match the prices to reflect such information due to risk aversion. Liquidity providers protect themselves from being in a less informed position and reveal the updated new information status via observing the trades. Therefore, trades carry information that markets can learn and facilitate price discovery via impounding information. Studies, such as Easley and O'Hara (1987), Kyle, (1985) and Hasbrouck (1991), show that information can be captured from trade volumes, directions and order flows.

Hasbrouck (1991) models the interactive relationship between midquotes (the average of the bid and ask prices) and trades in an innovative vector autoregressive (VAR) specification. Hasbrouck's informativeness of trade model jointly captures the generating processes of quotes and trades using a VAR model. He regresses midquote revisions against lagged midquotes and trade indicators (contemporaneous and lagged), and regresses trade indicators against lagged midquotes and trades simultaneously [9]. Hasbrouck (1991) examines the price impact after each trade and imposes that both the contemporaneous and lagged trades can impact returns, but only the lagged returns can impact trades.

[9] Please refer to the methodology section of Chapter 3 for further details.

The impact of social media sentiment on price discovery could happen rapidly and frequently within intraday scope. According to French and Roll (1986), the variance of stock returns during intraday from open to close is five times higher than that of the close to open. They explain that public news arrives more often during trading hours while markets are open, and informed traders deliver private information to underlying asset prices through trading. Similarly, Busse and Green (2002) find that news before market opening causes less price response than intraday news which carries more pronounced impacts. They document that positive midday news triggers an immediate price reaction and can be fully incorporated within one minute into prices. Negative news shows opposite influence and it takes 15 minutes to be priced. Foucault et al. (2016) document that the fast price discovery process is facilitated by 'smart' traders.

In addition to informed investors, sentiment-driven traders may also influence price formation, such as informational efficiency. Sentiment can drive investor beliefs and trading decisions in a certain direction. If social media shapes numerous investors' behaviours in a collective manner, they will trade similarly at a point by placing the same direction orders (buy or sell). This effect creates an instantaneous large buy- or sell-force on the transaction price, pushing the transaction price away from its efficient price (underlying value of an asset with all public information priced). However, whether such sentiment-induced price movements are transitory price pressure (noise) or permanent effects (information) is still under debate (see., Sun et al., 2016; Gao et al., 2018).

The above reasons motivate us to study the impact of social media sentiment on stock markets under a market microstructure umbrella in Chapter 3 and Chapter 4.

2.3.2 Market quality and informational efficiency

The financial market quality is a concept in market microstructure related to market liquidity, volatility and informational efficiency (Indriawan, 2020). Such aspects are crucial for the well-functioning of financial markets, for example, whether investors' orders can be executed at their best prices and order sizes. Hence, it also indicates whether a market can provide quality service and attract investment opportunities. For customers, markets with high quality display transparent market functions, high liquidity and better informational efficiency, which incur lower transaction costs for them.

Modern technological changes increase the interest in market quality, especially for informational efficiency. The rise of new media innovations fosters rapid information exchange and dissemination. It highlights the importance of corresponding research in social media influencing informational efficiency: a discipline that studies how information is accurately and effectively incorporated into prices. According to Fama (1970), efficient market prices reflect the intrinsic value of assets and function as the cornerstone for allocating resources in capital markets. In general, if a market is informationally efficient, asset prices should promptly and accurately integrate all publicly available information. Intuitively, better information efficiency means less return dependence or fewer profit opportunities that can be inferred from past prices.

Immediacy and accuracy are two crucial aspects of information efficiency. Immediacy represents how quickly a market can digest new information and incorporate it into the relevant asset prices. The less delay in impounding news, the better immediacy. Accuracy refers to whether a market correctly reflects asset-relevant information, for example, positive (negative) news increase (decrease) prices. As such, prices can be proxied as accurate reflections of the fundamental values of underlying assets promptly.

The relationship between market informational efficiency and market participants matters to each other. On the one hand, higher market informational efficiency indicates better price informativeness for investors. For example, Dávila and Parlatore (2021) document that price informativeness is negatively associated with trading costs under the coexistence of informed and uninformed traders. On the other hand, Boehmer and Kelley (2009) document that equities with higher levels of investor informativeness (e.g., institutional traders) demonstrate more pricing efficiency. It indicates that market environment, in terms of pricing efficiency, increases when more information is available to investors (Breugem and Buss, 2019).

Informed traders enhance market efficiency by accelerating the incorporation of value-relevant information into stock prices, which is empirically found in both emerging markets (Bae et al., 2012) and developed markets (He and Shen, 2014). However, sentimental traders may trade in the opposite direction to the efficient price and impose negative impacts on market informational efficiency due to their informational disadvantage and limitations.

Market microstructure literature offers several measures for informational efficiency. The idea lies in that asset prices in an efficient market already reflect all public information and will not change until new fundamental value-relevant information arrives. Given that such information comes randomly, prices in a market without frictions should change in a random pattern accordingly. Thus, the degree to which prices deviate from such a random walk is an inverse measurement of informational efficiency. Simply put, a lower extent of random walk of asset prices indicates higher informational inefficiency.

This thesis uses two informational efficiency measures $Autocorrelation$ and $Variance\ Ratio$ to capture the extent to which asset prices deviate from a random walk following Hendershott and Jones (2005), O'Hara and Ye (2011), and Comerton-Forde and

Putniņš (2015). $Autocorrelation$ gauges the daily absolute midquote return autocorrelation at certain frequencies. This metric calculates informational efficiency by capturing both the under and overreaction of returns to the arrival of new information. Smaller values indicate that prices follow a random walk, and therefore, a more efficient market.[10]

The second informational efficiency measure is the absolute excess variance ratio. This measure indicates whether the relationship between the variance of returns at various horizons is linear. The underlying assumption for an efficient market is that the variance of its returns is equal to k times the variance measured at a higher frequency. A higher value indicates slower information incorporation and lower informational efficiency.

2.3.3 Market dynamics and spillovers

The literature has shown that different asset classes are interconnected to some extent. This connectivity is higher in turbulent periods, such as financial crises or economic downturns. Thus, one possible explanation for such connectedness among asset classes is from a market volatility perspective. For example, the safe-haven literature finds a relationship between equity with gold markets (Baur and McDermott, 2016), while the market fear and volatility literature find a link between equity and foreign currency markets (Goddard et al., 2015) or equity and commodity markets (Gao and Süss, 2015).

However, the real trading environment is more complex. For instance, the financial markets may be interconnected through investor sentiment spillover, given that the consensus is that sentiment affects different financial markets. The literature documents significant impacts of investor sentiment on various financial markets,

[10] Please refer to the methodology section of Chapter 4 for further details on autocorrelation and variance ratio.

including equity markets (Baker and Wurgler, 2006, 2007; Edmans et al., 2007), fixed income markets (Laborda and Olmo, 2014), exchange rates or commodity markets (Smales, 2014; Gao and Süss, 2015). In addition, periods of high (low) sentiment are associated with higher (lower) market returns or volatilities (Da et al., 2015; Behrendt and Schmidt, 2018). This indicates that investor sentiment can be another linkage under such a multi-asset setting.

Despite the extant studies on social media sentiment and different individual financial markets, such as equity (Rakowski et al., 2021), bonds (Alomari et al., 2021), foreign exchange (Goddard et al., 2015), and commodities (Fan et al., 2023), it remains as an underexplored gap in the literature that whether social media sentiment spillovers across different asset classes. This is critical to lend support for the behavioural factors for asset pricing and formulate strategy in balancing investment positions in diversified portfolios.

This research employs the Diebold and Yilmaz (2014) connectedness measure, which is related to the economic notion of variance decomposition. In this process, the forecast-error variance of a variable is decomposed into parts attributed to the various variables in the system. It can uncover the spillover relationship between each market's sentiment and volatility and show how social media sentiment casts its influence beyond one single financial market[11].

In summary, this thesis expands the literature on social media sentiment and financial markets by examining social media's effects on other vital aspects of markets, such as price impact, informational efficiency and spillovers.

[11] Please refer to the methodology section of Chapter 5 for further details.

Chapter 3

The Price Impact of Tweets: A High-Frequency Study

3.1 Introduction

The literature has documented that mass media outlets such as newspaper articles, opinion columns, and internet message boards affect the financial markets (Huberman and Regev, 2001; Antweiler and Frank, 2004; Tetlock, 2007; Barber and Odean, 2008; Dougal et al., 2012). In recent years, however, social media has become one of the main communication channels. Social media websites such as Seeking Alpha, Motley Fool, and social media applications such as Facebook and Twitter have dominated the ways in which people obtain and exchange information (Chen et al., 2014; Siganos et al., 2014; Gan et al., 2020; Audrino et al., 2020; Rakowski et al., 2021). These social media applications have the advantage of disseminating information at a much higher speed than the traditional mass media outlets. Following this trend, the U.S. Securities Exchange Commission (SEC) recognizes social media as an official news announcement channel (SEC, 2013).[12]

Studies on traditional news media have shown that the arrival of news is associated with movements in security prices (see, e.g., Tetlock, 2007; Fang and Peress, 2009; Engelberg and Parsons, 2011; Mangee, 2018). For example, using data at a daily frequency, Tetlock (2007) finds that strong pessimism from media can forecast market

[12] Source: https://www.sec.gov/news/press-release/2013-2013-51htm.

price declines but with a subsequent price correction. Using data at a monthly frequency, Fang and Peress (2009) show that media coverage explains the cross-sectional differences in stock returns across firms. Mangee (2018) documents that investor sentiment based on contextualized information from news media explains medium- to longer-term swings in aggregate stock prices. None of the above associations reveal the transmission of which news gets impounded into prices.

With social media being a fast and more efficient information dissemination channel, investors can quickly update their information set and revise their trading decisions. This may affect the financial markets in several ways. First, social media posts may induce a temporary price pressure that moves prices away from the fundamentals (Baker and Wurgler, 2006; Tetlock, 2007; Behrendt and Schmidt, 2018). Second, such posts may contain information that moves prices permanently toward a new equilibrium (Bollen et al., 2011; Azar and Lo, 2016; Gu and Kurov, 2020). To disentangle the above relations, it is necessary to study the connection between social media sentiment and security prices in a high-frequency setting. Therefore, in the current study, we examine the immediate effect of social media activity on stock prices.

There is fast-growing literature that examines the linkage between social media and security prices at the intraday level. Sun et al. (2016), for instance, study the impact of online news and media sentiment on S&P500 index returns. They find that intraday returns are predictable using lagged half-hour investor sentiment. Renault (2017) uses the social media platform *StockTwits*[13] to test the intraday sentiment effect and finds that online investor sentiment helps forecast intraday stock index returns. In particular, the first half-hour change in investor sentiment predicts the last half-hour S&P 500 index ETF return. At the firm level, Broadstock and Zhang (2019) find firms' price dynamics

[13] StockTwits is a social microblogging platform dedicated to financial markets where users share information about the market and individual stocks, in the form of short messages.

are susceptible to social-media sentiment pricing factors. Schnaubelt et al. (2020) show that machine learning can be used to extract predictive information from tweets that can be translated to statistically and economically significant excess returns. While these studies have shown that social media and markets are related, the question remains on how social media sentiment transmits to the movements in security prices. For instance, does a positive sentiment lead to more trades? Do trades become more informative and have a higher price impact? Our study fills this gap in the literature by examining the mechanism that links sentiment and prices using high-frequency data.

To study social media sentiment, we use Twitter feeds (also called 'tweets') to construct a proxy for social media sentiment, which we refer to as *Twitter sentiment* hereafter (see, e.g., Gu and Kurov, 2020). This choice is based on several reasons. First, according to Alexa[14], Twitter is one of the top social networking and microblogging services globally. In 2020 and 2021, there were more than 500 million tweets per day (Rakowski et al., 2021). This translates to a very granular dataset, with each tweet being time-stamped to the nearest second, allowing a study at the intraday level. Second, unlike other social media platforms with postings of images and videos, Twitter specializes in instant messages with a cap of 280 characters. The textual nature of tweets allows for the extraction of social media sentiment. It overcomes many issues related to an indirect data source, such as answering bias (e.g., survey), the idiosyncratic non-sentiment-related indicator[15] (e.g., trading volume, option implied volatilities), or confounding causality (e.g., Google search queries). Third, historical tweets data is reliable and has been used in many studies (see, e.g., Azar and Lo, 2016; Schnaubelt et al., 2020; Rakowski et al., 2021).

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[14] Alexa.com is a subsidiary of Amazon.com, Inc., and is the world's leading provider of web traffic data and analytics.

[15] This refers to the indicator being more a proxy of equilibrium of economic forces than investor sentiment (Baker and Wurgler, 2007).

We focus on tweets related to the SPDR S&P 500 ETF (ticker symbol: SPY) as a representation of the U.S. stock market. Baker and Wurgler (2007) define investor sentiment as a belief about future cash flows and investment risks that are not justified by economic fundamentals. As such, sentiment may not be derived from financial market conditions, and therefore, exogenous to economic fundamentals. Therefore, to assess the impact of social media sentiment on stock prices, we rely on the assumption that investor sentiment is an exogenous shock to the financial markets (see, e.g., Baker and Wurgler, 2007; Siganos et al., 2014; Behrendt and Schmidt, 2018). This assumption is common in the literature.[16] In fact, Siganos et al. (2014) use Facebook gross national happiness index as a proxy of sentiment and find that sentiment on Sunday affects stock returns on Monday, suggesting causality from sentiment to stock markets. Based on this assumption, we modify Hasbrouck's (1991) informativeness of trades model by interacting the sentiment measure with the trade variable in the vector autoregression (VAR) model.[17] This modified VAR model allows us to measure the price impact of social media sentiment through its impact on trades.

We find that Twitter sentiment intensifies the impact of trades on returns. Trades have a greater price impact with an increase in the number of tweets or a higher degree of bullishness. This finding suggests that as there is more social media discussion related to the stock market, the price impact of trades becomes stronger. Similarly, the impact of buyer-initiated trades on stock prices is stronger when the market sentiment is bullish. This price impact persists even after controlling for volatility, liquidity shocks, and the effect of quotes on returns. Furthermore, both bullish and bearish tweets amplify the effect

[16] According to De Long et al. (1990), rational arbitrageurs are sentiment-free traders, while irrational traders are more apt to exogenous sentiment. Studies have also documented that investor sentiment could be driven by exogenous factors such as weather (Hirshleifer and Shumway, 2003; Goetzmann et al., 2015), seasonal affective disorders (Kamstra et al., 2003), day-of-the-week (Birru, 2018; Hirshleifer et al., 2020), daylight saving change (Kamstra et al., 2000), or sporting events (Edmans et al., 2007).

[17] Similar modification is applied in Dufour and Engle (2000) where they assess the price impact of trade duration on security prices.

of trades on returns, indicating no asymmetric price impact of Twitter sentiment. Finally, this impact of Twitter sentiment on prices causes a permanent price movement, showing that Twitter sentiment contains information.

Our study contributes to the literature in several ways. First, we add to the understanding of the impact of social media sentiment at the intraday level (see, e.g., Sun et al., 2016; Renault, 2017, Broadstock and Zhang, 2019). By modeling the channel by which sentiment affects stock price movements, our findings reveal a significant impact from social media sentiment to stock prices through its impact on trades at the intraday level, a mechanism that, to our best knowledge, has not previously been documented in the literature. Second, by examining whether social media sentiment temporarily or permanently affects prices, we contribute to the ongoing debate on the informativeness of social media (see, e.g., Sprenger et al., 2014b; Karagozoglu and Fabozzi, 2017; Schnaubelt et al., 2020). Our findings support the view that Twitter sentiment contains information about the stock market.

The remainder of the paper proceeds as follows. Section 3.2 discusses the related literature. Section 3.3 introduces data sources and how we construct Twitter sentiment. In Section 3.4, we present the methodology. We report the empirical results in Section 3.5 and the robustness tests in Section 3.6. Section 3.7 concludes.

3.2 Literature Review

In recent years, there has been a growing literature that studies the impact of social media on the financial markets (see, e.g., Gan et al., 2020; Audrino et al., 2020; Rakowski et al., 2021). Such relation is attributable to investors' limited attention and cognitive processing ability and the attention-grabbing nature of social media posts (Peng and Xiong, 2006; Gan et al., 2020). These studies find that investor sentiment can be extracted from social media posts, and this sentiment causes market movements (Antweiler and Frank, 2004;

Danbolt et al., 2015).[18]

As one of the main social media platforms, Twitter has been recognized as an important tool for disseminating companies' information. Specifically, the SEC issued an official report in 2013 allowing companies to use social media outlets like Twitter to disseminate key information. In fact, studies have shown that tweets may contain company-specific news. Sprenger et al. (2014b), for instance, apply computational linguistics to distinguish between good and bad news. They find that investor discussion on Twitter systematically mirrors external news, validating the use of the platform for financial market research. Azar and Lo (2016) find that sentiments extracted from tweets can successfully predict a firm's forthcoming quarterly earnings and announcement returns. Leitch and Sherif (2017) document a negative relationship between Twitter trends on the announcement of CEO succession and stock returns in the U.K. and the U.S.

Numerous studies have explored the linkage between Twitter sentiment and the financial markets. For example, Bollen et al. (2011) show that the mood extracted from tweets can predict the stock market. In particular, the accuracy of the Dow Jones Industrial Average (DJIA) predictions can be significantly improved by the inclusion of Twitter sentiment in the model. Sprenger et al. (2014a) construct proxies for investor sentiment by measuring the bullishness and agreement level of tweets. They find that increased bullishness is associated with rising stock prices. Giannini et al. (2019) use Twitter sentiment to measure investor disagreement. They find that both convergence of opinion and divergence of opinion are associated with greater trading volume reaction to earnings news.

[18] There are various approaches to measure investor sentiment. For instance, several studies use market-based proxies such as trading volumes, grey market prices or option implied volatilities to measure sentiment (Baker and Wurgler, 2007; Laborda and Olmo, 2014). Other studies use weekly or monthly released survey-based indices (Brown and Cliff, 2004; Kurov, 2008) and search-based proxy such as Google query volume (Da et al., 2011; Vozlyublennaia, 2014). However, extracting sentiment from social media content is more useful to investors who need to quickly update their information set and revise their trading decisions.

While the above studies show a linkage between Twitter sentiment and financial markets, such association does not reveal the transmission of which information from social media gets impounded into prices. This can be attributed to the use of low frequency (daily or monthly) data in many of the previous studies, whereas social media involves a faster update of investor information sets and trading decisions. As such, it remains an open question whether Twitter sentiment induces a temporary price pressure that moves prices away from the fundamentals or whether it is actually informative and able to move prices permanently.

There is an ongoing debate about if Twitter sentiment provides a noisy or an informative signal. Gu and Kurov (2020) show that Twitter sentiment predicts stock returns without subsequent reversals. In particular, the results show that Twitter sentiment provides new information about analyst recommendations, analyst price targets, and quarterly earnings. Behrendt and Schmidt (2018), on the other hand, show that Twitter sentiment captures noise, where noise traders create a temporary buy- or sell-pressure on the stock price, pushing the prices temporarily away from fundamentals but followed by a significant price reversion. Studying the linkage between Twitter sentiment and stock market returns at the intraday level will help disentangle the above two components and uncover the mechanism through which Twitter sentiment affects the stock price processes.

There are several high-frequency studies relating investor sentiment on stock prices. Renault (2017), for instance, uses the social media platform *StockTwits* and aggregates individual message sentiment at half-hour intervals. He finds that the first half-hour change in tweets sentiment predicts the last half-hour S&P 500 index ETF return. He argues that this "very short-lived" anomaly is due to the price pressure caused by sentiment-driven noise trading. Agrawal et al. (2018) find that the demand for and supply of liquidity are influenced by investor sentiment and that market makers can profit by using extreme bullish and bearish emotions in social media as a real-time barometer for the end of momentum and a return to mean reversion. In contrast, Sun et al. (2016) find that the first half-hour effect of sentiment persists during the last two hours of a trading session but argue this sentiment effect is independent of the intraday momentum effect and it contains economic values rather than just noise. This standpoint is empirically supported by the evidence from Nofer and Hinz (2015), who develop a profitable trading strategy based on Twitter sentiment in Germany's stock market. From market-wide to firm-level, Broadstock and Zhang (2019) find that company stocks returns are sensitive to both firm-specific and market-wide sentiment. Studying the effect of Twitter sentiment in an event study, Liew and Wang (2016) find that Twitter sentiment matters for IPO first-day performances, but the nature of this relationship appears very complex at the intraday level. Instead, Schnaubelt et al. (2020) argue that using the investor sentiment as a real-time barometer is profitable when tracking clustered tweets related to attention-grabbing events. While the above studies show that social media sentiment influences stock returns at the intraday level, they do not reveal the mechanisms on how Twitter sentiment gets incorporated into stock prices.

The closest paper to ours is Kurov (2008), who examines the impact of investor sentiment on the trading behaviours of index futures traders. He finds that higher investor sentiment leads to more active trading. He also documents that order flow is less informative when investors are optimistic. However, the study uses low-frequency sentiment measures (weekly) to study the impact of sentiment on high-frequency stock prices data (at a minute frequency). More specifically, he uses two sentiment measures based on weekly surveys conducted by *the Investor Intelligence* (representing the outlook of about 150 independent market newsletters) and the American Association of Individual Investors (AAII), respectively. This difference in data frequency creates a non-synchronicity issue between prices and the sentiment measure, i.e., the intraday market reaction is matched with investor sentiment over the week. In addition, sentiment measure based on survey data is prone to answering bias, information distortion, and unavoidable "cross-validation" limitations (see, e.g., Vosen and Schmidt, 2011; Schober et al., 2016; Conrad et al., 2021). In contrast, Twitter sentiment directly reflects the mood of users' and is naturally available at a high-frequency, hence alleviating the non-synchronicity issue and biases related to survey-based sentiment measures.

3.3 Data

3.3.1 Tweets and sentiment extraction

We focus on the SPDR S&P 500 Trust ETF (ticker: SPY) as a representation of the US stock market[19]. We collect tweets from Twitter. Following Sprenger et al. (2014a), we use *cashtags* to search for tweets related to a particular security, i.e., '$SPY' to obtain tweets related to SPY. Since Twitter officially introduced cashtags only in July 2012, we focus our sample period from August 1, 2012, to December 31, 2018, a total of 1,610 trading days. There are 2.18 million tweets related to $SPY in total. Every tweet is reported in Eastern Time (ET) and timestamped to the nearest second. We focus on tweets during the trading hour between 9:35 and 15:55 ET to match our stock market data.[20] Each tweet is cleaned from irrelevant characters, including emojis and links.

Similar to Azar and Lo (2016) and other studies on this topic, we use an extensive electronic lexical database as a language processing tool to assign a tone score for each tweet in order to group it into negative, neutral, or positive categories (ranging from -1 to

[19] SPY is designed to track the S&P 500 stock market index. It is one of the largest and oldest ETFs in the US market, widely and actively traded by vast number of investors. According to Chen et al. (2016), comparing to other S&P500 index or US market derivatives, SPY dominates the price-discovery process in the S&P 500 index markets.

[20] We exclude the first and last five minutes of trading to minimize the confounding effects of market opening and closing.

+1). More specifically, we use a lexical database *WordNet*[21], which is widely adopted for social media sentiment evaluation and classification (Navigli, 2009; Bhala and Abirami, 2014; AlMousa et al., 2021; Kocoń and Maziarz, 2021). We access WordNet via a Python package *TextBlob*, which provides an Application Programming Interface (API) for natural language processing, including phrase extraction, sentiment analysis, and classification. Specifically, we consider a tweet as positive if its tone score is positive, negative if the score is negative, and neutral when this is zero. In the robustness section, we show that the main results do not hinge on how we define the negative, neutral and positive tweets (See., tweets sentiment extraction examples in Appendix I).

To assess the accuracy of our method, we follow Antweiler and Frank (2004) and manually conduct a pilot test on 1000 tweets and group them into negative, neutral, or positive categories before applying the dictionary to the entire dataset. Our method provides the correct groupings in approximately 90% of the training dataset. This is comparable to Antweiler and Frank (2004) who obtain an accuracy of 88% for their training dataset.

We aggregate the tweets data to a minute frequency to ensure a continuous series. We then use these aggregated data to construct three sentiment measures commonly used in the literature (see, e.g., Antweiler and Frank, 2004; Sprenger et al., 2014a), which we generally call *Twitter sentiment.* First, to assess whether the total number of tweets impacts stock market prices, we construct $MessageVol_t$, as follows

$$MessageVol_t = \ln\left(1 + M_t^{Positive} + M_t^{Negative} + M_t^{Neutral}\right), \quad (3.1)$$

[21] This database contains 155,327 nouns, verbs, adjectives and adverbs organized in 175,979 synsets (sets of one or more synonyms that are interchangeable in some context) of cognitive synonyms for a total of 207,016 word-sense pairs of English for sentiment analysis. Additionally, all synsets are interlinked through conceptual-semantic and lexical relations as the computational lexicon of English for word sense disambiguation (Navigli, 2009).

where $M_t^{Positive}$, $M_t^{Negative}$ and $M_t^{Neutral}$ are the sum of positive, negative, and neutral tweets in the minute interval t, respectively. Second, we construct a bullishness signal, $Bullishness_t$ as follows,

$$Bullishness_t = \ln\left[\frac{1+M_t^{Positive}}{1+M_t^{Negative}}\right]. \tag{3.2}$$

This measure captures the sentiment embedded in tweets during the minute interval t. Positive (negative) bullishness reflects positive (negative) sentiment. Third, we compute $AgreementIndex_t$ to measure the prevailing level of agreement among tweets as:

$$AgreementIndex_t = 1 - \sqrt{1 - \left(\frac{M_t^{Positive} - M_t^{Negative}}{M_t^{Positive} + M_t^{Negative}}\right)^2}\ . \tag{3.3}$$

This index ranges from 0 and 1, where a higher value indicates greater agreement.

Panel A of Table 3.1 reports daily summary statistics for tweets data. On average, there are 703 tweets related to SPY per day during the trading hours or roughly two tweets per minute. On average, tweets are slightly positive about the SPY, with a positive average bullishness of 0.16. This result is consistent with the existing literature that investors are generally more optimistic in the markets (Baker and Wurgler, 2006; Stambaugh et al., 2012; Kim and Kim, 2014). The average AgreementIndex is 0.42 with a slight variation in its percentiles from 0.31 (5th percentile) to 0.52 (95th percentile). This indicates, on average, there is more disagreement among tweets related to the stock market.

Table 3. 1. Summary Statistics

This table reports the daily summary statistics for the tweets (Panel A) and SPY market data (Panel B) for the sample period August 1, 2012 to December 31, 2018 (1,610 trading days) during the trading hours from 9:35 to 15:55 ET. *TotalTweets* is the total number of positive, negative and neutral tweets. *MessageVol* is the logarithm of the total number of tweets. *Bullishness* represents investors' sentiment. *AgreementIndex* indicates the degree of agreement among tweets. *Trades* is the total number of trades. *Volume* is the total trading volume. *OIBV* is the signed volume order flow. *MidReturn* is the daily return computed using intraday midquotes. S.D. is the standard deviation.

	Mean	S.D.	Median	5^{th} Percentile	95^{th} Percentile
Panel A: Tweets					
TotalTweets	703	348	621	350.45	1,293.55
MessageVol	0.84	0.25	0.79	0.51	1.29
Bullishness	0.16	0.07	0.15	0.07	0.31
AgreementIndex	0.42	0.07	0.43	0.31	0.52
Panel B: SPY					
Trades('000)	126	70	106	64	256
Volume('000)	71,170	32,848	65,169	33,120	1,320,718
OIBV('000)	196	2,163	137	-3,265	3,806
MidReturn(bps)	1.07	65.60	4.38	-109.56	92.28

3.3.2 Stock market data

For the stock market data, we collect transaction-level data of SPY during the market trading hours between 9:35 and 15:55 ET over the sample period from Refinitiv Tick History. The data contains all activity observed at the national best bid and offer, which includes recorded transactions and revisions in the bid and ask prices and depths, all time-stamped to the nearest millisecond. Our observations from the intraday data show a number of anomalous records that appear to be recording errors. Therefore, we remove transactions where trading volume is above the day's 99.9th percentile. We then follow Chordia et al. (2001) and drop observations using the following filters: (1) non-positive quoted spread; (2) quoted spread greater than 5; (3) effective spread/quoted spread greater than 4; (4) percentage effective spread/percentage quoted spread greater than 4; (5) quoted spread/transaction price greater than 0.4.

We treat multiple trades that are executed with the same timestamp as one trade, as they typically reflect a trade initiated by one market participant but executed against the limit orders of multiple market participants. In such cases, we use the value-weighted average price and aggregate the volume traded. Each trade is classified into buyer- and seller-initiated trades using the Lee and Ready (1991) algorithm. A trade is classified as buyer- (seller-) initiated if the transaction price is above (below) the prevailing midquote. For trades that occur at the midquote, we employ the tick rule and compare the current with the previous transaction price, i.e., buyer- (seller-) initiated if transaction price is above (below) the previous transaction price and undetermined otherwise. Similar to the tweets data, we aggregate the transaction-level data at a minute interval. We then compute the aggregate signed trading volume for each interval. Finally, to reduce the effect of outliers, we winsorize the minute level data per day at 2.5% each tail.

Panel B of Table 3.1 reports the daily statistics for SPY over the sample period. We report the daily number of trades, trading volume, signed order flow (OIBV), and midquote return. On average, there are 126,000 trades and 71 million ETF units traded each day. In terms of order flow, there are more buy transactions on average, as shown by the positive figure. The average daily midquote return is 1.07 basis points (bps).

3.4 Methodology

To investigate the price impact of social media sentiment on stock market, we build on Hasbrouck (1991) informativeness of trade model[22]. Hasbrouck jointly models the generating processes of quotes and trades using an l-lags vector autoregressive (VAR) specification as follows,

$$\begin{aligned} r_k &= \sum_{i=1}^{l} \alpha_i r_{k-i} + \sum_{i=0}^{l} \beta_i x_{k-i} + \varepsilon_{1,k}, \\ x_k &= \sum_{i=1}^{l} \mu_i r_{k-i} + \sum_{i=1}^{l} \delta_i x_{k-i} + \varepsilon_{2,k}, \end{aligned} \tag{3.4}$$

where r_k represents the revision in the quote midpoint after a trade k and x_k is a trade indicator that equals 1 for buyer-initiated and -1 for seller-initiated trades. The terms $\varepsilon_{1,k}$ and $\varepsilon_{2,k}$ are mutually and serially uncorrelated white noises that represent trade-unrelated and trade-related shocks, respectively. Hasbrouck (1991) imposes that in the first equation, both the contemporaneous and lagged trades can impact returns, but in the second equation, only the lagged returns can impact trades. This model is estimated using ordinary least squares (OLS).

To understand the role of sentiment on movements in prices, we modify the VAR model in Equation (3.4) by including a Twitter sentiment measure. More specifically, we interact the trade x in the VAR with a measure of Twitter sentiment. We therefore

[22] Hasbrouck's (1991) model analyses the price and trade dynamics and reveals that the price discovery process depends on the characteristics of trades and trade-related variables that might be informative. Employing social media sentiment to interact with Hasbrouck's model allows us to observe how social media sentiment engages with price and trade dynamics in a systematic VAR framework, studying social media sentiment's price impact with the intention to test the informational role of social media sentiment.

implicitly assume that sentiment is an exogenous variable in the VAR, i.e., sentiment could affect trades and returns, but not the other way round, as explained previously. Unlike Hasbrouck (1991) who examines the price impact after each trade, however, we replace x_k in Equation (3.4) with the signed volume order flow for each minute interval t.[23] Time aggregation of returns and order flow reduce the synchronicity issue between the trade prices and trade sizes (Kurov, 2008). At the same time, it allows us to ensure a continuous time series for our tweets and market data. Furthermore, Chordia et al. (2005) explain that signed volume order flow is a better proxy for trading activity and has a more meaningful relation to the direction and magnitude of price changes. Thus, our modified VAR model is as follows,

$$\begin{aligned} r_t &= \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i}) x_{t-i} + \varepsilon_{1,t} \\ x_t &= \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i}) x_{t-i} + \varepsilon_{2,t}, \end{aligned} \tag{3.5}$$

where $STMT_t$ is either the *MessageVol*, *Bullishness*, or *AgreementIndex* for each minute interval t, defined in the previous section and x_t is the signed volume order flow. Following Dufour and Engle (2000), we employ five lags in the VAR[24]. The coefficients of interest are θ_i, which are the coefficients of the interactions $STMT_{t-i} \cdot x_{t-i}$ in the return equation. These coefficients provide evidence of the impact of Twitter sentiment on prices at high frequency. If $\sum_{i=0}^{5} \theta_i$ is significantly different from zero, we can conclude that the Twitter sentiment affects SPY prices through its impact on trades. In addition, we compare the sign of the coefficients β_i and θ_i in the return equation. If both coefficients have the same (different) signs, it suggests that Twitter sentiment enhances (weakens) the impact of trades on prices.

[23] Brown et al. (1997), Kurov (2008) and Huang et al. (2021) also use time aggregation for the signed order flow to replace the trade variable in Hasbrouck (1991) VAR model.

[24] We also perform the regression using different lags ranging from 3, 10, and 20, and the main results are qualitatively similar to those obtained using 5 lags (see., Section 3.6.2).

3.5 Empirical Results

3.5.1 Price impact of tweets

To investigate the price impact of Twitter sentiment, we estimate Equation (3.5) for each day using OLS based on data aggregated at the one-minute frequency. To ease comparison, we normalize all variables in Equation (3.5). In Table 3.2, we report the average of those estimates along with their Newey-West corrected t-statistics.

Turning first to Panel A, we find that the three different sentiment measures provide similar results. For instance, the sum of α_i coefficients for *MessageVol* is -0.0736 and statistically significant at the 1% level. This indicates a mean reversion in returns. The sum of β_i coefficients is 0.4333, also statistically significant at the 1% level. This implies that midquote returns increase (decrease) with buy (sell) orders, consistent with Hasbrouck's (1991).

We are particularly interested in the coefficients θ_i, i.e., the coefficients of the interaction term $STMT_{t-i} \cdot x_{t-i}$ in the return equation. The coefficient for the contemporaneous effect θ_0 is positive and statistically significant for all three sentiment measures, indicating that the impact of sentiment on prices occurs relatively quickly. The sum of θ_i coefficients is positive and statistically significant at the 1% level for message volume and at the 5% level for bullishness. Our findings indicate that the impact of trades on SPY prices is affected by the increase in the number of tweets and the bullish sentiment in Twitter about SPY. Given that β_i and θ_i share the same sign, our results also indicate that the impact of trades on intraday returns is stronger when it is interacted with Twitter sentiment. Specifically, all else being equal, a one-unit increase in Twitter sentiment will significantly enhance the marginal effect of signed trades, resulting in an increase between 1.5% and 6.9%[25]. In other words, Twitter sentiment enhances the effect of trades on prices. This finding extends the results of Antweiler and Frank (2004), Sprenger et al. (2014a), and Schnaubelt et al. (2020) by showing that sentiment influences intraday stock market returns through its impact on trades. Similarly, we find that *AgreementIndex* has a positive marginal effect on the price impact of trades. However, we do not find this effect to be statistically significant, indicating that returns are not significantly affected by the divergence level of investors' opinions on Twitter.

[25] The values are calculated as 0.0064/0.4385 for Bullishness and 0.0297/0.4333 for Message Volume (summed coefficients for sentiment and signed order flow in Table 3.2).

Table 3. 2. Vector Autoregression Estimation for Twitter Sentiment

This table reports the coefficient estimates of the VAR model for Twitter sentiment impacts. The estimation model is as below, the results of return equation are presented in Panel A, and the results of trade equation are presented in Panel B.

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i}) x_{t-i} + \varepsilon_{1,t}$$

$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i}) x_{t-i} + \varepsilon_{2,t}$$

where x_t is volume of signed order flow at the time interval t, r_t is trade return calculated from the natural logarithm of midquote at the t-th minute, and $STMT_{t-i}$ is one of the following Twitter sentiment measures: (i) *MessageVol*: the logarithm of the total number of tweets, (ii) *Bullishness*: a measure of investors' sentiment, or (iii) *AgreementIndex*: a measure of agreement among tweets. All variables are normalized. Newey-West corrected t-statistics are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance level.

Panel A: Return equation	α_i		β_i		θ_i								
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*Lag0*	*Lag1*	*Lag2*	*Lag3*	*Lag4*	*Lag5*	*Sum of lags*	*t-stat*	*Adj-R²*
MessageVol	-0.0736***	(-17.49)	0.4333***	(66.06)	0.0185***	0.0043***	0.0022*	0.0016	0.0016	0.0014	0.0297***	(10.43)	0.33
Bullishness	-0.0758***	(-17.49)	0.4385***	(64.64)	0.0027*	0.0022*	-0.0004	0.0003	-0.0007	0.0025**	0.0064**	(2.08)	0.33
AgreementIndex	-0.0748***	(-17.29)	0.4382***	(67.78)	0.0051***	-0.0010	-0.0022*	0.0003	0.0008	0.0006	0.0036	(1.16)	0.33

Panel B: Trade equation	μ_i		δ_i		λ_i							
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*Lag1*	*Lag2*	*Lag3*	*Lag4*	*Lag5*	*Sum of lags*	*t-stat*	*Adj-R²*
MessageVol	-0.0043	(-0.46)	0.2512***	(68.49)	-0.0086***	-0.0086***	-0.0030**	-0.0038**	-0.0009	-0.0249***	(-8.50)	0.05
Bullishness	-0.0050	(-0.54)	0.2493***	(70.63)	-0.0016	0.0000	-0.0010	-0.0006	0.0017	-0.0016	(-0.50)	0.05
AgreementIndex	-0.0057	(-0.62)	0.2492***	(69.93)	-0.0018	-0.0001	-0.0008	0.0000	0.0003	-0.0024	(-0.80)	0.05

Panel B of Table 3.2 shows the impact of Twitter sentiment on the signed volume order flow. The sum of δ_i coefficients for the signed volume order flow is positive and statistically significant at the 1% level. This indicates persistence in order flow, i.e., purchases tend to follow purchases, and sales tend to follow sales. Examining the λ_i coefficients for the interaction terms, we observe that they are negative for all three sentiment measurements, although they are only statistically significant for the message volume. We interpret this finding as a higher message volume reduces the persistence in trades in the subsequent minutes. In other words, when there are more tweets about SPY, the persistence in order flow will be less pronounced. We do not observe this persistence to be affected by either the level of Bullishness or AgreementIndex.

In summary, Twitter sentiment is linked to intraday stock returns. In particular, the increase in volume and bullishness of tweets can intensify the impact of trades on intraday returns. These findings indicate that tweets may serve as a predictor of future stock market movements at the intraday level. In the next section, we further examine the informativeness of Twitter sentiment.

3.5.2 Analysis of the System's Dynamics

To further illustrate the impact of tweets, we examine their long-run price impact. More specifically, we apply a one standard deviation shock to each of our Twitter sentiment measures and compute the cumulative returns from the VAR in Equation (3.5). To initiate the loop, we give initial values equal to one (zero) for midquote returns and OIBV (Twitter sentiment) from the first to the fifth minute, and we give a Twitter sentiment shock with an initial value equal to one at the sixth minute. If tweets contain information, we expect a permanent price movement without reversion. Conversely, if tweets contain mostly noise, we should see a temporary price deviation followed by a correction. We compute the cumulated return dynamics daily over our sample period and plot its average in Figure 3.1.[26]

Figure 3.1 shows that the cumulative return for SPY increases with a one standard deviation increase in *MessageVol*, *Bullishness,* or *AgreementIndex*. Prices stabilize to a new equilibrium between ten to twenty minutes. This finding demonstrates that Twitter sentiment is informative about the fundamentals of SPY, i.e., the impact of social media on prices is permanent. Our results support the view that sentiment extracted from tweets contains information that can move prices permanently toward a new equilibrium (Bollen et al., 2011; Azar and Lo, 2016; Gu and Kurov, 2020).

[26] To remove the effect of the uninformative initial values in the loop, we remove the first five iterations of the cumulative returns.

Figure 3. 1. Analysis of the system's dynamics

This figure plots the cumulative returns following one standard deviation shock to the Twitter sentiment measures. The estimation model is based on the VAR in Equation (3.5). We compute the cumulative return for each day using returns at a minute frequency. We then present the average cumulative returns across the sample period. The left-axis is in percentages, and the bottom-axis is in minutes.

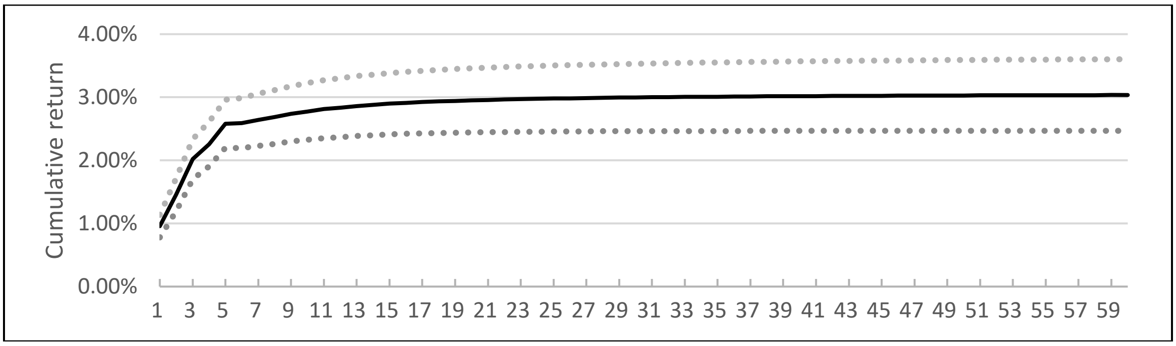

Figure 3.1.a. Shock to *MessageVol*

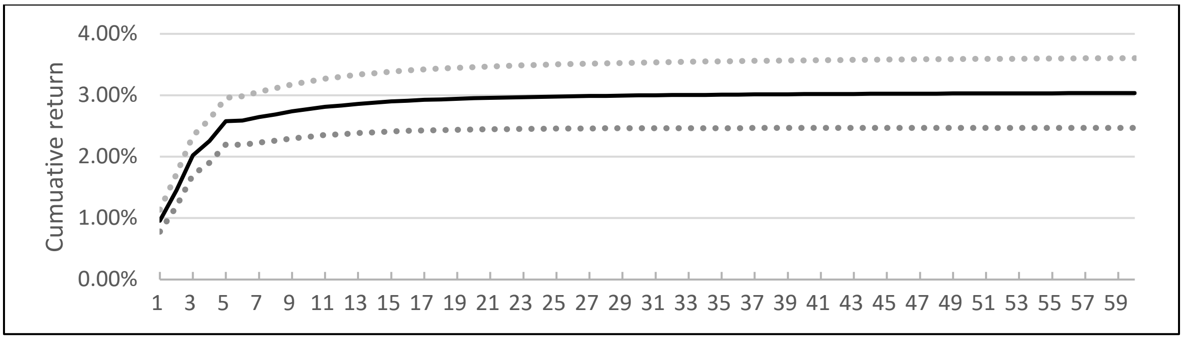

Figure 3.1.b. Shock to *Bullishness*

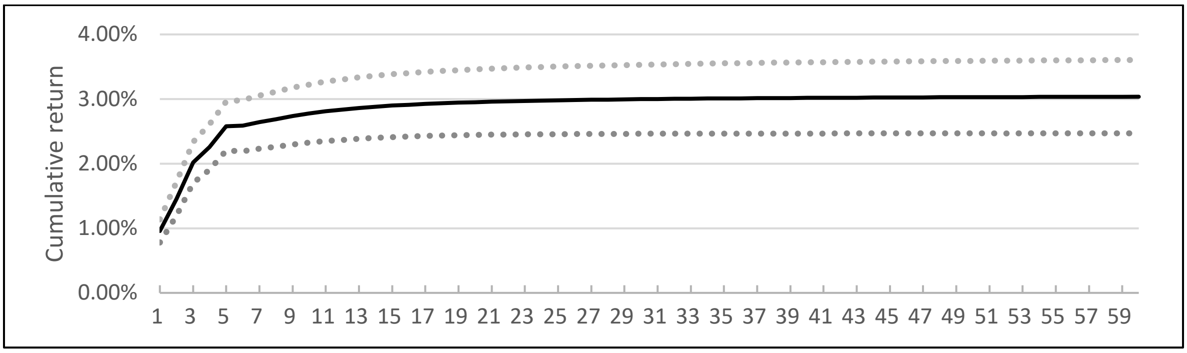

Figure 3.1.c. Shock to *AgreementIndex*

3.5.3 The importance of positive and negative tweets

Next, we examine if the impact of Twitter sentiment on stock returns is asymmetric. Currently, the literature shows mixed evidence on whether positive or negative sentiment has a stronger impact on prices. For example, Chen et al. (2004) and Barber and Odean (2008) show that positive sentiment has a stronger impact on returns than negative sentiment, whereas Akhtar et al. (2011, 2012) and Agrawal et al. (2018) find that negative sentiment on media exerts a stronger effect on stock markets than positive sentiment.[27] Others find that the impact of positive and negative sentiments is symmetric (see, e.g., Moseki and Rao, 2018; Al-Nasseri et al., 2021)

Given the mixed evidence above, we examine if there is an asymmetric effect from Twitter sentiment. We first classify tweets into positive and negative sentiment where POS_t and NEG_t represent the sum of all tweets with positive and negative tone scores during the minute interval *t*, respectively. We then modify the VAR model as follows,

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \tau_i POS_{t-i} + \omega_i NEG_{t-i}) x_{t-i} + \varepsilon_{1,t} ,$$

$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \zeta_i POS_{t-i} + \varsigma_i NEG_{t-i}) x_{t-i} + \varepsilon_{2,t} . \quad (3.6)$$

Table 3.3 reports the sum of the regression coefficients from Equation (3.6). The sum of coefficients for the interaction term with positive (τ_i) and negative (ω_i) sentiments in the return equation are positive (0.0132 and 0.0093, respectively) and significant at the 1% level. This finding indicates that both sentiments affect prices. These coefficients are

---

[27] The "positive sentiment effect" can be attributed to retail investors' limited cognitive processing ability (Chen et al., 2004) and attention-grabbing nature of the stock , e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns (Barber and Odean, 2008). The "negative sentiment effect" can be explained by the availability heuristics of investors, i.e., the tendency to form a judgment based on what is readily brought to mind (Akhtar et al., 2011, 2012).

positive as they reflect the marginal impact of trades on prices, i.e., positive (negative) order imbalance will lead to even higher (lower) stock returns with the arrival of either positive or negative social media sentiments.

We also test for asymmetry using a paired t-test for the difference in coefficients for the positive and negative sentiments. The reported t-statistic (0.81) shows that the null hypothesis of equal coefficients is not rejected. These results suggest that both positive and negative sentiments symmetrically intensify the impact of trades. This is in line with Moseki and Rao (2018) and Al-Nasseri et al. (2021) who document symmetric effects between positive and negative sentiments.

Table 3. 3. Vector Autoregression Estimation for Positive and Negative Twitter Sentiment

This table reports the coefficient estimates of the VAR model for positive and negative tweets. The estimation model is as below, the results for the return equation are presented in Panel A, and the results for the trade equation are presented in Panel B.

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \tau_i POS_{t-i} + \omega_i NEG_{t-i}) x_{t-i} + \varepsilon_{1,t}$$

$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \zeta_i POS_{t-i} + \varsigma_i NEG_{t-i}) x_{t-i} + \varepsilon_{2,t}$$

where x_t is volume of signed order flow at the time interval t, r_t is trade return calculated from the natural logarithm of midquote at the t-th minute. POS_t and NEG_t are the total number of positive and negative tweets over the minute interval t, respectively. The determination of a positive (negative) tweet is based on the tone score greater (less) than 0 explained in Section 3.1. All variables are normalized. Newey-West corrected t-statistics are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance level.

	τ_i		ω_i		Paired coefficients test	
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*t-stat*	*Adj-R^2*
Panel A: Return equation	0.0132^{***}	(4.22)	0.0093^{***}	(2.76)	(0.81)	0.34

	ζ_i		ς_i		Paired coefficients test	
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*t-stat*	*Adj-R^2*
Panel B: Trade equation	-0.0078^{**}	(-2.53)	-0.0079^{**}	(-2.37)	(0.03)	0.05

3.5.4 The role of volatility and liquidity

It is possible that Twitter sentiment may be proxying for other factors such as market uncertainty and liquidity. Shu and Chang (2015), for instance, show that market uncertainty is often associated with investor sentiment, while Dumas et al. (2009) find that optimistic anticipation of the future leads to overconfidence among investors and results in overreaction and volatility in the stock markets. Other studies also document that liquidity is often associated with investor sentiment. Liu (2015) uses liquidity measures developed by Amihud (2002) and shows that stock market is more liquid when market sentiment is higher, i.e., investors are more bullish. Baker and Stein (2004) show that overconfident investors tend to underreact to the information related to either order flow or equity issuance. Thus, high liquidity signals high sentiment caused by irrational investors.

To ensure that the price reaction to Twitter sentiment is not due to market uncertainty and liquidity, we control for volatility and liquidity shocks using the VAR model below,

$$
\begin{aligned}
r_t &= \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i} + \gamma_i VIX_{t-i} + \eta_i LiqShock_{t-i}) x_{t-i} + \varepsilon_{1,t}, \\
x_t &= \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i} + \rho_i VIX_{t-i} + \varphi_i LiqShock_{t-i}) x_{t-i} + \varepsilon_{2,t},
\end{aligned}
\tag{3.7}
$$

where VIX_t is the Chicago Board Options Exchange (CBOE) volatility index at minute *t,* downloaded from Refinitiv Tick History. We use the VIX as a proxy for the U.S. market volatility. $LiqShock_t$ is the measure for liquidity shock. To construct this measure, we start by computing Amihud (2002) illiquidity ratio below,

$$
Amihud_t = \frac{|r_t|}{\$Volume_t} \tag{3.8}
$$

where r_t is the log return of SPY at minute *t*, and $\$Volume_t$ is the dollar trading volume during the same interval. We then follow Bali et al. (2014) and normalize this measure. More specifically, we take the negative difference between the Amihud ratio at minute *t* and the average value of its past 10 minutes and then divide by the standard deviation of the past 10 minutes Amihud ratio. The normalized liquidity shocks $LiqShock_t$ is computed as follows,

$$LiqShock_t = \frac{-[Amihud_t - \text{Mean}(Amihud_{t-11,t-1})]}{SD(Amihud_{t-11,t-1})} \tag{3.9}$$

where $\text{Mean}(Amihud_{t-11,t-1})$ is the average Amihud illiquidity measure for SPY over the prior 10 minutes and $SD(Amihud_{t-11,t-1})$ is its standard deviation.[28] By normalizing the liquidity measure, we remove the expected component, leaving the unexpected or shock component in liquidity. A positive (negative) $LiqShock$ indicates an unexpected increase (decrease) in SPY liquidity.

Table 3.4 reports the results of the VAR in Equation (3.7). For brevity, we only report the sum of coefficients for interaction terms with the exogenous variables, i.e., the Twitter sentiment, volatility, and liquidity. For the Twitter sentiment measures, we find that the sum of parameters θ_i for message volume and bullishness remain positive at 1% and 10% significant level, respectively. This finding suggests that the importance of Twitter sentiment is not subsumed by market uncertainty or liquidity. For the uncertainty measure, we observe that the VIX also significantly affects SPY prices through its impact on trades, i.e., during periods of high market volatility or uncertainty, the price impact of trades is stronger. This is in line with the overconfident investor argument of Dumas et al. (2009). Furthermore, we observe that the impact of liquidity shock is negative and statistically significant, as shown by the negative sum of parameters η_i. This finding

[28] The results are qualitatively similar when we use the previous 5 or 30 minutes. These results are available from the authors.

suggests that periods of unexpected high liquidity weaken the price impact of trade, consistent with Baker and Stein (2004).

Table 3. 4. Vector Autoregression Estimation for Twitter Sentiment Controlling by Volatility and Liquidity

This table reports the coefficient estimates of the VAR model for Twitter sentiment impacts controlling by stock market volatility and liquidity. The estimation model is as below, the results for the return equation are presented in Panel A, and the results the trade equation are presented in Panel B.

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i} + \gamma_i VIX_{t-i} + \eta_i LiqShock_{t-i}) x_{t-i} + \varepsilon_{1,t}$$

$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i} + \rho_i VIX_{t-i} + \varphi_i LiqShock_{t-i}) x_{t-i} + \varepsilon_{2,t}$$

where x_t is volume of signed order flow at the time interval t, r_t is trade return calculated from the natural logarithm of midquote at the t-th minute, and $STMT_{t-i}$ is one of the Twitter sentiment measures: (i) *MessageVol*: the logarithm of the total number of tweets, (ii) *Bullishness*: a measure of investors' sentiment, or (iii) *AgreementIndex*: a measure of agreement among tweets. VIX_{t-i} is the volatility index from Chicago Board Options Exchange to represent the market volatility at the time interval t. Standardized liquidity shocks is calculated as $LiqShock_t = \frac{-[Amihud_t - \text{Mean}(Amihud_{t-11,t-1})]}{SD(Amihud_{t-11,t-1})}$, where $Amihud_{t-11,t-1}$ is the average value of $Amihud$ over the prior 10 minutes. All variables are normalized. Newey-West corrected t-statistics are in parentheses. ***, ** and * indicates 1%, 5% and 10% significance level.

Panel A: Return equation	θ_i Sum of lags	t-stat	γ_i Sum of lags	t-stat	η_i Sum of lags	t-stat	Adj-R^2
MessageVol	0.0207***	(7.39)	0.0221***	(7.74)	-0.4150***	(-91.70)	0.47
Bullishness	0.0052*	(1.86)	0.0244***	(8.88)	-0.4134***	(-94.74)	0.47
AgreementIndex	0.0012	(0.45)	0.0234***	(8.25)	-0.4141***	(-91.26)	0.47

Panel B: Trade equation	λ_i Sum of lags	t-stat	ρ_i Sum of lags	t-stat	φ_i Sum of lags	t-stat	Adj-R^2
MessageVol	-0.0260***	(-7.96)	-0.0151***	(-4.66)	-0.0384***	(-8.32)	0.06
Bullishness	-0.0026	(-0.77)	-0.0160***	(-4.90)	-0.0400***	(-8.76)	0.06
AgreementIndex	-0.0035	(-1.03)	-0.0155***	(-4.80)	-0.0398***	(-8.84)	0.06

3.5.5 The price impact of Twitter sentiment via limit orders

Brogaard et al. (2019) show that limit orders can play a more important role in price discovery than market orders in modern financial markets[29]. Given that high-frequency traders are more active in submitting limit orders than market orders, limit order submissions can lead to a positive price impact. We, therefore, study whether Twitter sentiment has a price impact via limit orders as an alternative channel.[30] To do so, we further modify our VAR model and endogenize limit order activity (proxied using quote-intensity-to-trade (QIT) ratio) in the VAR system as follows,

$$\begin{aligned}
r_t &= \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i}) x_{t-i} + \sum_{i=0}^{5} (\zeta_i + \eta_i STMT_{t-i}) QIT_{t-i} + \varepsilon_{1,t}, \\
x_t &= \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i}) x_{t-i} + \sum_{i=1}^{5} (\iota_i + \nu_i STMT_{t-i}) QIT_{t-i} + \varepsilon_{2,t}, \\
QIT_t &= \sum_{i=1}^{5} \Omega_i r_{t-i} + \sum_{i=1}^{5} (\xi_i + \pi_i STMT_{t-i}) x_{t-i} + \sum_{i=1}^{5} (\kappa_i + \psi_i STMT_{t-i}) QIT_{t-i} + \varepsilon_{3,t},
\end{aligned} \tag{3.10}$$

where QIT_t is the quote-intensity-to-trade ratio at minute *t*, defined as the total number of revisions in either bid or ask prices and depths at the best quotes of the limit order book divided by the total number of trades during that minute interval. Our prior is that higher limit order activity leads to greater revisions in prices.

Table 3.5 reports the results of the VAR in Equation (3.10). We focus on Panel A, which shows the impact of sentiment and limit order activity on returns. The sum of the coefficients θ_i for the interaction term $STMT \cdot x$ are positive and highly significant at the 1% level across all three Twitter sentiment measures. This finding suggests that after controlling for the activity in the limit order, the impact of Twitter sentiment on returns

[29] Brogaard et al. (2019) document that price discovery could occur in absence of trades but via limit orders.

[30] According to Goettler et al. (2009), Hoffmann (2014) and Roşu (2019), high-frequency traders tend to place market orders for immediate execution when they possess valuable information and place limit orders at other times.

becomes stronger. Consistent with Brogaard et al. (2019), the sum of the coefficients ζ_i for QIT shows that more activity in the limit order book positively affects the SPY returns, showing that limit orders contain information that facilitates price discovery. However, none of the aggregated coefficients η_i for the interaction term $STMT \cdot QIT$ is statistically significant, indicating that Twitter sentiment does not influence returns via limit order activity.

In Panel B, we do not observe any consistent significant effect of QIT on trades, except for the negative relationship for message volume. For the QIT equation in Panel C, we observe that both higher midquote returns and positive signed order flow reduce the quote-intensity-to-trade ratio. However, the sum of coefficients π_i and ψ_i for the interaction terms of trades and QIT, respectively, are positive for each sentiment measure and significant at 1% significance level. This observation indicates that Twitter sentiment can mitigate the negative impact of trades on QIT, but strengthen the QIT autocorrelation effects. Overall, Table 3.5 confirms that the impact of Twitter sentiment on SPY prices is through trades, not limit order activity.

Table 3. 5. Vector Autoregression Estimation for Twitter Sentiment 3 equations

This table reports the coefficient estimates of the VAR model for Twitter sentiment impacts. The estimation model is as below, the results for the return equation are presented in Panel A, the results for the trade equation are presented in Panel B, and the results for the limit order activity equation are presented in Panel C.

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i}) x_{t-i} + \sum_{i=0}^{5} (\zeta_i + \eta_i STMT_{t-i}) QIT_{t-i} + \varepsilon_{1,t}$$

$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i}) x_{t-i} + \sum_{i=1}^{5} (\iota_i + \nu_i STMT_{t-i}) QIT_{t-i} + \varepsilon_{2,t}$$

$$QIT_t = \sum_{i=1}^{5} \Omega_i r_{t-i} + \sum_{i=1}^{5} (\xi_i + \pi_i STMT_{t-i}) x_{t-i} + \sum_{i=1}^{5} (\kappa_i + \psi_i STMT_{t-i}) QIT_{t-i} + \varepsilon_{3,t}$$

where x_t is volume of signed order flow at the time interval t, r_t is trade return calculated from the natural logarithm of midquote at the t-th minute, and $STMT_{t-i}$ is one of the Twitter sentiment measures: (i) *MessageVol*: the logarithm of the total number of tweets, (ii) *Bullishness*: a measure of investors' sentiment, or (iii) *AgreementIndex*: a measure of agreement among tweets. QIT_{t-i} is quote-intensity-to-trade ratio for the minute interval t, where quote intensity is defined as the summed number of changes in either price or depth at the best quotes on the limit order book. All variables are normalized. Newey-West corrected t-statistics are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance level, respectively.

Panel A: Return equation	α_i *Sum of lags*	*t-stat*	β_i *Sum of lags*	*t-stat*	θ_i *Sum of lags*	*t-stat*	ζ_i *Sum of lags*	*t-stat*	η_i *Sum of lags*	*t-stat*	*Adj-R^2*
MessageVol	-0.087***	(-22.31)	0.445***	(67.31)	0.014***	(7.47)	0.031***	(10.44)	0.001	(0.31)	0.33
Bullishness	-0.086***	(-20.94)	0.448***	(66.47)	0.013***	(7.13)	0.006*	(1.94)	-0.003	(-1.18)	0.33
AgreementIndex	-0.086***	(-21.14)	0.449***	(68.35)	0.013***	(7.04)	0.003	(1.08)	-0.004	(-1.17)	0.33

Panel B: Trade equation	μ_i *Sum of lags*	*t-stat*	δ_i *Sum of lags*	*t-stat*	λ_i *Sum of lags*	*t-stat*	ι_i *Sum of lags*	*t-stat*	ν_i *Sum of lags*	*t-stat*	*Adj-R^2*
MessageVol	0.003	(0.33)	0.235***	(68.04)	-0.004*	(-1.81)	-0.027***	(-9.07)	-0.001	(-0.52)	0.05
Bullishness	0.001	(0.08)	0.235***	(68.78)	-0.003	(-1.20)	-0.001	(-0.33)	0.005	(1.60)	0.05
AgreementIndex	-0.001	(-0.10)	0.235***	(68.44)	-0.003	(-1.48)	-0.002	(-0.57)	0.002	(0.51)	0.05

Panel C: Limit order activity equation	Ω_i *Sum of lags*	*t-stat*	ξ_i *Sum of lags*	*t-stat*	π_i *Sum of lags*	*t-stat*	κ_i *Sum of lags*	*t-stat*	ψ_i *Sum of lags*	*t-stat*	*Adj-R^2*
MessageVol	-0.017***	(-4.40)	-0.009***	(-2.93)	0.717***	(130.27)	0.005**	(2.28)	0.024***	(9.06)	0.34
Bullishness	-0.018***	(-4.88)	-0.008**	(-2.47)	0.718***	(131.96)	-0.002	(-0.93)	0.010***	(3.54)	0.33
AgreementIndex	-0.018***	(-4.68)	-0.008**	(-2.53)	0.719***	(130.71)	0.003	(1.03)	0.012***	(4.24)	0.34

3.6 Robustness Tests

To ensure the robustness of our results, we perform several tests. First, we use a different threshold to classify positive and negative tweets. Second, we consider VAR models with a different set of lags. Third, we employ a different lexical database to classify tweets into positive, negative, and neutral.

3.6.1 Using different thresholds when classifying tweets

Previously, we considered a tweet as positive (negative) if its tone score is above (below) zero. However, a tweet with a tone score of 0.1 (or -0.1), for instance, may not be distinguishable from a neutral tweet with a tone score of 0. These borderline tweets may affect the accuracy of our Twitter sentiment measure and weaken our results as the tweets we consider positive and negative may contain tweets that are, effectively, neutral-sounding. Thus, to ensure that our results are robust, we consider tweets with a tone score greater than 0.3 as positive and those with a score less than -0.3 as negative. The remaining tweets are considered neutral. We re-estimate Equation (3.5) based on the new sentiment classification.

Panel A of Table 3.6 shows that the sum of interaction coefficients is positive (0.0297 for *MessageVol*, 0.0071 for *Bullishness,* and 0.0120 for *AgreementIndex*) and statistically significant at the 5% level or better for the return equation. Since we focus on tweets with more extreme values, the impact of sentiment is expected to be stronger, as indicated by the larger magnitudes of the coefficients. In sum, these results lend support to our main findings that Twitter sentiment affects stock market returns through trades.

Table 3. 6 Vector Autoregression Estimation for Twitter Sentiment ($POS > 0.3$ and $NEG < -0.3$)

This table reports the coefficient estimates of the VAR model for Twitter sentiment impacts. The estimation model is as below, the results of return equation are presented in Panel A, and the results of trade equation are presented in Panel B.

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i}) x_{t-i} + \varepsilon_{1,t}$$
$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i}) x_{t-i} + \varepsilon_{2,t}$$

where x_t is volume of signed order flow at the time interval t, r_t is trade return calculated from the natural logarithm of midquote at the *t*-th minute, and $STMT_{t-i}$ is one of the Twitter sentiment measures: (i) *MessageVol*: the logarithm of the total number of tweets, (ii) *Bullishness*: a measure of investors' sentiment, or (iii) *AgreementIndex*: a measure of agreement among tweets. All sentiment measures are based on positive and negative tweets classified using tone score greater than 0.3 and less than -0.3. All other scores are consider neutral tweets. All variables are normalized. Newey-West corrected t-statistics are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance level, respectively.

Panel A: Return equation	α_i		β_i		θ_i		
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*Sum of lags*	*t-stat*	*Adj-R^2*
MessageVol	-0.0736***	(-17.49)	0.4333***	(66.06)	0.0297***	(10.43)	0.33
Bullishness	-0.0748***	(-17.43)	0.4370***	(65.78)	0.0071**	(2.37)	0.33
AgreementIndex	-0.0747***	(-17.92)	0.4373***	(66.09)	0.0120***	(3.77)	0.33

Panel B: Trade equation	μ_i		δ_i		λ_i		
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*Sum of lags*	*t-stat*	*Adj-R^2*
MessageVol	-0.0043	(-0.46)	0.2512***	(68.49)	-0.0249***	(-8.50)	0.05
Bullishness	-0.0040	(-0.45)	0.2496***	(69.88)	-0.0054*	(-1.82)	0.05
AgreementIndex	-0.0052	(-0.57)	0.2497***	(70.29)	-0.0095***	(-2.91)	0.05

3.6.2 VAR with different lags

In all our VAR regressions, we employ five lags following Dufour and Engle (2000). To examine if our findings are sensitive to the choice of lags, we re-estimate Equation (3.5) using different sets of lags, e.g., three, ten, and twenty lags. We report the key results (interaction terms between sentiment and trades) in Table 3.7. They are qualitatively similar to those reported in Table 3.2, indicating that our results are robust to the choice of lags.

3.6.3 Robustness with a different dictionary

Renault (2017) explains that the accuracy of sentiment categorization can influence the final predictability of sentiment measures. As another robustness test, we use a different dictionary to classify tweets into positive, negative, and neutral groups. In particular, we use the Harvard IV-4 psychological dictionary to classify tweets.[31] We then re-construct our Twitter sentiment measures based on tweets classified using this dictionary and use them in our VAR model (Equation 3.5).

Table 3.8 reports the results using the new sentiment measures. Turning first to Panel A, we observe the mean reversion effect in intraday return (i.e., the sum coefficients of lagged returns) and the positive impact of order flow (i.e., the sum coefficients of the signed trading volume), consistent with the results Table 3.2. For the interaction terms between Twitter sentiment and trades, we observe positive coefficients for message volume and AgreementIndex (statistically significant at the 1% level). The sum of coefficients of bullishness remains positive, albeit insignificant. In Panel B of Table 3.8,

[31] Harvard IV-4 is a general-purpose dictionary developed by the Harvard University. According to its official documentary, the Harvard IV-4 is not particularly developed for natural language processing (NPL) objectives such as analyzing social media tweets as we do in the current study. However, the Harvard IV-4 dictionary has been used for processing messages from official news media coverage (e.g., see Tetlock et al., 2008; Price et al., 2012; Mangee, 2018).

for all three sentiment measures, the results are qualitatively similar to those reported in Panel B of Table 3.2.

It is important to note that when it comes to natural language processes, a context-related dictionary is more powerful than a general dictionary, as explained in Price et al. (2012). In line with this argument, there are two possible explanations why the sum of coefficients for bullishness is no longer significant after using the Harvard-IV psychological dictionary. First, tweets contain more slang and sarcasm, which may differ from the Harvard IV-4 context originally designed for. Second, the method to classify tweets using Harvard IV-4 Dictionary does not categorize combinations of words that often possess different meanings from the individual words (Tetlock, 2007). In our case, the social media sentiment-related lexical database *WordNet*, at least in part, performs better for classifying texts in social media.[32]

[32] According to the General Inquirer, for creating a helpful category for content analysis, the extensive electronic lexical database such as Wordnet can be considerable for improvement. See, for instance, https://inquirer.sites.fas.harvard.edu/homecat.htm

Table 3. 7. Vector Autoregression Estimation for Twitter Sentiment with different lags

This table reports the coefficient estimates of the VAR model for Twitter sentiment impacts using different lags. The estimation model is as below, the results of return equation are presented in Panel A, and the results of trade equation are presented in Panel B.

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i}) x_{t-i} + \varepsilon_{1,t}$$

$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i}) x_{t-i} + \varepsilon_{2,t}$$

where x_t is volume of signed order flow at the time interval t, r_t is trade return calculated from the natural logarithm of midquote at the t-th minute, and $STMT_{t-i}$ is one of the Twitter sentiment measures: (i) *MessageVol*: the logarithm of the total number of tweets, (ii) *Bullishness*: a measure of investors' sentiment, or (iii) *AgreementIndex*: a measure of agreement among tweets. All variables are normalized. Newey-West corrected t-statistics are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance level, respectively.

Panel A: Return equation	θ_i *Sum of 3 lags*	*t-stat*	θ_i *Sum of 10 lags*	*t-stat*	θ_i *Sum of 20 lags*	*t-stat*
MessageVol	0.0242***	(9.64)	0.0370***	(9.72)	0.0402***	(6.93)
Bullishness	0.0039	(1.58)	0.0090**	(2.28)	0.0166***	(2.91)
AgreementIndex	0.0020	(0.77)	0.0088**	(2.12)	0.0111*	(1.82)

Panel B: Trade equation	θ_i *Sum of 3 lags*	*t-stat*	θ_i *Sum of 10 lags*	*t-stat*	θ_i *Sum of 20 lags*	*t-stat*
MessageVol	-0.0180***	(-7.33)	-0.0394***	(-9.67)	-0.0587***	(-8.37)
Bullishness	-0.0022	(-0.92)	-0.0049	(-1.03)	-0.0108	(-1.55)
AgreementIndex	-0.0021	(-0.82)	-0.0035	(-0.75)	-0.0115*	(-1.66)

Table 3. 8. Vector Autoregression Estimation for Twitter Sentiment with a different dictionary

This table reports the coefficient estimates of the VAR model for Twitter sentiment impacts where we use the Harvard-IV psychological dictionary to classify positive, negative and neutral tweets. The estimation model is as below, the results of return equation are presented in Panel A, and the results of trade equation are presented in Panel B.

$$r_t = \sum_{i=1}^{5} \alpha_i r_{t-i} + \sum_{i=0}^{5} (\beta_i + \theta_i STMT_{t-i}) x_{t-i} + \varepsilon_{1,t}$$

$$x_t = \sum_{i=1}^{5} \mu_i r_{t-i} + \sum_{i=1}^{5} (\delta_i + \lambda_i STMT_{t-i}) x_{t-i} + \varepsilon_{2,t}$$

where x_t is volume of signed order flow at the time interval t, r_t is trade return calculated from the natural logarithm of midquote at the *t*-th minute, and $STMT_{t-i}$ is one of the Twitter sentiment measures: (i) *MessageVol*: the logarithm of the total number of tweets, (ii) *Bullishness*: a measure of investors' sentiment, or (iii) *AgreementIndex*: a measure of agreement among tweets. All variables are normalized. Newey-West corrected t-statistics are in parentheses. ***, ** and * indicate 1%, 5% and 10% significance level, respectively.

Panel A: Return equation	α_i		β_i		θ_i		
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*Sum of lags*	*t-stat*	*Adj-R²*
MessageVol	-0.0736***	(-17.49)	0.4333***	(66.06)	0.0297***	(10.43)	0.33
Bullishness	-0.0751***	(-17.69)	0.4380***	(65.16)	0.0002	(0.05)	0.33
AgreementIndex	-0.0746***	(-18.06)	0.4381***	(64.90)	0.0082***	(2.61)	0.33

Panel B: Trade equation	μ_i		δ_i		λ_i		
	Sum of lags	*t-stat*	*Sum of lags*	*t-stat*	*Sum of lags*	*t-stat*	*Adj-R²*
MessageVol	-0.0043	(-0.46)	0.2512***	(68.49)	-0.0249***	(-8.50)	0.05
Bullishness	-0.0054	(-0.60)	0.2490***	(68.27)	-0.0050	(-1.56)	0.05
AgreementIndex	-0.0066	(-0.72)	0.2500***	(70.00)	-0.0038	(-1.07)	0.05

3.7 Conclusion

This study examines the price impact of tweets on stock markets. Using the SPDR S&P 500 Trust ETF (SPY) to proxy for the U.S. stock market, we explore the mechanism by which social media sentiment impacts SPY prices.

We find that Twitter sentiment enhances the impact of trades on intraday returns. Trades have a greater price impact when there are more tweets. Also, the impact of buyer-initiated trades on stock prices is stronger when the market sentiment is bullish. Twitter sentiment causes a price impact that is permanent, suggesting that Tweets are informative. This price impact persists after controlling for market volatility and liquidity shocks. We also test if Twitter sentiment affects prices through limit order activity but do not find that is the case. Our results highlight the importance of social media sentiment in stock market price movements at the intraday level.

Chapter 4

Social Media Sentiment, Investor Herding and Informational Efficiency

4.1 Introduction

Informationally efficient prices arise from prices promptly and accurately integrating all publicly available information. This process hinges on market participants adjusting their beliefs and trading in response to new information arrivals. Numerous research has examined the degree to which market is informationally efficient, i.e., how it rapidly incorporates information and correctly prices the intrinsic value of underlying assets. However, many of these studies assume that investors are rational. In contrast, an alternative strand of literature started with the seminal papers of Shiller (1981) and De Long et al. (1990), departs from this assumption and considers that the investors are not rational and hence, are affected by sentiment. In this paper, we study how sentiment extracted from Twitter posts impacts price informational efficiency.

In the context of acquiring new information, investors rely on public news to update their knowledge and make informed investment decisions (De Long et al., 1990). Nowadays, however, social media has become the dominant source of information dissemination (Gan et al., 2020). While social media facilitates interactions among individuals and connects investors with financial markets, it can also lead to collective investment behaviours among market participants (Bukovina, 2016). As a result, investor sentiment becomes intertwined with the quality of a market, causing stock return continuations, increasing market frictions and potentially affecting the efficiency of asset prices.

From a behavioural standpoint, investors are not perfectly rational. Their investment decisions can be influenced by various factors, including their own mood, market sentiment, and other seemingly irrelevant external factors.[33] Interactions on social media platforms can alter the information environment of individuals and generate cycles of responses, potentially leading to sentimental hype. These impacts can subsequently affect investors' trading behaviours, asset prices, and the overall market efficiency. However, whether social media sentiment increases or decreases market efficiency remains unclear. To the best of our knowledge, the current study is the first to directly investigate the relationship between social media sentiment and informational efficiency, while also delving into the underlying mechanisms involved.

Previous studies suggest a likely relationship between sentiment and informational efficiency. On the one hand, sentiment has the potential to enhance efficiency. For instance, Vozlyublennaia (2014) demonstrates that increased investor attention, measured through Google searches, reduces return predictability, and therefore, improves informational efficiency. Gu and Kurov (2020) show that social media sentiment extracted from Twitter posts provides new information about analyst recommendations, analyst price targets and quarterly earnings. Given that social media sentiment can convey firm-level information, it is reasonable to expect that it may contribute to enhancing informational efficiency.

[33] Previous studies examine how social mood (Nofsinger, 2005), weather (Hirshleifer and Shumway, 2003), sporting events (Edmans et al., 2007), and music choices (Edmans et al., 2022) affect the stock markets.

On the other hand, social media sentiment may disrupt informational efficiency, especially in a high-frequency trading environment. For example, Da et al. (2011) highlight that investors may not effectively utilize their information sets due to variations in their ability to process new information. This effect could be more pronounced in high-frequency trading environments where investors have limited time to react and cope with rapid influx of social media messages. Additionally, social media sentiment disseminates information to a wider range of audiences, which can collectively foster irrational behaviours among investors in the stock market, such as herding (Li et al., 2023), overactions (Jiao et al., 2020) and irrationality to surprises (Karampatsas et al., 2023). These factors collectively contribute to the potential for irrational investment decisions that deviate from fundamental principles, ultimately diminishing market efficiency.

In this study, we employ a textual analysis approach to extract sentiment from social media content and investigate its impact on informational efficiency at high frequency. We focus on the aggregated tone of Twitter posts, commonly referred to as 'tweets', as a proxy for social media sentiment. To measure informational efficiency, we employ two commonly used metrics: return autocorrelation and variance ratio, consistent with previous studies such as Hendershott and Jones (2005), O'Hara and Ye (2011), and Comerton-Forde and Putniņš (2015). We regress these metrics on the sentiment measure to explore whether increased sentiment leads to changes in information efficiency. Our findings demonstrate that as social media sentiment increases, there is an increased return autocorrelation and variance ratio, indicating a decrease in informational efficiency. We account for various influential market factors, employ different sentiment analysis approaches, and consider different intervals for sentiment construction, all of which lend support to the robustness of our finding.

The current study also delves into the underlying mechanism for the above finding through the role of herding behaviour. It is important to note that certain market participants have access to professionally curated reports and commercial databases that provide real-time trading data, enabling them to extract information from the trading activities of others. For other participants, however, these resources may be inaccessible or come at a high cost, leading them to rely more heavily on information obtained through other sources such as social media (Bukovina, 2016). This reliance on social media can result in herding behaviour, potentially impacting informational efficiency. We consider two herding behaviour metrics: dollar-based herding (Cai et al., 2019) and the Williams Percent Range (Zhou, 2018). Utilizing a vector autoregressive (VAR) model, we show that a higher social media sentiment leads to heightened herding activity, but not the inverse relationship. This finding complements Da et al. (2011) and Shen et al. (2017) who show that higher sentiment leads to higher trading frictions, and eventually slowing down the market information incorporation process.

Our study relates to literature on the impact of social media sentiment on informational efficiency, expanding studies such as Kurov (2008) and Vozlyublennaia (2014). We use intraday data to construct the informational efficiency measures and synchronous real time investor sentiment measure. Unlike the low frequency survey data used to proxy for investor sentiment in Kurov (2008), the granularity of intraday data enables in-depth and more accurate analysis of market dynamics, offering better insights on market efficiency and investors' reactions to news.[34] Our empirical analysis reveals that these impacts exhibit distinct characteristics, particularly in a high-frequency setting. Our study also explores the mechanism through which social media sentiment influences market informational efficiency. We demonstrate that, driven by social media, investors collectively engage in herding activities. This can have a detrimental effect on market

[34] It is well-known that survey data has some shortages such as answering bias and lagged information due to long data collection process and low update frequency. Intraday data, on the other hand, allows for textual analytic sentiment to be matched with real-time market price dynamics. Thus, sentiment extraction using intraday data overcomes the non-synchronicity issue and answering bias, and is more suitable to study the impact of sentiment on informational efficiency.

efficiency, in line with previous studies such as Kumar and Lee (2006) and Barber et al. (2008). For instance, Kumar and Lee (2006) show that as individuals trade in the same direction as others, retail sentiment can trigger stock return co-movements. Barber et al. (2008) document that individual investors herd and their trades forecast future returns.

Our study has important implications for various stakeholders. Firstly, we provide evidence that social media sentiment has a substantial impact on the quality of equity markets, beyond the influence of other conventional market-based factors. This finding holds significant relevance for market participants, indicating that they should consider social media sentiment as a crucial factor when formulating investment strategies. Secondly, for regulators and policymakers, our study highlights the potential of social media as an additional surveillance tool within the market regulatory framework. Recognizing the influence of social media sentiment can aid in enhancing market oversight to effectively monitor and manage potential risks and market disruptions.

The remainder of the paper proceeds as follows. In Section 4.2, we provide an overview of the relevant literature. Section 4.3 outlines the data used in our analysis and elaborates the construction of our variables of interest. Section 4.4 presents the results on the linkage between social media sentiment and informational efficiency. In Section 4.5, we explore the transmission channel underlying such linkage. Section 4.6 concludes.

4.2 Literature Review

Numerous studies have highlighted the significance of investors' behaviour and reaction to news. While there is a group of 'smart' investors and high-frequency traders who can exploit the arrival of news (see, e.g., Busse and Green, 2002; Grinblatt et al., 2012; and Foucault et al., 2016), most market participants are not equipped with such processing skills. These investors collectively exhibit irrational reactions to news, resulting in less efficient prices. For instance, investors' underreaction to new information can result in short-term stock price continuation, indicating market inefficiency (Zhang, 2006). Moreover, De Bondt and Thaler (1985) and Tetlock (2011) show that investors' overreaction to news contributes to price deviations from fundamentals, and therefore, market inefficiency.

Despite these insights, there is a limited amount of research directly examining the relationship between social media sentiment, investors behaviour and market informational efficiency. While social media has become a dominant channel of information sharing in recent years, existing studies predominantly focus on the role of social media sentiment in predicting returns. For instance, Chen et al. (2014) find that social media opinions are a significant source for future stock returns and earnings surprises predictions. The consensus among these studies is that a high sentiment is contemporaneously associated with positive returns, followed by a subsequent correction.[35] Bollen et al. (2011), for instance, demonstrate that incorporating social media sentiment significantly improves their model's predictive power on the Dow Jones Industrial Average (DJIA) index. More predictable returns indicate a potential negative impact of social media sentiment on market efficiency. Similarly, Kim et al. (2014) document that incorporating investor sentiment enhances profitability, which is indicative of reduced market efficiency. Furthermore, Duz Tan and Tas (2021) discover that social media sentiment predicts future returns even after controlling for news sentiment, implying that social media activity contains unique information beyond traditional news sources.

This linkage between social media sentiment and market efficiency can be particularly strong in shorter time horizons. This can be attributed to the slow reaction

[35] Investor sentiment has significant predictive power for US stock returns (Baker and Wurgler, 2006) and other markets such as Canada, France, Germany, Japan and the UK (Baker et al., 2012). Siganos (2014) documents that Facebook Gross National Happiness Index positively predicts following day stock market returns, but with a partial price reversal over the following weeks.

time of retail investors (De Long et al., 1990). Supporting this notion, Sun et al. (2016) discover that lagged half-hour SPY ETF investor sentiment can predict subsequent intraday S&P 500 index returns. Their findings demonstrate that social media sentiment holds economic value, exhibits distinctions from intraday momentum effects, and has a lasting impact. De Jong et al. (2017) demonstrate that the lagged innovation of tweets impacts the returns of 87% of the stocks in the DJIA at the minute level, alleviating concerns about sentiment's impact being limited to specific stocks or markets. Guégan and Renault (2021) further support these findings by documenting that pricing efficiency in cryptocurrency markets decreases as the frequency increases, indicating heightened market inefficiencies at shorter horizons. Collectively, this evidence reinforces the influence of social media sentiment on market informational efficiency.

Furthermore, research has highlighted the association between increased sentiment and feedback trading, a form of investor herding, which in turn is linked to greater return predictability and market inefficiency.[36] For instance, Kurov (2008) studies feedback trading using E-mini S&P 500 and E-mini Nasdaq-100 data. Using weekly survey data as a proxy for investor sentiment, he finds that positive feedback trading appears to be more active in periods of high investor sentiment. Similarly, Chau et al. (2011) observe a connection between Baker and Wurgler's (2006) investor sentiment index and the returns of three major ETFs (S&P 500 ETF Trust, Dow Jones Industrial Average ETF Trust, and the Invesco QQQ ETF). They demonstrate that optimistic (pessimistic) investors are more (less) likely to adopt trend-chasing investment strategies at the daily level. Conversely, however, Kaplanski and Levy (2014) document that sophisticated investors can exploit sentiment and restore efficiency in the US market.

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[36] Positive feedback trading is a strategy which buys when prices move up and sell when prices move down. Such a strategy may be due to behavioral biases on the part of some investors. In the presence of positive feedback trading, it may be optimal for rational speculators to jump on the bandwagon. The interaction between feedback traders and rational speculators moves prices away from fundamentals in the short run (De Long et al., 1990).

These studies indicate that social media sentiment may play a role on market efficiency through the collective imbalanced orders of irrational traders, contributing to herding behaviour.

Recent studies have shed light on the role of sentiment-driven herding behaviours in explaining anomalies such as abnormal returns observed during periods of extremely high sentiment in US and European markets (Filip and Pochea, 2023). Through a causality test, Blasco et al. (2012) find that sentiment and past returns drive herding behaviours among investors, and buyer (seller)-initiated herding is more pronounced when past returns are positive (negative). As individuals tend to follow the same sign of orders than others, retail sentiment can trigger stock return co-movements (Kumar and Lee, 2006). This observation is further corroborated by Barber et al. (2008) and Da et al. (2011), who document that increased investor attention can lead to higher trading volume and abnormal returns due to net buying pressure of retail investors. However, it is important to note that sentiment-driven irrational behaviours, such as feedback trading or herding, are not limited to retail investors alone. They are also observed among fund managers (Lakonishok et al., 1992; Menkhoff and Nikiforow, 2009), analysts (Welch, 2000; Clement and Tse, 2005), and institutional investors. For instance, Nofsinger and Sias (1999) show a positive correlation between herding and lagged returns among institutional investors, with the effect being even stronger than in individual investors.

Interactions among investors on social media platforms have emerged as a potential avenue for investor herding, as discussed in Fenzl and Pelzmann (2012). The extensive user engagement on platforms like Twitter, involving sharing and responding to news and messages related to stocks, leads to enhanced connectivity among investors and contributes to collective investment behaviours (Bukovina, 2016). As a result, market-wide herding behaviours can arise, influencing the net orders placed in the market and subsequently, harming market efficiency.

4.3 Data and Measures of Informational Efficiency

4.3.1 Tweets and sentiment extraction

We focus on the SPDR S&P 500 ETF Trust (ticker: SPY) as a representation of the US equity market. We collect tweets using Twitter's official Application Programming Interface (API). Following Sprenger et al. (2014a), we use cashtags ($) to search for tweets related to a particular security, i.e., '$SPY' to obtain tweets related to SPY. Our sample period is from August 1, 2012 to March 31, 2022 since Twitter only officially introduced cashtags on July 31, 2012. We collected 6.85 million tweets and every tweet is reported in the US Eastern Standard Time (EST) and time-stamped to the nearest second. Figure 4.1 plots the average number of tweets mentioning $SPY by the day of the week and by the hour of the day. The volume of tweets is significantly higher during trading days and, particularly, during trading hours between 9:30 and 16:00 EST. Thus, we focus on these periods for our analyses. We clean each tweet by removing irrelevant characters, including punctuations, emojis and internet links. These filters lead to a total of 2,433 trading days in consideration.

We use the WordNet lexical database as a language processing tool to transform qualitative into quantitative data. It was developed by the Cognitive Science Laboratory of Princeton University and has been widely adopted for social media sentiment evaluation and classification (see e.g., Navigli, 2009; Vidhu Bhala and Abirami, 2014; AlMousa et al., 2021). Using WordNet in natural language processing allows us to score each tweet between -1 and 1. We consider a tweet as positive if its score is greater than

Figure 4. 1. SPY tweets volume by different frequencies

Figure 4.1.A plots the number of SPY-related tweets by day of the week. Figure 4.1.B plots the SPY-related tweets by hour of the day. The sample period is from August 1, 2012, to March 31, 2022.

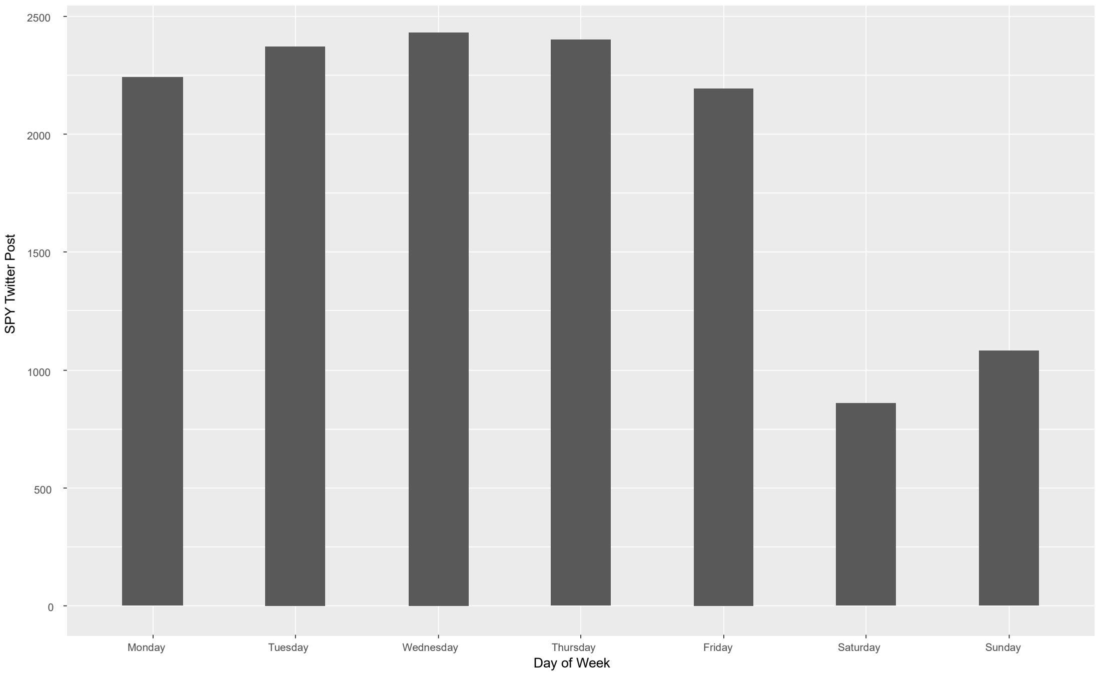


Figure 4.1.A. SPY-related tweets by day of the week

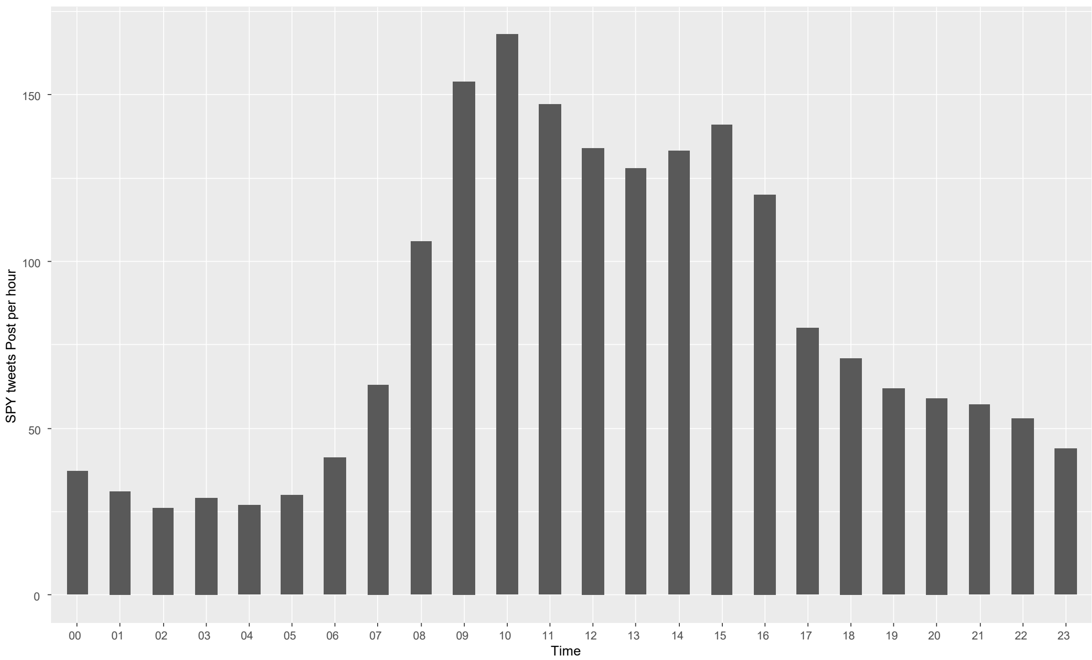


Figure 4.1.B. SPY-related tweets by the hour of the day

zero, negative if the score is less than zero, and neutral when the score is zero.[37]

We aggregate the directional tone from tweets to a daily level, which we then use to construct our social media sentiment index. Following studies such as Antweiler and Frank (2004), Sprenger et al. (2014a), and Leung and Ton (2015), we construct our social media sentiment, $Sentiment_t$, as follows,

$$Sentiment_t = \ln\left[\frac{1+M_t^{Positive}}{1+M_t^{Negative}}\right], \tag{4.1}$$

where $M_t^{Positive}$ and $M_t^{Negative}$ are the sum of positive and negative tweets during market trading hours on day *t*, respectively. This measure captures the overall sentiment embedded in tweets for each day. A high (low) $Sentiment$ reflects a more optimistic (pessimistic) view on the SPY.

Panel A of Table 4.1 reports the daily summary statistics for the social media sentiment. The sentiment on the SPY is positive, with an average value of 0.76. This is consistent with the existing literature which shows that investors are generally optimistic about the financial markets (Baker and Wurgler, 2006; Stambaugh et al., 2012).

Figure 4.2 plots the five-day moving average sentiment (dotted line) and the daily SPY price (solid line) over the sample period from August 2012 to March 2022. The visualised two series display an intuitive co-movement between SPY prices and social media sentiment, motivating us to explore further regarding the role of sentiment on informational efficiency.

[37] In addition to this sentiment classification method, we employ other methods, such as the Harvard IV-4 sentiment list (Tetlock, 2007), the Loughran-McDonald sentiment list (Loughran and McDonald, 2014), and SentiWordNet (Azar and Lo, 2016) in our robustness section.

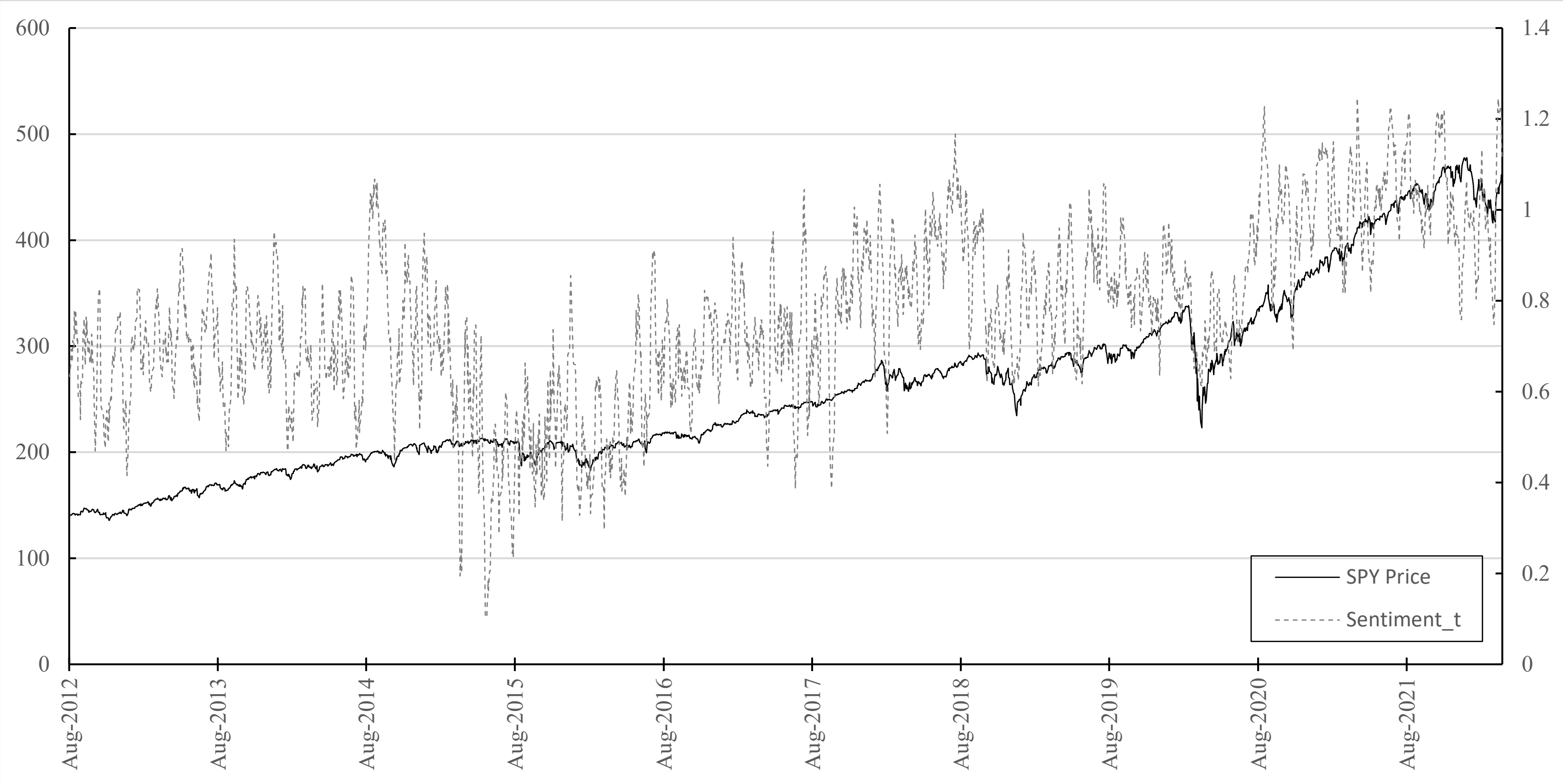
Table 4. 1. Summary statistics and correlation table

This table reports the daily summary statistics for tweets and market variables across the sample period from August 1, 2012, to March 31, 2022. $Sentiment$ is the social media sentiment index from Equation (4.1). $Autocorrelation^{PCA}$ is the first principal component of absolute midquote return autocorrelation constructed using various frequencies, e.g., 1-, 10-, and 30-sec, for each trading day from 9:40 to 15:50. $VarianceRatio^{PCA}$ is the first principal component of variance ratio constructed using various frequencies, e.g., [10-sec, 30-sec], [30-sec, 60-sec] and [10-sec, 60-sec] for each trading day from 9:40 to 15:50 EST. Both metrics are scaled so that they range from zero to one. $Return$ is the daily return of SPY, $Volatility$ is the realized volatility constructed using SPY midquote returns at a one-minute frequency, $Volume$ is the log of daily total dollar volume, $Depth$ is the log of daily average bid-ask depth, VIX is the daily S&P 500 implied volatility index.

	$Sentiment$	$Autocorrelation^{PCA}$	$VarianceRatio^{PCA}$	$Return$	$Volatility$	$Volume$	$Depth$	VIX
Panel A Descriptive statistics								
Mean	0.76	0.16	0.12	0.00	0.01	23.67	8.24	17.18
Std. dev.	0.31	0.13	0.09	0.01	0.01	0.43	0.70	7.06
Median	0.76	0.13	0.10	0.00	0.01	23.61	8.13	15.20
5th Percentile	0.28	0.02	0.01	-0.02	0.00	23.07	7.26	10.63
95th Percentile	1.23	0.39	0.29	0.01	0.01	24.45	9.57	29.32
AR(1)	0.39	0.06	0.06	-0.14	0.46	0.71	0.91	0.97
Obs.	2,432	2,432	2,432	2,432	2,432	2,432	2,432	2,432
Panel B Correlation Matrix								
$Sentiment$	1							
$Autocorrelation^{PCA}$	0.04	1						
$VarianceRatio^{PCA}$	0.03	0.27	1					
$Return$	0.23	0.03	0.03	1				
$Volatility$	-0.05	-0.02	-0.02	-0.06	1			
$Volume$	-0.03	-0.07	-0.02	-0.19	0.22	1		
$Depth$	0.14	-0.10	-0.03	-0.13	0.17	0.72	1	
VIX	0.02	-0.06	-0.04	-0.17	0.26	0.62	0.69	1

Figure 4. 2. Social media sentiment and SPY price

This figure plots the five-day moving average social media sentiment (dotted line) and daily SPY prices (solid line) from August 1, 2012, to March 31, 2022.



4.3.2 Stock market data

For our stock market data, we obtain transaction-level data of SPY from Refinitiv Tick History. The data contains all activity observed at the national best bid and ask, time-stamped to the nearest millisecond. We omit the first and last ten minutes of trading to avoid the confounding effects of market opening and closing. To minimize the effect of recording errors, we exclude transactions where trading volume is above the day's 99.9th percentile. We then follow Chordia et al. (2001) and remove observations containing non-positive quoted spread, quoted spread greater than 5, effective spread/quoted spread greater than 4, percentage effective spread/percentage quoted spread greater than 4, and quoted spread/transaction price greater than 0.4.

For multiple trades that are executed with the same time-stamp, we treat them as one trade as they often reflect a trade initiated by one market participant but executed against the limit orders of multiple participants. In such cases, we use the value-weighted average transaction price and aggregate the volume traded. We then follow Lee and Ready (1991) trade signing algorithm to classify each trade into buyer- and seller-initiated trades. A trade is classified as buyer- (seller-) initiated if the transaction price is above (below) the prevailing midquote. For trades that occur at the midquote, we employ the tick rule and compare the current price with the previous. The construction of informational efficiency measures considered in this study requires price data at various frequencies. As such, we aggregate the transaction-level data to 1-, 10-, 30- and 60-sec intervals. Finally, we winsorize all the continuous series at the 1% each tail to reduce the effect of outliers.

4.3.3 Informational efficiency measures

We follow Comerton-Forde and Putniņš (2015) and construct two informational efficiency measures[38]. These metrics measure the extent to which asset prices deviate from a random walk. First, we calculate the daily absolute midquote return autocorrelation at different frequencies. This metric gauges efficiency by capturing both the under and overreaction of returns to information arrival. Smaller values indicate that prices follow a random walk, and therefore, a more efficient market. The equation is defined below,

$$Autocorrelation_{t,k} = \left|Corr\left(r_{t,k,n}, r_{t,k,n-1}\right)\right|. \tag{4.2}$$

$r_{t,k,n}$ is the n^{th} midquote return measured at intraday frequency k for a given day t, where $k \in$ {1-sec, 10-sec, 30-sec}. Using the absolute values of autocorrelation across three different frequencies, we apply a principal component analysis (PCA) and extract the first principal component, $Autocorrelation^{PCA}$. We then re-scale it so that it ranges from zero (most efficient) to one (least efficient). As explained in Comerton-Forde and Putniņš (2015), the absolute autocorrelation at a single frequency contains some degree of measurement noise. The first principal component reduces this noise and, therefore, is a more accurate measure of efficiency.

The second informational efficiency measure is the absolute excess variance ratio. This measure indicates whether the relationship between the variance of returns at various horizons is linear. The underlying assumption for an efficient market is that the variance

[38] We choose two commonly used informational efficiency measures in the literature, consistent with previous studies such as Hendershott and Jones (2005), O'Hara and Ye (2011), and Comerton-Forde and Putniņš (2015).

of its returns is equal to k times the variance measured at a higher frequency (Lo and MacKinlay, 1988). The equation is as follows,

$$VarianceRatio_{t,kl} = \left|\frac{\sigma_{t,kl}^2}{k\sigma_{t,l}^2} - 1\right|, \tag{4.3}$$

where $\sigma_{t,l}^2$ and $\sigma_{t,kl}^2$ are the variance of l-second and k-second midquote return for a trading day *t*. We use different combinations for (l, kl), i.e., (10-sec, 30-sec), (10-sec, 60-sec) and (30-sec, 60-sec). Similar to the previous metric, we apply a PCA and extract the first principal component, $VarianceRatio^{PCA}$. A higher value indicates slower incorporation of information, and therefore, lower informational efficiency.

Panel A of Table 4.1 further reports the statistical summary of the market efficiency measures. The autocorrelation and variance ratios are, on average, 0.16 and 0.12, respectively, indicating some degree of informational inefficiency. For comparison, Frijns et al. (2023) report a cross-sectional mean of 0.093 for autocorrelation and 0.082 for variance ratio across the S&P 500 constituent stocks. Interestingly, the initial autocorrelation, denoted as AR(1), for the market efficiency metrics is notably modest, hovering around 0.06. This observation implies that instances of market inefficiency are promptly rectified, lacking any enduring impact over time. In the next section, we examine the relationship between social media sentiment and market informational efficiency.

4.4 Empirical results

4.4.1 Baseline specification

We assess the relationship between social media sentiment and informational efficiency. Our baseline model regresses the informational efficiency measures on the social media sentiment as follows,

$$Y_t = \alpha + \beta \cdot Sentiment_{t-1} + \delta \cdot Y_{t-1} + \gamma \cdot Controls_t + \varepsilon_t, \tag{4.4}$$

where Y_t is one of the two measures of informational efficiency on day t, i.e., $Autocorrelation^{PCA}$ or $VarianceRatio^{PCA}$. To avoid endogeneity issues, social media sentiment is lagged one day[39], $Sentiment_{t-1}$. The parameter of interest is β which reflects the impact of social media sentiment on informational efficiency. We include the lagged dependent variable, Y_{t-1}, to control for persistence in the informational efficiency metrics. $Controls_t$ are variables known to influence the patterns of return serial correlations, as highlighted by McKenzie and Faff (2003) and McKenzie and Kim (2007). These variables include the daily SPY return, realized volatility, dollar volume, average bid and ask depth, and the stock market implied volatility. The contemporaneous setup for these control variables is consistent with studies on market quality such as Hendershott et al. (2011) and Brogaard et al. (2015) while the motivation for using these controls is as follows. First, stock returns have been positively associated with return autocorrelation.[40]

[39] The causal relation between social media sentiment and market informational efficiency is the interest of this study, the lagged specification is consistent with the literature (Frijns et al., 2023).

[40] Positive return autocorrelation is more frequently observed during a market upward trend, while negative return autocorrelation in more likely during market downturn (McKenzie and Faff, 2003). In addition, Valadkhani (2022) shows that prices of large ETF, such as SPY, increase more during market uptrend compared to the decrease during market downturn.

Second, empirical evidence by Chau et al. (2011) indicates that realized volatility exerts a negative influence on serial correlations.[41] The feedback trading hypothesis suggests that increased volatility tends to reduce the presence of positive feedback traders, thereby mitigating autocorrelation. Third, heightened trading volume, often a reflection of more informed trading, bolsters market efficiency (McKenzie and Faff, 2003). Consequently, increased trading volume lowers the potential for short-term return predictability, fostering greater market efficiency. Fourth, the bid-ask depth is anticipated to amplify informational efficiency by integrating trading-induced price impacts and information into prevailing prices. Finally, we incorporate the S&P 500 implied volatility index (VIX) to account for overall market uncertainty, with the prevailing expectation of an inverse correlation between VIX and autocorrelation (or variance ratio). The daily SPY return and VIX are collected from Refinitiv Workspace and the CBOE, respectively. The remaining control variables are retrieved from Refinitiv Tick History.

We report the correlations between our variables in Panel B of Table 4.1. Sentiment has low but positive associations with both autocorrelation and variance ratio. This indicates that the market is less (more) efficient in optimistic (pessimistic) periods. The relationships between the informational efficiency metrics and the control variables are in line with our expectations. That is, return is positively correlated with autocorrelation and variance ratio, while other control variables negatively correlate with them.

Table 4.2 reports the regression estimates of Equation (4.4) with the autocorrelation as the dependent variable. Column (1) indicates that sentiment positively and significantly impacts the autocorrelation of SPY. A higher social media sentiment reduces informational efficiency the following day. Columns (2) to (6) show that this

[41] We define the daily realized volatility as the square root of the sum of the squared SPY midquote returns at 1-minute frequency from 9:30 to 16:00 EST.

effect persists after we include the control variables. In line with Table 4.1, the lagged autocorrelation has a positive and significant but small coefficient, suggesting that autocorrelation is not highly persistent. Moreover, the coefficients for the control variables are consistent with the expected sign discussed previously. For instance, return is positively associated with autocorrelation. Realized volatility and the VIX have a negative effect on autocorrelation, i.e., an improvement in informational efficiency. This can be explained using the feedback trading hypothesis where increased volatility reduces the number of positive feedback traders in the market. Higher dollar volume reduces autocorrelation, and accordingly, improves informational efficiency. Finally, the average bid-ask depth is negatively associated with autocorrelation.[42]

Column (7) shows that the effect of social media sentiment on informational efficiency is robust to the inclusion of various controls. We observe that social media sentiment remains impactful on autocorrelation. A one standard deviation increase in sentiment is associated with a 0.009 higher autocorrelation (or a 7.2% increase in autocorrelation).[43] The findings indicate that investor behaviour is not entirely rational and can be influenced by content shared on Twitter related to the SPY. Social media interactions may reshape investors' informational landscape, foster a collective enthusiasm within a market, and influence investment choices. Our results support the notion that investor sentiment interlaces with stock returns and causes pricing frictions, in line with the observation of Da et al. (2011). Our findings are also consistent with Shen

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[42] There are two explanations for this finding. First, the average bid-ask depth serves a direct indicator of order-induced price impact, a conduit for information-driven trading activities, as outlined in Hasbrouck (1991). Second, higher average bid-ask depth weakens the impact of bid-ask bounce (Roll, 1984), thereby contributing to a more subdued impact and an improved level of informational efficiency.

[43] This is calculated as $0.030 \times 0.31 = 0.009$ where the regression coefficient (0.03) is multiplied by the standard deviation of the sentiment index (0.31) reported in Table 4.1. This is equivalent to a $(0.030 \times 0.31) \div 0.13 = 7.2\%$ increase in autocorrelation, where 0.13 is the full sample standard deviation of autocorrelation shown in Table 4.1.

et al. (2017), who ascertain that markets display greater irrationality and diminished efficiency during optimistic periods.

In Table 4.3, we report the regression estimates of Equation (4.4) with the variance ratio as the dependent variable. Consistent with the previous table on autocorrelation, we also find that sentiment has a negative impact on the variance ratio. A one standard deviation increase in sentiment is associated with a 0.005 higher variance ratio (or the 5.2% of its full sample standard deviation).[44] The results confirm that higher social media sentiment reduces informational efficiency, deviating the prices from the fundamental values and lowering the information incorporation process.

[44] This is calculated as 0.015×0.31=0.005 where the regression coefficient (0.015) is multiplied by the standard deviation of the sentiment index (0.31) reported in Table 4.1. This is equivalent to a (0.015×0.31)÷0.09=5.2% increase in variance ratio, where 0.09 is the full sample standard deviation of variance ratio shown in Table 4.1.

Table 4. 2. Autocorrelation and social media sentiment

This table reports the coefficient estimates of Equation (4.4) with the first principal component of autocorrelation, $Autocorrelation_t^{PCA}$ as the market efficiency measure. It is constructed using 1-, 10-, and 30-sec absolute midquote autocorrelations for each trading day from 9:40 to 15:50 EST. The metric is scaled so that it ranges from zero to one. $Sentiment$ is the social media sentiment index from Equation (4.1). $Return$ is the daily return of SPY, $Volatility$ is the realized volatility constructed using SPY midquote returns at a one-minute frequency, $Volume$ is the log of daily total dollar volume, $Depth$ is the log of daily average bid-ask depth, VIX is the daily S&P 500 implied volatility index. The Newey-West corrected t-statistics are in parenthesis. ***, ** and * indicate 1%, 5% and 10% significance level.

	Dependent: $Autocorrelation_t^{PCA}$													
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
$Sentiment_{t-1}$	0.022**	(2.26)	0.021**	(2.26)	0.019**	(2.05)	0.021**	(2.33)	0.028***	(3.08)	0.022**	(2.44)	0.030***	(3.21)
$Autocorrelation_{t-1}^{PCA}$			0.061**	(2.36)	0.057**	(2.25)	0.054**	(2.20)	0.051**	(2.11)	0.057**	(2.23)	0.052**	(2.19)
$Return_t$			0.055*	(1.88)									0.393	(1.33)
$Volatilty_t$					-1.044**	(-2.32)							0.897	(0.83)
$Volume_t$							-0.021***	(-3.35)					-0.003	(-0.27)
$Depth_t$									-0.018***	(-4.44)			-0.021***	(-2.96)
VIX_t											-0.001***	(-2.91)	0.001	(0.28)
Adj. R^2	0.002		0.006		0.007		0.007		0.010		0.014		0.014	
Obs.	2,432		2,432		2,432		2,432		2,432		2,432		2,432	

Table 4. 3. Variance Ratio and social media sentiment

This table reports the coefficient estimates of Equation (4.4) with the first principal component of variance ratio, $VarianceRatio_t^{PCA}$ as the market efficiency measure. It is constructed using the absolute variance ratio of [10-sec, 30-sec], [30-sec, 60-sec] and [10-sec, 60-sec] for each trading day from 9:40 to 15:50 EST and the metric is scaled from zero to one. $Sentiment$ is the social media sentiment index from Equation (4.1). $Return$ is the daily return of SPY, $Volatility$ is the realized volatility constructed using SPY midquote returns at a one-minute frequency, $Volume$ is the log of daily total dollar volume, $Depth$ is the log of daily average bid-ask depth, VIX is the daily S&P 500 implied volatility index. The Newey-West corrected t-statistics are in parenthesis. ***, ** and * indicate 1%, 5% and 10% significance level.

	Dependent: $VarianceRatio_t^{PCA}$													
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
$Sentiment_{t-1}$	0.013**	(2.00)	0.012*	(1.95)	0.011*	(1.81)	0.012**	(1.96)	0.015**	(2.28)	0.013**	(2.07)	0.015**	(2.27)
$VarianceRatio_{t-1}^{PCA}$			0.053***	(2.85)	0.051***	(2.80)	0.052***	(2.75)	0.051***	(2.79)	0.051***	(2.62)	0.052***	(2.77)
$Return_t$			0.410*	(1.83)									0.377	(1.61)
$Volatilty_t$					-0.066	(-1.42)							0.468	(0.56)
$Volume_t$							-0.005	(-1.18)					0.004	(0.55)
$Depth_t$									-0.006**	(-2.17)			-0.004	(-0.76)
VIX_t											-0.001**	(-2.51)	-0.001	(-1.17)
Adj. R^2	0.001		0.005		0.004		0.004		0.005		0.006		0.006	
Obs.	2,432		2,432		2,432		2,432		2,432		2,432		2,432	

4.4.2 Social media sentiment constructed using alternative dictionaries

We first assess the robustness of our main results to the choice of the natural language processing dictionary. Different dictionaries may differ in the way they extract the tone from a text (Bukovina, 2016). This can influence the measurement of social media sentiment, and accordingly, its predictive power. We extract the tone score of tweets using the three following dictionaries: Harvard IV-4 dictionary (Tetlock, 2007), Loughran-McDonald sentiment list (Loughran and McDonald, 2014), and SentiWordNet (Azar and Lo, 2016). After each tweet is classified into positive, negative or neutral categories via each new method, we aggregate them to a daily level following Equation (4.1), respectively.

Table 4.4 reports the regression results for autocorrelation (Panel A) and variance ratio (Panel B) on social media sentiment indices constructed using three different dictionaries. Our results are robust to the choice of the natural language processing dictionary. More specifically, all three new sentiment indices have a positive impact on both informational efficiency measures. They are also statistically significant in most cases. These results provide support that a higher sentiment is associated with a lower informational efficiency.

Table 4. 4. Informational efficiency and social media sentiment constructed using alternative dictionaries

This table reports the coefficient estimates of Equation (4.4) with two market efficiency measures, $Autocorrelation_t^{PCA}$ (Panel A) and $VarianceRatio_t^{PCA}$ (Panel B). Both metrics are constructed for each trading day from 9:40 to 15:50 EST and scaled from zero to one. $Sentiment$ is the social media sentiment index from Equation (4.1) constructed using one of the three different dictionaries, the Harvard IV-4 sentiment list (Tetlock, 2007), the SentiWordNet (Azar and Lo, 2016), and the Loughran-McDonald sentiment list (Loughran and McDonald, 2014). $Return$ is the daily return of SPY, $Volatility$ is the realized volatility constructed using SPY midquote returns at a one-minute frequency, $Volume$ is the log of daily total dollar volume, $Depth$ is the log of daily average bid-ask depth, VIX is the daily S&P 500 implied volatility index. The Newey-West corrected t-statistics are in parenthesis. ***, ** and * indicate 1%, 5% and 10% significance level.

	Panel A: $Autocorrelation_t^{PCA}$						Panel B: $VarianceRatio_t^{PCA}$					
	Harvard IV-4		*SentiWordNet*		*Loughran-McDonald*		*Harvard IV-4*		*SentiWordNet*		*Loughran-McDonald*	
$Sentiment_{t-1}$	0.022**	(2.48)	0.021*	(1.74)	0.024***	(3.20)	0.015**	(2.13)	0.016*	(1.89)	0.007	(1.29)
$Dependent_{t-1}$	0.054**	(2.32)	0.054**	(2.27)	0.054**	(2.32)	0.053***	(2.85)	0.052***	(2.76)	0.053***	(2.82)
$Return_t$	0.358	(1.19)	0.377	(1.26)	0.386	(1.29)	0.357	(1.53)	0.368	(1.60)	0.372	(1.59)
$Volatilty_t$	0.660	(0.60)	0.415	(0.38)	0.720	(0.67)	0.417	(0.50)	0.272	(0.33)	0.279	(0.34)
$Volume_t$	-0.002	(-0.16)	-0.004	(-0.36)	-0.003	(-0.32)	0.005	(0.68)	0.004	(0.54)	0.004	(0.48)
$Depth_t$	-0.022***	(-3.01)	-0.019***	(-2.74)	-0.021***	(-3.03)	-0.006	(-1.09)	-0.004	(-0.79)	-0.003	(-0.61)
VIX_t	0.001	(0.30)	0.001	(0.51)	0.001	(0.42)	-0.001	(-1.18)	-0.001	(-1.00)	-0.001	(-1.08)
Adj. R^2	0.012		0.011		0.014		0.006		0.005		0.004	
Obs.	2,432		2,432		2,432		2,432		2,432		2,432	

4.4.3 Social media sentiment constructed using different time period windows

In our main specification, we construct sentiment using tweets posted during the trading hours between 9:30 to 16:00 EST. The choice of this time interval may affect the degree of social media sentiment and therefore, our findings. To alleviate this concern, we reconstruct the daily social media sentiment index using tweets posted during different intraday time intervals. First, we consider tweets posted during the previous day from 00:00 to 23:59:59 EST. Second, we consider tweets posted during the pre-market period from 00:00 to 09:30 EST, i.e., tweets posted just before the market opens and the market information measures are calculated. Similar to the previous, each tweet is classified into positive, negative or neutral categories. We aggregate them to a daily level following Equation (4.1) and estimate Equation (4.4) for the two market efficiency measures with the newly constructed sentiment indices. The results are reported in Table 4.5.

Our findings remain robust regardless of the periods used to construct social media sentiment. Sentiment positively and significantly affects autocorrelation (Panel A) and variance ratio (Panel B), both during the full day and the pre-market open. However, we acknowledge that the effect is weaker for the latter. This is likely due to lower Twitter activity before 9:30AM (see Figure 4.1.B.). However, the finding that tweets from pre-market open impacts autocorrelation implies that although there is less Twitter activity before the market opens, this information is still useful in explaining the same-day informational efficiency.

Overall, our findings remain robust regardless of the language dictionary used to extract social media sentiment, and the time period window used to construct the social media sentiment. Therefore, we conclude that a higher social media sentiment reduces informational efficiency.

Table 4. 5. Informational efficiency and social media sentiment constructed using alternative intervals

This table reports the coefficient estimates of Equation (4.4) with two market efficiency measures, $Autocorrelation_t^{PCA}$ (Panel A) and $VarianceRatio_t^{PCA}$ (Panel B). $Sentiment$ is the social media sentiment index from Equation (4.1) constructed using alternative intervals, from 00:00 to 23:59:59 EST (Full day) or from 00:00 to 09:29:59 EST (Pre-market open). $Return$ is the daily return of SPY, $Volatility$ is the realized volatility constructed using SPY midquote returns at a one-minute frequency, $Volume$ is the log of daily total dollar volume, $Depth$ is the log of daily average bid-ask depth, VIX is the daily S&P 500 implied volatility index. The Newey-West corrected t-statistics are in parenthesis. ***, ** and * indicate 1%, 5% and 10% significance level.

	Panel A: $Autocorrelation_t^{PCA}$				Panel B: $VarianceRatio_t^{PCA}$			
	Full day		Pre-market open		Full day		Pre-market open	
$Sentiment_{t-1}$	0.033***	(3.20)	0.014**	(2.29)	0.013*	(1.86)	0.006	(1.25)
$Dependent_{t-1}$	0.052**	(2.25)	0.054**	(2.29)	0.052***	(2.77)	0.053***	(2.84)
$Return_t$	0.400	(1.33)	0.296	(0.97)	0.378	(1.62)	0.335	(1.42)
$Volatilty_t$	1.064	(0.97)	0.68	(0.63)	0.454	(0.54)	0.322	(0.39)
$Volume_t$	-0.002	(-0.17)	-0.003	(-0.31)	0.005	(0.57)	0.004	(0.51)
$Depth_t$	-0.021***	(-2.98)	-0.019***	(-2.71)	-0.003	(-0.68)	-0.003	(-0.54)
VIX_t	0.001	(0.20)	0.001	(0.23)	-0.001	(-1.19)	-0.001	(-1.19)
Adj. R^2	0.014		0.012		0.005		0.004	
Obs.	2,432		2,432		2,432		2,432	

4.5 Social Media Sentiment and Investor Herding

In this section, we explore the mechanism underlying the linkages between social media sentiment and informational efficiency. Previous studies document that psychological and social forces may explain aggregate financial market behaviour (see, e.g., Fenzl and Pelzmann 2012; Filip and Pochea, 2023). Fenzl and Pelzmann (2012), for instance, demonstrate that nonmean-reverting dynamism in financial markets can result from irrational herding impulses sensed by market participants in complex and uncertain situations. Filip and Pochea (2023) further show that herding is a persistent phenomenon in the U.S. and European stock markets. Herding behaviour occurs under both extreme positive and negative sentiments. Based on this evidence, we argue that high social media sentiment may accelerate herding behaviour. Subsequently, it will cause prices to deviate from fundamental values and lower informational efficiency.

To investigate whether investors' herding is the mechanism that explains the negative relationship between social media sentiment and market efficiency, we employ the following vector autoregressive (VAR) model, (see Kurov, 2008; and Blasco et al., 2012)[45],

$$Herding_t = \zeta_1 + \sum_{i=1}^{l} \lambda_i Sentiment_{t-i} + \sum_{i=1}^{l} \mu_i Herding_{t-i} + \varepsilon_{1,t},$$

$$Sentiment_t = \zeta_2 + \sum_{i=1}^{l} \eta_i Sentiment_{t-i} + \sum_{i=1}^{l} \theta_i Herding_{t-i} + \varepsilon_{2,t}, \quad (4.5)$$

where $Herding_t$ is one of the herding measures on day t. We use five lags based on the Schwartz Bayesian Information Criterion (SIC).

[45] Kurov (2008) uses a VAR model to capture the relationship between net order flows and returns, finding significant evidence of feedback trading. Blasco et al. (2012) uses a VAR model to explore the herding-sentiment connection and herding-return relation and find that sentiment and past returns drive herding behaviors among investors.

There are several measures for capturing herding activity. We construct two different herding indicators following Cai et al. (2019) and Zhou (2018).[46] Inspired by Lakonishok et al. (1992), Cai et al. (2019) develop the dollar-based herding (*DH*) measure. This measure considers trading volume for measuring the intensity of herding behaviour and is measured as follows,

$$DH_t = \frac{|Buy\ Amount_t - Sell\ Amount_t|}{Buy\ Amount_t + Sell\ Amount_t}, \tag{4.6}$$

where DH_t is the herding on day t, measured as the absolute difference between buyer-initiated ($Buy\ Amount_t$) and seller-initiated ($Sell\ Amount_t$) dollar volumes. A higher DH value indicates higher degree of herding intensity.

Second, we use the Williams Percent Range (*WR*) which measures herding activity as follows,

$$WR_t = -\frac{P_{t-1,t-11}^{high} - p_t^{close}}{P_{t-1,t-11}^{high} - P_{t-1,t-11}^{low}} \times 100 \tag{4.7}$$

where the $P_{t-1,t-11}^{high}$ and $P_{t-1,t-11}^{low}$ are the highest and lowest prices over the prior ten days, from $t-11$ to $t-1$, and p_t^{close} is the closing price on day t. To ease interpretation, we multiply this metric by -1. Thus, a higher (lower) WR represents a higher intensity of overbought (oversold). Following Zhou (2018), if WR is greater than -20, the asset is regarded as overbought, and when WR is less than -80, the asset is regarded as oversold. We report the VAR results from Equation (4.5) in Panels A and B of Table 4.6, respectively.

[46] We only consider one asset (SPY) and, therefore, we cannot calculate herding measures such as cross-sectional absolute deviations and cross-sectional standard deviations which require a cross section of assets (see e.g., Christie and Huang, 1995; Chang et al., 2000; or Lakonishok et al., 1992).

Table 4. 6. Investor herding and social media sentiment

This table reports the coefficient estimates of Equation (4.5) with two herding measures, Dollar Based Herding, DH (Panel A) and Williams Percent Range, WR (Panel B), as described in Equation (4.6) and (4.7), respectively. Higher DH indicates a higher level of herding. Higher (lower) WR indicates the asset is overbought (oversold). $Sentiment$ is the social media sentiment index from Equation (4.1). The Schwartz Bayesian Information Criterion (SIC) is used to choose the optimal number of lags. All variables are normalized. The Newey-West corrected t-statistics are in parenthesis. ***, ** and * indicate 1%, 5% and 10% significance level.

	Panel A: DH_t				Panel B: WR_t			
	$Herding_t$		$Sentiment_t$		$Herding_t$		$Sentiment_t$	
$Sentiment_{t-1}$	0.059**	(2.40)	0.235***	(9.48)	0.032**	(2.15)	0.224***	(8.13)
$Sentiment_{t-2}$	0.005	(0.23)	0.140***	(6.24)	-0.02	(-1.28)	0.138***	(5.80)
$Sentiment_{t-3}$	0.021	(0.94)	0.137***	(6.17)	-0.008	(-0.53)	0.143***	(6.10)
$Sentiment_{t-4}$	-0.043*	(-1.74)	0.111***	(4.89)	0.023	(1.37)	0.119***	(4.96)
$Sentiment_{t-5}$	-0.012	(-0.47)	0.103***	(4.67)	0.003	(0.22)	0.114***	(4.99)
$Herding_{t-1}$	0.106***	(5.27)	0.006	(0.32)	0.700***	(31.37)	0.033	(1.13)
$Herding_{t-2}$	0.060***	(2.84)	0.015	(0.84)	0.092***	(3.23)	-0.005	(-0.15)
$Herding_{t-3}$	0.038	(1.62)	-0.033*	(-1.74)	-0.003	(-0.13)	-0.034	(-0.93)
$Herding_{t-4}$	0.055***	(2.64)	0.004	(0.22)	-0.028	(-1.17)	-0.009	(-0.31)
$Herding_{t-5}$	0.072***	(3.01)	-0.007	(-0.41)	-0.013	(-0.57)	-0.027	(-0.98)
Adj. R^2	0.034		0.272		0.576		0.274	
Obs.	2432		2432		2432		2432	

Turning first to Panel A, we observe that the coefficient of the first sentiment lag is significant and positive at 0.059 (t-statistic of 2.40) for the DH_t and 0.032 (t-statistic of 2.15) for WR_t. This indicates that a higher sentiment is associated with a higher herding behaviour (DH) and greater likelihood of overbought (WR) the following day. This result implies that investors mimic the trading of others during optimistic periods. This collective reaction eventually leads to an imbalance between buy and sell transactions, causing prices to deviate from their fundamental values. We interpret the positive effect of sentiment on both herding measures being caused by short-selling constraints. In particular, while investors may herd during optimistic times, they are unable to short sell during pessimistic times. This is consistent with Barber and Odean (2008) who explain that individual investors tend to be net buyers for stocks experiencing high abnormal trading volume and stocks with extreme returns, but they can only sell stocks they already own. We do not observe any reserve causality from herding to sentiment. This observation is consistent with Blasco et al. (2012) who find that investor sentiment Granger causes herding but not vice versa.

To understand the dynamic relationship between sentiment and herding behaviour, we follow the literature and plot the cumulative generalized impulse response functions (Pesaran and Shin, 1998). Specifically, we plot how one standard deviation shock in the social media sentiment impacts the DH and WR herding measures in Figures 3 and 4, respectively.

Figure 4.3 illustrates that a one standard deviation shock from social media sentiment significantly increases the dollar-based herding in the following 8 days before the effect disappears. We find a similar pattern with the WR herding measure in Figure 4.4, but this effect only lasts for two days. These results suggest that an optimistic view on the SPY leads to a significant and short-lived increase in herding behaviour among investors. As a result, informational efficiency decreases.

Figure 4. 3. Generalized impulse response from social media sentiment to DH Herding

This figure plots the cumulative impulse response function for one standard deviation shock of the sentiment on the Dollar Based Herding, DH as described in Equation (4.6). The higher value of Dollar Based Herding means a higher level of herding. The red dotted lines are the 95% upper and lower bands.

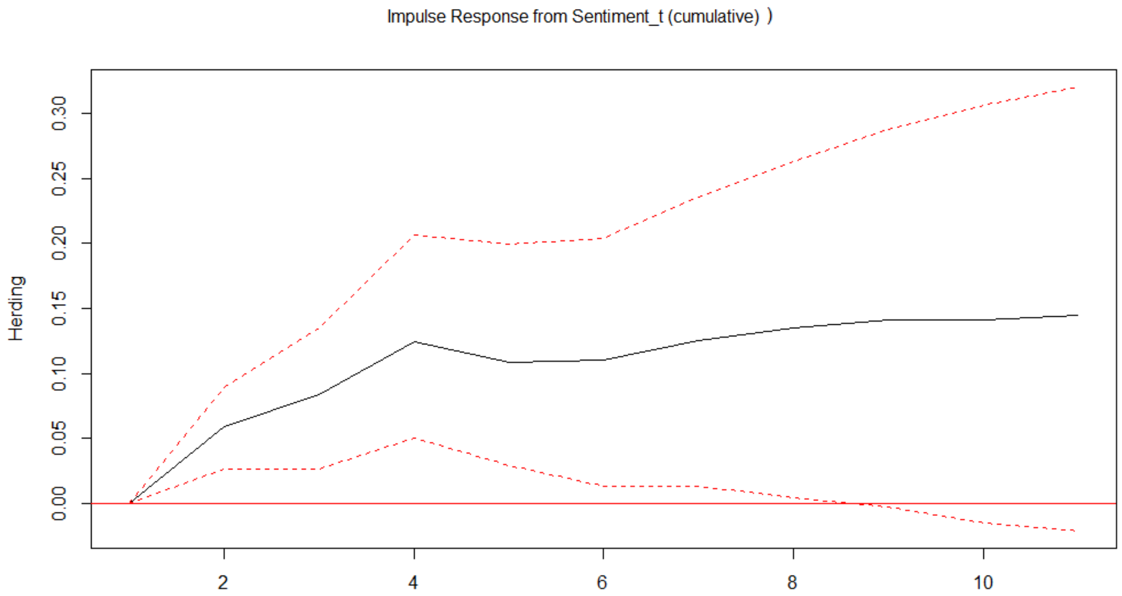
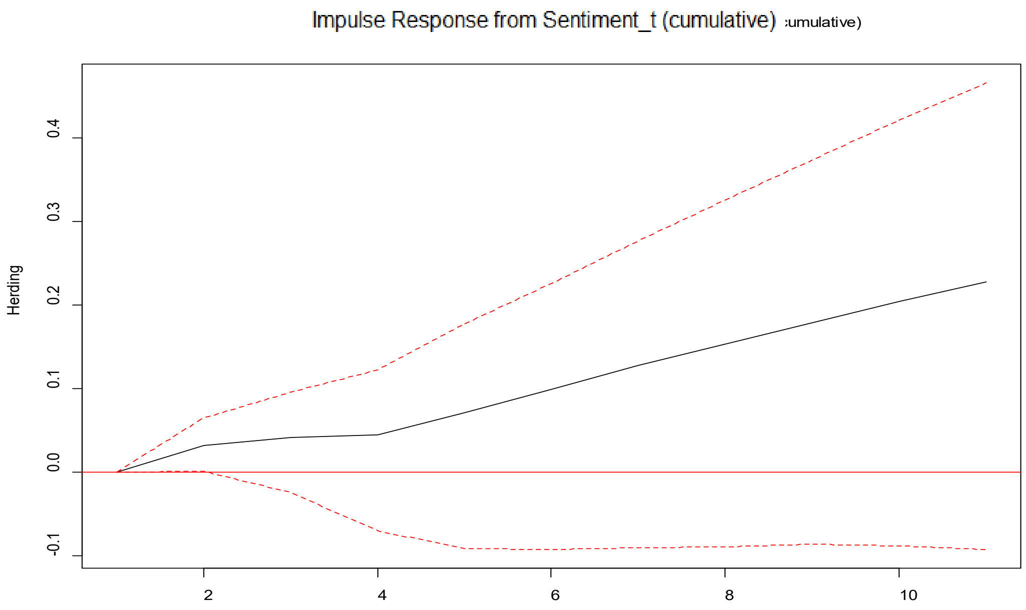


Figure 4. 4. Generalized impulse response from social media sentiment to WR Herding

This figure plots the cumulative impulse response function for one standard deviation shock of the sentiment on the Williams Percent Range, WR, as described in Equation (4.7). The higher (lower) value of WR means overbought (oversold). The red dotted lines are the 95% upper and lower bands.



One potential concern about the WR herding measure is that we treat WR as continuous variables in the VAR model specification in Equation (4.5). Zhou (2018) argues that WR score higher than -20 is defined as overbought and a score lower than -80 is classified as oversold. Given that an overbought and an oversold asset can imply investors' herding behaviour, we redefine the WR herding measure as an indicator variable which equals one on days when the WR value is less than -80 or greater than -20, and zero otherwise. We run a logistic regression using the WR herding indicator as the dependent variable, and the lagged social media sentiment as the main independent variable. We employ the same control variables as with Equation (4.4).

We report the coefficients, odds ratio and t-statistics of the logistic regression in Table 4.7. Odds ratio is the exponentiated coefficient, representing the proportional change of parameters. The coefficient for the lagged sentiment is positive at 0.045 (with an odds ratio of 1.046), statistically significant at the 1% level. In probabilistic terms, this coefficient can be interpreted as a one unit increase in social media sentiment is associated with a higher likelihood of herding behaviour the following day by a factor of 1.046. In other words, the probability of herding increases by a factor of 74% with an increase of one standard deviation in sentiment[47]. Furthermore, the Pseudo-R^2 is high at 0.80, indicating this model fits the data well. These results are in line with the findings of the VAR model reported in Table 4.6.

[47] We use sigmoid function to calculate and obtain 74%. Specifically, it equals $\frac{1}{1+e^{-1.046}}$, where e is Euler's number.

Table 4. 7. Logistic regression of investor herding and social media sentiment using classified Williams Percent Range

This table reports the coefficient estimates of logistic regression of categorized William Percent Range (WR) herding and social media sentiment. The estimate specification is similar to Equation (4.4) but with the dependent variable being the herding metric $Herding_t$, which takes a value of 1 if WR is less than -80 (i.e., oversold) or greater than -20 (overbought), and 0 otherwise. $Sentiment_{t-1}$ is the lagged social media sentiment index from Equation (4.1). $Return$ is the daily return of SPY, $Volatility$ is the realized volatility constructed using SPY midquote returns at a one-minute frequency, $Volume$ is the log of daily total dollar volume, $Depth$ is the log of daily average bid-ask depth, VIX is the daily S&P 500 implied volatility index. Odds ratios are the exponentiated coefficients, representing the proportional change of parameters. The Pseudo-R^2 measure ranges from 0 to 1, a higher value indicates a better fit of the model to the data. The Newey-West corrected t-statistics are in parenthesis. ***, ** and * indicate 1%, 5% and 10% significance level.

	Dependent: $Herding_t$		
	Coef.	Odds ratio	t-stat
$Sentiment_{t-1}$	0.045***	1.046	(4.57)
$Herding_{t-1}$	0.353***	1.423	(18.21)
$Return_t$	-0.012	0.988	(-1.08)
$Volatility_t$	-0.082***	0.921	(-4.14)
$Volume_t$	0.055***	1.056	(3.22)
$Depth_t$	-0.067***	0.935	(-3.96)
VIX_t	0.058***	1.060	(3.12)
Pseudo R^2		0.80	
Obs.		2432	

4.6 Conclusions

We examine the impact of social media sentiment on informational efficiency. We employ a natural language processing analysis to extract sentiment from tweets and analyze its impact on the efficiency of the SPDR S&P 500 ETF (SPY) prices. Using autocorrelation and variance ratio as informational efficiency measures, our findings indicate that higher social media sentiment reduces informational efficiency the following day. This finding highlights the influence of optimistic social media sentiment on market inefficiency.

We also delve into the underlying transmission channel. Our study shows that higher social media sentiment intensifies investors' herding activity the following day. Heightened sentiment leads to collective trading behaviours which result in one-sided buying or selling actions. Such herding behaviour acts as an obstacle to the efficient dissemination of information and diminishes informational efficiency.

Our study has important implications for various stakeholders. For market participants, our findings highlight the importance of incorporating social media sentiment as a crucial factor when devising investment strategies. For regulators and policymakers, our study highlights the potential of social media as an additional surveillance tool within the market regulatory framework. Recognizing the influence of social media sentiment can aid in enhancing market oversight to effectively monitor and manage potential risks and market disruptions.

Chapter 5

Spillover between investor sentiment and volatility: The role of social media

5.1 Introduction

It has been well documented that sentiment extracted from traditional news media influences financial markets (see, e.g., Fang and Peress, 2009; Engelberg and Parsons, 2011; Dougal et al., 2012). Over the last decade, however, social media has become investors' leading source of information. The Reuters Institute digital news survey (Newman et al., 2021) documents that 56% of the respondents worldwide use social media to access news and information. In line with this technological change, recent academic literature has highlighted the importance of social media sentiment for the equity markets (see, e.g., Rakowski et al., 2021; Al-Nasseri et al., 2021), bonds (Alomari et al., 2021), foreign exchange (Goddard et al., 2015; Sibande et al., 2023), and commodities (Han et al., 2017; Fan et al., 2022).

Despite the extant studies on social media and financial markets, it remains underexplored whether sentiment from social media spillovers across different asset classes. The literature has shown that different asset classes are interconnected. For example, the safe haven literature finds a relationship between equity with gold markets (see, e.g., Baur and McDermott, 2016; Triki and Maatoug, 2021), while the investor fear and attention literature find a link between equity and foreign currency markets (Goddard et al., 2015; Smales and Kininmonth, 2016) or equity and commodity markets (Gao and Süss, 2015; Fernandez-Perez et al., 2020). We posit that the linkages between various asset classes can be further explained by sentiment spillover, i.e., how investors' sentiment from one asset influences the sentiment of other asset classes. Whether such sentiment transmission exists remains an empirical question.

Understanding sentiment spillover is crucial when disentangling the underlying relation among asset classes. Existing studies mainly focus on volatility spillover, and as such, the linkage between two assets is often interpreted from the uncertainty transmission perspective (Andrada-Félix et al., 2018; Sharif et al., 2020; Bouri et al., 2021; Mensi et al., 2021). Andrada-Félix et al. (2018), for instance, argue that volatility reflects the extent to which the market evaluates and assimilates new information. As such, volatility spillover captures how perceptions of uncertainty about economic fundamentals are manifested in prices across various asset classes. In this study, we argue that linkages between assets can also be explained through a behavioural explanation. That is, during periods of heightened uncertainty about fundamentals, investors consider social media as an additional source of information. They exchange their opinions via social platforms and are influenced by other investors' sentiment. In a recent study, Umar et al. (2021) demonstrate the sentiment-driven pricing in the case of meme stocks, such as the GameStop stock. In this paper, we examine whether sentiment spillovers from one asset to other asset classes.

Beyond the linkages between sentiments, we also assess the spillover effects between sentiment and volatility across asset classes. Existing studies mainly focus on examining sentiment and volatility spillover separately (Andrada-Félix et al., 2018;

Audrino and Tetereva, 2019).[48] However, we can expect cross-linkages between sentiment and volatility. For instance, the crude oil literature documents that oil price volatility influences stock market sentiment. Oil price uncertainty leads to the postponement of investment decisions (Elder and Serletis, 2010) and increases the unemployment rate (Kocaasland, 2019). This reduces investor sentiment in the equity markets (Chalmers et al., 2013; Bennani, 2020). Other studies, such as Da et al. (2015) and Goddard et al. (2015), also explore the sentiment and volatility linkage but within the same asset class.[49] To the best of our knowledge, this is the first paper that examines the effects of social media sentiment on asset volatility across various asset classes.

In this study, we assess the relationship between sentiment and implied volatility across various asset classes. We employ Diebold and Yilmaz's (2012, 2014; hereafter, DY) measure of connectedness, which measures the shares of forecast-error variation in an asset due to shocks arising elsewhere. Of particular interest in this study, we investigate the linkages across the equity, bond, precious metal, energy, and foreign exchange markets. The key novelty of our work compared to the previous studies is that we consider investor sentiment specific to each of the above asset classes. We leverage the Refinitiv MarketPsych Analytics (RMA) social media sentiment data. The RMA analyzes millions of real-time social media references from thousands of global media outlets daily and measures investor sentiment scores for each asset. Specifically, we use the following social media sentiment indices from RMA: (1) the stock market sentiment, (2) the bond market sentiment, (3) the Euro/USD sentiment, (4) the gold sentiment, and (5) the oil sentiment. For volatility measures, we use the Chicago Board Options Exchange (CBOE)

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[48] Andrada-Félix et al. (2018) investigate the interconnection between implied volatility indices for five different asset classes such as stock, energy, currency, metal and bond. Audrino and Tetereva (2019) study the sentiment spillover effects for US and European companies.

[49] Da et al. (2015), for instance, show that investor sentiment proxied using internet search volume predicts temporary increases in stock market volatility. Goddard et al. (2015) find that investor attention in the foreign exchange markets comoves with contemporaneous foreign exchange market volatility and predicts subsequent volatility.

implied volatility indices. An implied volatility index measures investors' expectations about the future volatility of the underlying asset (Whaley, 2009). The forward-looking nature of implied volatility indices makes them superior to historical volatility (see e.g., Blair et al., 2001; Jiang and Tian, 2005). We employ the implied volatility indices for the US equity market (the CBOE Volatility Index), the US bond market (the 10-year T-Note Volatility Index), the foreign exchange market (Eurocurrency Volatility Index), the gold market (the Gold Volatility Index), and the crude oil market (the Crude Oil Volatility Index). We further assess the block connectedness between the sentiment block and the volatility indices block using the generalized connectedness framework developed by Greenwood-Nimmo et al. (2016, 2021).

Measuring connectedness over the sample period from August 2008 to May 2020, we obtain several key findings. First, our sentiment and volatility indices are interconnected with a total connectedness of 30.4%. There is a stronger spillover from volatility to the sentiment of the same market, but a marginal effect in the opposite direction. Second, informational spillover comes mainly from volatility indices to sentiment indices, with the VIX being the most significant net transmitter to other assets. Third, the connectedness between market sentiment and volatility increases during turbulent economic periods, such as the Global Financial Crisis (GFC), Brexit, the US-China trade war, and the COVID-19 pandemic. However, the sentiment indices can switch from being a net receiver to a net transmitter of shocks during turbulent periods.

We contribute to several strands of literature. First, this study sheds light on social media sentiment spillover across financial markets. The existing literature mainly focuses on the effect of general market sentiment on different asset classes. Zhang et al. (2022), for example, explore the spillover effects from COVID-19 media coverage to different asset classes such as crude oil, gold, and cryptocurrency. In contrast, we examine sentiment specific to each asset class rather than general market sentiment. Hence, our findings provide a better understanding of the importance of social media irrespective of the asset classes. Second, we show that, in general, social media sentiment is a net receiver rather than a major trigger of market volatility. However, during periods of market turmoil, social media sentiment can turn into a net transmitter of shocks. This evidence is consistent with the “echo chamber” effect (Jiao et al., 2020). In particular, social media repeat existing news media signals, but some investors interpret repeated signals as genuinely new information. This channel explains why social media sentiment is on average a net receiver of shocks but turns into a net trigger in turbulent times.

The remainder of the paper proceeds as follows. Section 5.2 reviews the literature. Section 5.3 presents the methodology. Section 5.4 introduces the volatility and sentiment datasets and provides descriptive statistics. In Section 5.5, we report our empirical findings and robustness tests. Section 5.6 concludes.

5.2 Literature Review

It is well documented that investor sentiment is associated with volatility in the financial markets (see e.g., Da et al., 2015; Behrendt and Schmidt, 2018; Liang et al., 2020; Gan et al., 2020). Da et al. (2015), for example, document that low sentiment (proxied using the Google searches of keywords such as ‘recession’ and ‘crisis’) predict short-term return reversals and temporary increases in volatility. Behrendt and Schmidt (2018) and Liang et al. (2020) find that stock market social media sentiment has a pronounced impact on individual stock volatility and can forecast stock market volatility. Gan et al. (2020) show that stock market volatility is more sensitive to social media than news sentiment. A separate study by Sprenger et al. (2014a), interestingly, find a reverse causality where high stock volatility leads to an increased relevant discussion on social media as uncertainty causes investors to exchange information and consult their peers, and this is reflected in the social media sentiment.

The linkage between investor sentiment and volatility has also been documented in assets other than stocks. Goddard et al. (2015), for instance, find that investor sentiment in the foreign exchange markets comoves with contemporaneous foreign exchange market volatility and predicts subsequent volatility. Furthermore, Karagozoglu and Fabozzi (2017) show that a signal constructed from social media sentiment can be used to predict VIX-related ETFs. In commodities, Gao and Süss (2015) demonstrate that commodity futures with high volatility are more likely to be exposed to sentiment.

Despite the significant interest in studying market sentiment and volatility, the literature has largely overlooked the potential spillover effects from sentiments across different asset classes. However, recent studies have started to address this gap in the literature. For instance, Alomari et al. (2021) examine the effects of news and social media sentiments on both stock and bond market volatility, while Yousaf et al. (2022) explore the connectedness between the S&P500 Twitter Sentiment Index and the returns of various asset classes. Moreover, the crude oil literature has highlighted the impact of oil price uncertainty on stock returns. Oil price uncertainty can lead to postponement of investment decisions (Elder and Serletis, 2010) and increases in the unemployment rate (Kocaasland, 2019), resulting in a slowing down of economic activity that can dampen investor sentiment in the equity markets (Chalmers et al., 2013; Bennani, 2020). All these findings suggest that spillover effects from other asset classes may contaminate the sentiment and volatility of a particular asset class.

In this study, we propose that sentiment and volatility linkages between asset classes may be further explained by a behavioural channel. Specifically, we suggest that sentiment from other asset classes may impact asset-specific sentiment and volatility, particularly during periods of heightened uncertainty regarding underlying fundamentals. This is because investors often seek out additional sources of information during such periods, including social media. Consequently, the exchange of opinions on social media can contribute to increased volatility across multiple assets. For example, Umar et al. (2021) demonstrated the impact of sentiment-driven pricing on meme stocks like GameStop. Building on this, our study aims to explore whether sentiment spillovers from one asset to another can be observed across different asset classes. To accomplish this, we utilize asset-specific sentiment measures from RMA and use the Diebold and Yilmaz (2012, 2014) connectedness methodology to disentangle their interconnected effects. We explain this methodology next.

5.3 Methodology

We first discuss the DY approach as our primary measure of connectedness among different sentiment and volatility indices. We then discuss the generalized connectedness framework developed by Greenwood-Nimmo et al. (2016, 2021) to capture the connectedness within and between sentiment and volatility blocks.

5.3.1 Diebold-Yilmaz connectedness measure

To measure the connectedness of five market sentiments and five market volatility indices, we follow the DY approach. This approach is related to the economic notion of variance decomposition, in which the forecast-error variance of a variable is decomposed into parts attributed to the various variables in the system. Consider fitting a reduced-form, N-dimensional covariance-stationary vector autoregression (VAR) model: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \cdots, E(u_t, u_t') = I$. The contemporaneous aspects of connectedness are summarized in Θ_0, and dynamic aspects in $\{\Theta_1, \Theta_2, \ldots\}$. Transformations of $\{\Theta_1, \Theta_2, \ldots\}$ via variance decompositions can reveal connectedness.

We employ the "variance decomposition table" of Diebold and Yilmaz (2014) to understand the connectedness measures. Table 5.1 reports the variance decompositions where x_1 to x_N are the sentiment or volatility variables of each asset, H is the number of periods ahead forecast. The upper-left NxN block contains variance decompositions with denoted D^H where $D^H = [d_{ij}^H]$[50]. In particular, the pairwise directional connectedness from j to i as defined:

$$C_{i\leftarrow j}^H = d_{ij}^H \,. \tag{5.1}$$

The pairwise directional connectedness from $i\ to\ j$ is $C_{j\leftarrow i}^H = d_{ji}^H$ where $C_{i\leftarrow j}^H \neq C_{j\leftarrow i}^H$, generally, and therefore, we define the net pairwise directional connectedness from i to j as follows:

$$C_{ij}^H = C_{j\leftarrow i}^H - C_{i\leftarrow j}^H. \tag{5.2}$$

For the rightmost column sum or bottom row sum (both $i \neq j$) means the share of forecast error variance of x_i coming from or going to shocks arising in all other variables. Thus, we label the rightmost column and the bottom row as "From others" and "To others" total directional connectedness measures. Hence, we define total directional connectedness from others to i as:

$$C_{i\leftarrow \bullet}^H = \sum_{\substack{j=1 \\ j\neq i}}^N d_{ij}^H, \tag{5.3}$$

while the total directional connectedness from i to others is defined as:

$$C_{\bullet\leftarrow i}^H = \sum_{\substack{j=1 \\ i\neq j}}^N d_{ji}^H. \tag{5.4}$$

[50] We denote d_{ij}^H by the ij-th H-step forecast error variance decomposition component, capturing the fraction of variable i's H-step forecast error variance due to shocks in variable j. The off-diagonal entries of D^H are the parts of the N forecast error variance decompositions of relevance from connectedness method.

Table 5. 1. Connectedness table

This table shows the schematic for the connectedness table for N assets. The rightmost column contains the row sums (total directional connectedness FROM others), the bottom row contains the column sums (total directional connectedness TO others), and the bottom-right cell contains the grand average (the overall connectedness).

	x_1	x_2	...	x_N	From others
x_1	d_{11}^H	d_{12}^H	...	d_{1N}^H	$\sum_{j=1}^{N} d_{1j}^H, j \neq 1$
x_2	d_{21}^H	d_{22}^H	...	d_{2N}^H	$\sum_{j=1}^{N} d_{2j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}^H	d_{N2}^H	...	d_{NN}^H	$\sum_{j=1}^{N} d_{Nj}^H, j \neq N$
To others	$\sum_{i=1}^{N} d_{i1}^H, i \neq 1$	$\sum_{i=1}^{N} d_{i2}^H, i \neq 2$	...	$\sum_{i=1}^{N} d_{iN}^H, i \neq N$	$\frac{1}{N}\sum_{ij=1}^{N} d_{ij}^H, i \neq j$

Accordingly, we define net total directional connectedness for *i* as:

$$C_i^H = C_{\bullet\leftarrow i}^H - C_{i\leftarrow\bullet}^H. \tag{5.5}$$

Lastly, the grand total of the off-diagonal entries in D^H on the bottom-right of Table 5.1 (equivalently, the sums of the rightmost column or the bottom row), measures total connectedness among all variables as:

$$C^H = \frac{1}{N}\sum_{\substack{i,j=1 \\ j\neq i}}^{N} d_{ij}^H. \tag{5.6}$$

For the case of non-orthogonal shocks, the variance decompositions are not as easily calculated because the variance of a weighted sum is not an appropriate sum of variances. Following Diebold and Yilmaz (2014), we, therefore, use the generalized variance decomposition (GVD) proposed by Koop et al. (1996) and Pesaran and Shin

(1998) to decompose the forecast error variance.[51] The H-step GVD matrix $D^{gH} = \left[d_{ij}^{gH}\right]$ is defined[52] as:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma \Theta_h' e_j\right)}, \tag{4.7}$$

where e_j is a vector with jth element unity and zeros elsewhere; Θ_h is the coefficient matrix (by multiplying the h-lagged shock vector) in the infinite moving-average representation from the non-orthogonalized VAR; Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR; σ_{jj} is the jth diagonal element of Σ. Particularly, the generalized connectedness index is $\widetilde{D}^g = \left[\tilde{d}_{ij}^g\right]$ with the necessary normalization $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$. By construction, $\sum_{j=1}^N \tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^N \tilde{d}_{ij}^g = N$. Thus, the connectedness measures can be calculated by using $\widetilde{D}^g = \left[\tilde{d}_{ij}^g\right]$ matrix. The DY approach's forecast error variance decomposition is directly computed from the estimated parameters and covariance matrix of the VAR system.[53]

5.3.2 Greenwood-Nimmo connectedness measure

To investigate whether changes in sentiment induce volatility variations and vice versa, we first combine the five sentiment and five market volatility indices into two separate groups, which we refer to as the sentiment block and volatility block, respectively. We are interested in capturing the connectedness within and between sentiment and volatility blocks. Hence, instead of assessing the spillover effect for each variable individually, we

[51] GVD is invariant to ordering of the variables in the VAR system.

[52] Note that under this circumstance, row sums of d_{ij}^{gH} are not necessarily unity because shocks do not have to meet the orthogonality setting.

[53] This calculation is subject to no additional restrictions beyond estimation and identification requirements, accounting for the contemporaneous effects and providing a measurement of connections embedded in the model.

measure block connectedness between sentiment and volatility. This analysis will enable us to determine whether sentiment or volatility as a block is the main source of spillover effects observed in our study.

We follow Greenwood-Nimmo et al.'s (2016) block connectedness methodology. This approach exploits aggregation of the estimated connectedness matrix to create generalized connectedness measures into different desired levels (e.g., markets, countries) for comparisons. A similar methodology was also employed in recent studies such as Raddant and Kenett (2021) and Greenwood-Nimmo et al. (2021). In our case, we combine the ten variables in the system into two blocks based on their nature and then aggregate the estimated connectedness matrix according to the block structure. The technical details of this methodology can be found in Appendix II.

5.4 Data

In this section, we discuss the two sets of data employed in this study. First, we describe the implied volatility indices for the five asset classes we consider in our sample. Second, we explain the social media sentiment data as our measure of asset-specific investor sentiment.

5.4.1 Market volatility

To proxy for stock market volatility, we employ the CBOE Volatility Index (ticker: *VIX*). Using prices of options on the S&P 500 index, the VIX is designed to reflect investors' consensus for the upcoming 30-day expected volatility of the US equity market. For the bond market, we use CBOE/CBOT 10-year US Treasury Note volatility index (*TYVIX*). TYVIX measures the expected volatility in its underlying 10-year Treasury Note futures over the next 30 days. For the foreign exchange market, we employ the CBOE Euro

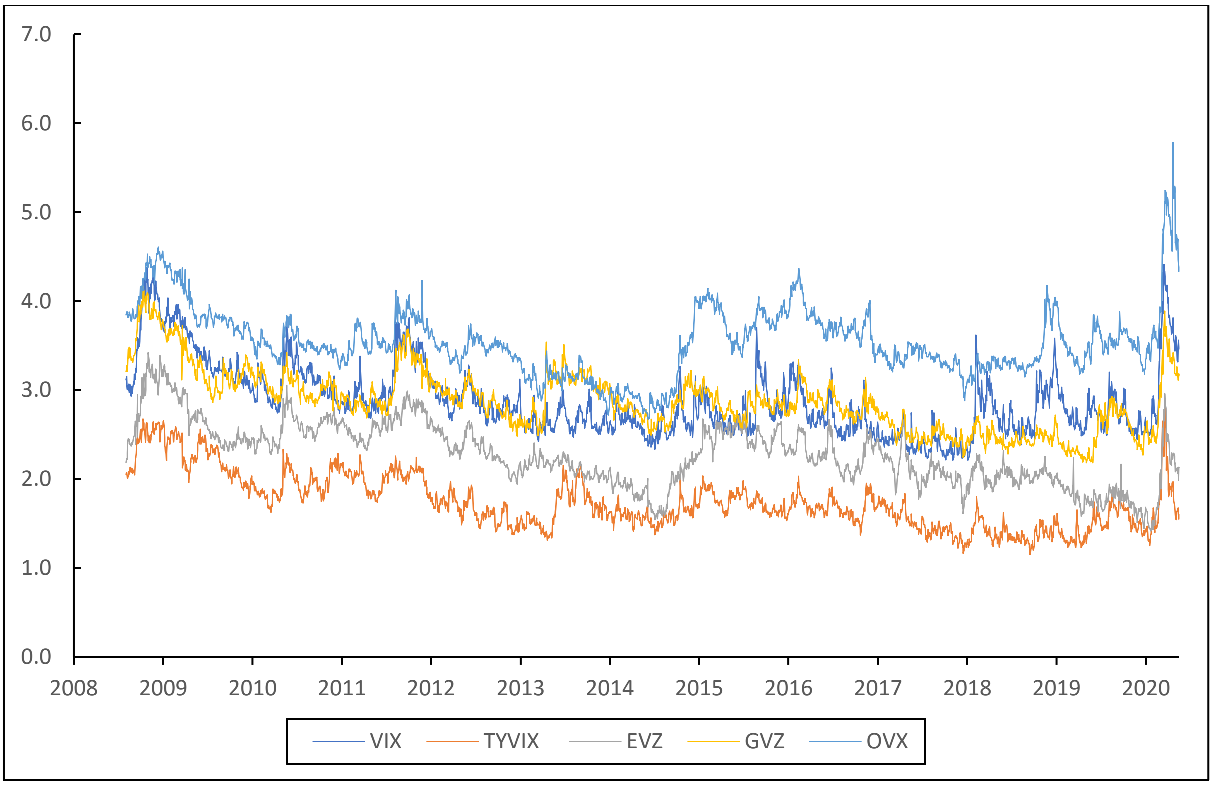
Currency Volatility Index (*EVZ*). EVZ estimates the expected 30-day volatility of the Euro/USD exchange rate by tracking the underlying options midquote prices on the Currency Shares Euro Trust. As an indicator of precious metals markets, we use the CBOE Gold ETF Volatility Index (*GVZ*). GVZ measures the expected 30-day volatility of underlying options midquote values on the SPDR Gold Shares ETF. For the energy market volatility, we use the CBOE Crude Oil ETF Volatility Index (*OVX*) as an estimate of the expected 30-day volatility of crude oil options as priced by the United States Oil Fund ETF. All volatility data is obtained from Refinitiv Datastream at a daily frequency. Our sample period is from August 1, 2008, to May 15, 2020. This period covers a series of significant economic events, such as the GFC, Brexit, the US-China trade war, and the COVID-19 pandemic. The starting period is when the EVZ was first introduced, and the ending period is when TYVIX was discontinued.

Figure 5.1 plots the daily implied volatility indices (in logs).[54] We observe some volatility spikes across markets that coincide with various economic events. For example, all indices surged in September 2008 due to the collapse of Lehman Brothers. Similarly, the spike around April 2010 was during the European sovereign debt crisis. From May to August 2011, the US debt-ceiling crisis and the US credit rating downgrade (from AAA to AA+) raised concerns about credit defaults. Countries holding large amounts of US dollars were concerned about their potential losses, aggravating investor uncertainty. In 2016, Brexit triggered economic distress among global investors. Finally, all implied volatilities soared to their historical highest during the COVID-19 pandemic at the beginning of 2020.

[54] The generalized variance decomposition requires normality. We, therefore, approximate it by taking natural logarithms in the volatility indices.

Figure 5. 1. Implied volatility over time

This figure plots the daily implied volatility index across various asset classes, including the CBOE S&P500 volatility index (VIX), the 10-year Treasury Note volatility index (TYVIX), the Euro Currency implied volatility index (EVZ), the Gold ETF volatility index (GVZ) and the crude oil volatility index (OVX). The sample period is from August 1, 2008, to May 15, 2020. All series are in natural logarithms.



5.4.2 Sentiment data

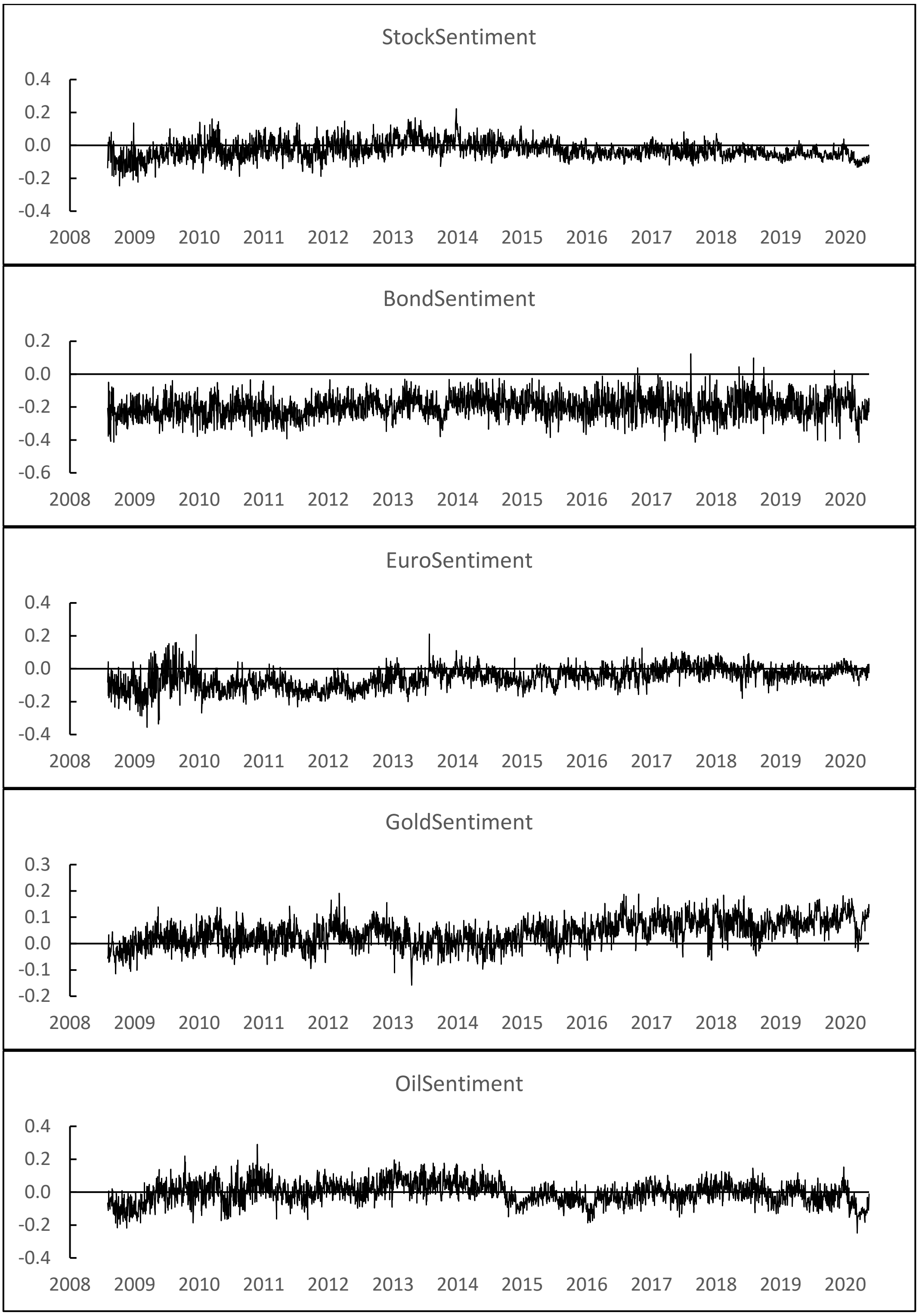
As our measure of asset-specific investor sentiment, we employ the Refinitiv MarketPsych Analytics (RMA) sentiment data (formerly Thomson Reuters MarketPsych Indices, TRMI). The RMA provides advanced and comprehensive asset-specific sentiment data for various assets from all major countries at daily, hourly and minute frequencies, dating back to 1998. The RMA analyzes millions of real-time mainstream news (e.g., Reuters markets coverage, the Wall Street Journal, the Financial Times, the New York Times) and social media messages (including the top 30% of most followed blogs, microblogs, and forums worldwide, such as Reddit, Twitter, Yahoo! Finance, SeekingAlpha and StockTwits) and processes them with a high-speed AI-based machine learning algorithm for natural language processing (NLP). The extensive source coverage and advanced NLP of RMA ensure the precision of data quantification with the superiority of less information distortion, addressing heterogeneous issues (Zhang et al., 2022). This is crucial when it comes to the reliability and predictive power of sentiment data. The RMA sentiment data has been used in recent studies, including Papakyriakou et al. (2019), Michaelides et al. (2019), and Gan et al. (2020).

The RMA provides sentiment scores in three categories: *News*, *Social*, and *News&Social* (a combination of news and social). For this study, we concentrate on the sentiment indicators from the *Social* category and employ the other two in our robustness tests. We collect the following five daily sentiment indices from RMA: (1) the stock market sentiment (RMA code: *ETFUS500*), (2) the bond market sentiment (*US-bondSentiment*), (3) the Euro/USD sentiment (*EUR*), (4) the gold sentiment (*GOL*), and (5) the oil sentiment (*CRU*). The sentiment score is calculated as the volume-weighted average difference between positive and negative mentions of the underlying asset over a 24-hour window. It ranges from -1 to 1 and represents the degree of market optimism or pessimism for the underlying asset. A positive sentiment score suggests that investors are optimistic and have a bullish expectation for the underlying market. A negative score indicates that investors are pessimistic and have bearish expectations. A zero score indicates neutral sentiment. The RMA updates the sentiment data every calendar day at 3:30 pm US Eastern time.

Figure 5.2 plots the various sentiment indices over the sample period. The plots show that the equity, foreign exchange, and oil sentiment indices fluctuate around zero. In contrast, the bond market sentiment is almost persistently negative and highly volatile, while gold sentiment is relatively stable and positive over the sample period. We also observe that the sentiment indices vary over time. For instance, oil sentiment switched from bullish to bearish when the OPEC decided against cutting production despite the abundance of oil supply back in 2015. Many of the spikes in sentiment also coincide with the spike in volatility shown in Figure 5.1. For example, during the GFC in 2008 and the COVID-19 pandemic in 2020, all sentiment indices turned into a bearish territory, reflecting general pessimism across various markets. Investor sentiment gradually bounced back once uncertainty was reduced. The intuitive coincidence enlightens us to investigate the sentiment and volatility connection across markets further.

Figure 5. 2. Sentiment score over time

This figure plots the daily Refinitiv MarketPsych Analytics (RMA) sentiment score across various asset classes, including stock, bond, currency, precious metal, and energy. The sample period is from August 1, 2008, to May 15, 2020.



5.4.3 Descriptive statistics and correlation

We report the descriptive statistics for the volatility and social sentiment indices in Panel A of Table 5.2. On average, *StockSentiment* and *EuroSentiment* have negative average scores (-0.03 and -0.06, respectively). *BondSentiment* is particularly bearish over the sample period, with a score of -0.20. *GoldSentiment* has an overall positive sentiment (0.04), which could be due to the fact that our sample period coincides with several major crises, and gold is often considered a safe haven asset (see, e.g., Baur and McDermott, 2016). *OilSentiment*, on the other hand, has neutral sentiment (0.00) overall.

In terms of volatility, crude oil (OVX), equity (VIX), and gold markets (GVZ) have the highest uncertainty with (log) index values of 3.55, 2.89, and 2.88, respectively. The foreign exchange (EVZ) and the bond market (TYVIX) report the lowest average volatility (2.28 and 1.75, respectively). The augmented Dickey-Fuller (ADF) test in the last row of Panel A shows that both the sentiment and volatility indices are stationary.

Panel B reports the correlation coefficients among the implied volatility and sentiment indices. Turning first to the sentiment correlations in the upper left section, we observe that sentiment indices across different markets are positive but only weakly correlated. The strongest sentiment correlation is between equity and oil markets, with a correlation coefficient of 0.41. This is consistent with Gao and Süss (2015), who also document a close connection between equity and commodity markets, particularly energy.

Second, the implied volatilities at the bottom right section are positively correlated with average values higher than 0.56, indicating a stronger co-movement among market volatilities compared to sentiments. Notably, the correlations between the bond and the gold market volatilities (0.83) and between the bond and the foreign exchange volatilities

(0.80) are high, which is in line with the literature (Andrada-Félix et al., 2018). The bottom left section shows that correlations between sentiment and volatility are mostly negative (e.g., -0.57 between OilSentiment and OVX and -0.51 between EuroSentiment and EVZ). This indicates that market volatility is negatively associated with market sentiment.

Table 5. 2. Descriptive statistics and correlation matrix

This table summarizes the data used in this study. The sample period is from August 2008 to May 2020. Panel A reports the descriptive statistics, and Panel B reports the correlation matrix. All volatility series (VIX, TYVIX, EVZ, GVZ, OVX) are in natural logarithms. ADF is augmented Dickey-Fuller test. ***, ** and * represents 10%, 5% and 1% significance level.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*
Panel A: Descriptive Statistics										
Obs.	2968	2968	2968	2968	2968	2968	2968	2968	2968	2968
mean	-0.03	-0.20	-0.06	0.04	0.00	2.89	1.75	2.28	2.88	3.55
median	-0.03	-0.20	-0.05	0.04	-0.01	2.79	1.69	2.27	2.86	3.51
SD	0.05	0.07	0.07	0.05	0.07	0.40	0.31	0.36	0.35	0.39
5th percentile	-0.11	-0.31	-0.17	-0.04	-0.12	2.39	1.32	1.71	2.38	2.95
95th percentile	0.07	-0.08	0.04	0.12	0.10	3.74	2.39	2.89	3.56	4.25
skew	0.34	0.14	-0.19	-0.04	-0.01	1.12	0.74	0.23	0.68	0.90
kurtosis	3.84	3.26	3.35	2.72	3.12	4.11	3.16	2.87	3.59	5.34
ADF	-20.79***	-29.33***	-21.98***	-21.96***	-18.70***	-5.41***	-6.31***	-5.23***	-5.32***	-3.43***
Panel B: Correlation Matrix										
StockSentiment	1									
BondSentiment	0.13***	1								
EuroSentiment	0.08***	0.11***	1							
GoldSentiment	-0.02	0.11***	0.29***	1						
OilSentiment	0.41***	0.13***	0.10***	0.03	1					
VIX	-0.41***	-0.22***	-0.43***	-0.32***	-0.37***	1				
TYVIX	-0.20***	-0.24***	-0.42***	-0.42***	-0.24***	0.77***	1			
EVZ	-0.17***	-0.20***	-0.51***	-0.37***	-0.21***	0.70***	0.80***	1		
GVZ	-0.17***	-0.18***	-0.45***	-0.49***	-0.24***	0.77***	0.83***	0.75***	1	
OVX	-0.44***	-0.16***	-0.22***	-0.02	-0.57***	0.72***	0.57***	0.58***	0.56***	1

5.5 Empirical Results

This section reports our empirical results. We first report the results for the static connectedness across all the variables. We then proceed to the connectedness between the sentiment and volatility blocks. Finally, we show the dynamic connectedness over our sample period.

5.5.1 Static connectedness analysis

Table 5.3 reports the full-sample connectedness table for the sentiment and volatility indices. The top row represents the transmitting variables, while the first column represents the affected variables. We first focus on the diagonal elements, which measure each variable's own connectedness. These elements show the greatest values, ranging from 55.79% for the *VIX* to 93.85% for *BondSentiment*, indicating that the series are relatively independent of each other. For example, consider StockSentiment, the forecast error variance of StockSentiment rising from its own shock is 71.26%, a higher diagonal value indicates that an index is less connected to others. The summed contribution to the forecast error variance of StockSentiment from all other indices is 28.74%. Second, the off-diagonal elements represent the connectedness between the studied variables. Among the sentiment indices, the highest pairwise connectedness is from *OilSentiment* to *StockSentiment* (3.92%), while the next highest is from *StockSentiment* to *OilSentiment* (3.39%). Among the volatility indices, the highest pairwise connectedness is observed from *VIX* to *OVX* (15.65%). These observations suggest that there is a strong interconnection between stock and oil markets in both sentiment and volatility indices. The linkage between equity and oil markets can be explained by the financialization of commodity futures. Commodities, such as crude oil, has been widely held by institutional investors for diversification purpose. Therefore, shocks in one market are quickly transmitted to the other market (Büyükşahin and Robe, 2014; Christoffersen and Pan, 2018).

Across sentiment and volatility indices, the pairwise connectedness is stronger from volatility to sentiment indices than the opposite, as shown by the top right block. For instance, the highest volatility to sentiment spillover is from the *VIX* to *StockSentiment* (14.22%), which means that 14.22% of StockSentiment index shock originated from VIX. This is followed by the spillover from the *OVX* to *OilSentiment* (11.83%). In contrast, the highest sentiment to volatility spillover is from *OilSentiment* to the *OVX* (4.06%), followed by the spillover from *StockSentiment* to the *VIX* (2.17%). As further evidence, we refer to the net directional connectedness at the bottom row of Table 5.3. All implied volatilities are net transmitters, while all sentiment indices are net receivers of informational shock. Most notably, the VIX is the largest net spillover transmitter (40.80%), suggesting that stock market volatility is the dominant shock generator to all the sentiment and volatility indices. This is in line with existing literature, which finds that stock market volatility provides useful signals for investors in other asset classes, including bonds and commodities (see, e.g., Laborda and Olmo, 2014; Gao and Süss, 2015). On the opposite extreme, the *StockSentiment*, *GoldSentiment,* and *OilSentiment* are the main receivers with negatively high net connectedness -18.92%, -13.88%, and -11.95%, respectively.

Table 5. 3. Full sample connectedness

This table reports the full-sample GVD connectedness for sentiment and volatility indices using RMA Social Media sentiment and CBOE volatility indices from August 1, 2008, to May 15, 2020. The diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness either between the sentiment indices (upper-left grey shade), between the implied volatility indices (bottom-right grey shade), or between the sentiment indices and implied volatility indices. All results are based on VARs of order two and GVDs of 10-day ahead forecast errors. The ijth entry of the upper left 10×10 submatrix is the estimated ijth pairwise directional connectedness contribution to the forecast-error variance of market i's sentiment (or implied volatility) rising from sentiment (or implied volatility) shocks to market j. The off-diagonal row sums (last column) and column sums (second last row) are the total directional connectedness from all others (different markets' sentiment or implied volatility) to i and to all others (different markets' sentiment or implied volatility) from i.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*	from others
StockSentiment	71.26	0.34	0.40	0.44	3.92	14.22	1.39	1.09	1.24	5.71	28.74
BondSentiment	0.49	93.85	0.04	0.21	0.55	1.44	2.36	0.45	0.37	0.25	6.15
EuroSentiment	0.37	0.07	85.47	0.23	0.91	3.80	0.81	5.73	2.28	0.34	14.53
GoldSentiment	0.24	0.17	0.74	81.82	0.85	4.22	1.71	2.39	7.10	0.75	18.18
OilSentiment	3.39	0.35	0.65	1.27	72.67	6.13	1.25	0.61	1.84	11.83	27.33
VIX	2.17	0.30	1.28	0.21	2.06	55.79	10.13	7.48	10.73	9.85	44.21
TYVIX	1.15	0.70	0.36	0.05	1.70	14.39	58.12	9.35	8.83	5.35	41.88
EVZ	0.31	0.54	1.36	0.29	0.55	10.63	10.20	59.64	10.93	5.54	40.36
GVZ	0.43	0.08	1.92	1.53	0.78	14.52	8.21	9.23	56.63	6.67	43.37
OVX	1.28	0.04	0.16	0.07	4.06	15.65	7.11	4.34	6.58	60.71	39.29
to others	9.82	2.59	6.91	4.30	15.38	85.01	43.17	40.68	49.90	46.29	Total
Net (To-From)	-18.92	-3.56	-7.62	-13.88	-11.95	40.80	1.29	0.32	6.53	6.99	30.40

The total connectedness of all the sentiment and volatility indices is 30.4%, indicating that almost 70% of variation comes from the index's idiosyncratic innovations. The magnitude of our total connectedness is close to the total connectedness of 31.3% among four major foreign exchange rates (Antonakakis, 2012), 33.5% among media coverage, oil, gold, and bitcoin volatilities (Zhang et al., 2022), or 38.8% among five implied volatility indices (Andrada-Félix et al., 2018). Overall, we find that the sentiment and volatility indices are mildly connected. The largest net contributor is the stock market volatility, and the largest net receiver is the stock market sentiment.[55]

In addition to the connectedness among the individual series, we measure the connectedness between sentiment and volatility blocks following Greenwood-Nimmo et al. (2016, 2021). We report the full sample static block connectedness results in Table 5.4. We observe that the sentiment and volatility blocks have high average own connectedness values at 81.01% and 58.18%, respectively. This indicates that the two blocks have high idiosyncratic innovations and, therefore, are weakly connected with one another. The total connectedness within the sentiment block is 3.13%, suggesting that the sentiment indices are segmented. In contrast, the volatility block shows that the volatility indices are interconnected with a total block connectedness of 37.15%. The main finding of the block connectedness analysis is that volatility indices are the main source of shocks to sentiment indices, with a net contribution of 11.19%. The entire system has a total connectedness of only 10.27%, suggesting that sentiment and volatility have a weak block-connection.

[55] Our results are based on VARs of order 2 and GVDs of 10-day ahead forecast errors. We used alternative VARs from one to four lags and obtain qualitatively similar results. We also employed 5 days and 15 days as alternative forecast horizons, since the longer the forecast horizon, the more time the indices have to react to shocks from other indices. As expected, the longer forecast horizon is, the higher total connectedness with 27%, 30%, and 33% for 5, 10, and 15 days, respectively. Therefore, our results are robust to the choice of forecast horizons.

Table 5. 4. Full sample block connectedness

This table reports the full sample static block connectedness. Five sentiments and five volatilities are aggerated as one sentiment block and one volatility block, respectively. We gauge spillovers between and within the two blocks. The sample period is from August 1, 2008, to May 15, 2020. *Average own connectedness* represents the mean of five indices idiosyncratic innovations. *Total connectedness within block* represents the interconnection level of five indices in the block.

	Sentiment Block	**Volatility Block**
Sentiment Block	84.14	15.86
Average own connectedness	81.01	–
Total connectedness within the sentiment block	3.13	–
Volatility Block	4.67	95.33
Average own connectedness	–	58.18
Total connectedness within the volatility block	–	37.15
Net (To–From)	-11.19	11.19
Total connectedness across Blocks	–	10.27

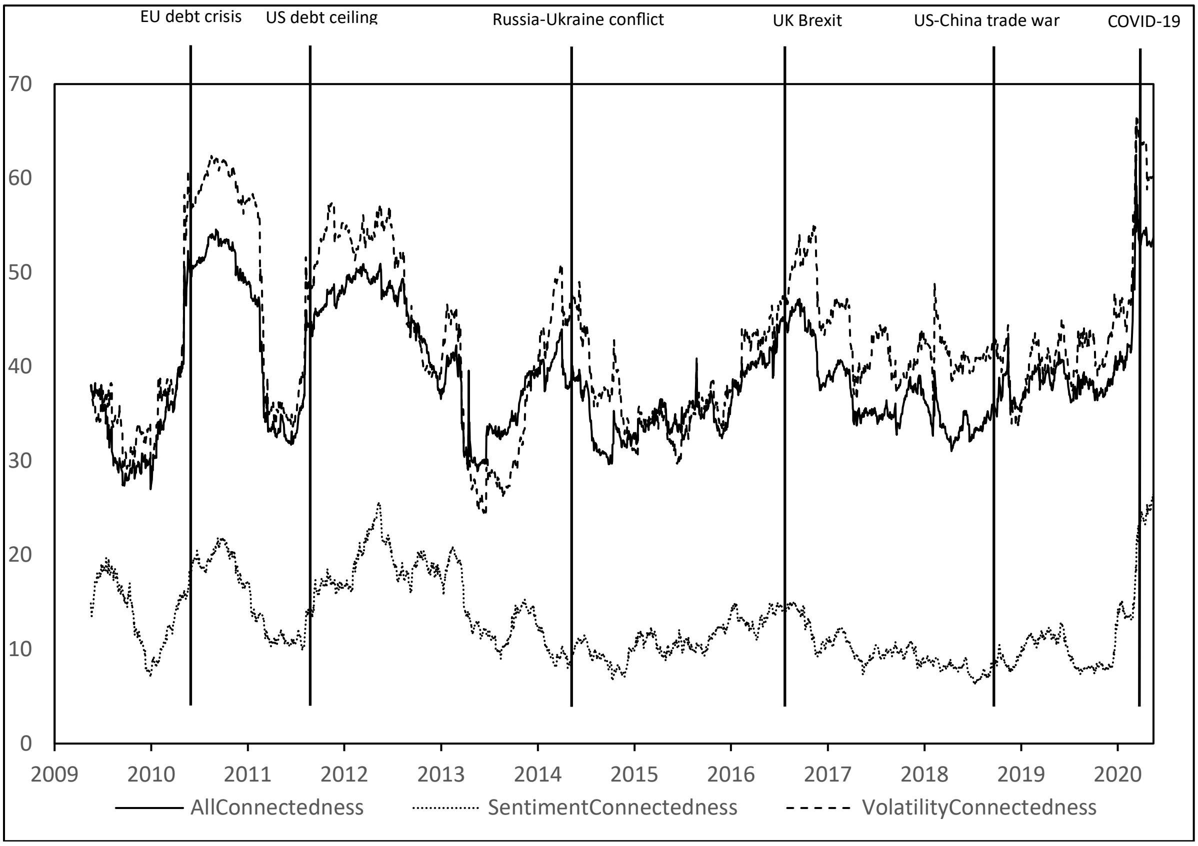
5.5.2 Dynamic connectedness analysis

The previous section shows the static connectedness of the ten variables based on the full period sample. Next, we examine how the connectedness among the sentiment and volatility indices evolves over time. This analysis is informative as it highlights the importance of economic events on the linkage between sentiment and volatility indices. We follow the DY approach and conduct a connectedness analysis using a 200-day rolling window.

In Figure 5.3, we plot the dynamic total connectedness (solid black line), connectedness for the sentiment block (dashed black line), and connectedness for the volatility block (dotted grey line). The three plots fluctuate over time, with a similar pattern between the sentiment and volatility blocks. In line with the results in Table 5.4, the connectedness for the volatility block is consistently higher than the connectedness for the sentiment block. The total connectedness fluctuates strongly in turbulent periods. We observe several periods where the total dynamic connectedness deviates from its full sample average value of 39%. The total connectedness reached a value of 50% in 2010, coinciding with the European sovereign debt crisis. The next spike in total connectedness was in the middle of 2011, with a value of 45%, triggered by the US debt-ceiling crisis and the US credit rating downgrade. Total connectedness also spiked in June 2016 due to Brexit and in early 2020 during the COVID-19 global pandemic crisis, with an all-time high of around 62%. In addition, we also observed two short-duration spikes over the average level in early 2014 during the Russia-Ukraine conflict and in the second half of 2018 during the US-China trade war. In sum, the total connectedness increases in turbulent economic periods as uncertainty about the financial markets are associated with fears and pessimism across various asset classes (see, e.g., Antonakakis and Kizys, 2015; Zhang et al., 2022).

Figure 5. 3. Dynamic total connectedness

This figure plots the connectedness value over the sample period from August 1, 2008, to May 15, 2020. The solid line represents the total connectedness among all sentiment and volatility measures. The dashed line represents the connectedness among the sentiment measures. The dotted line represents the connectedness among the volatility measures.



The 200-day rolling window is standard in the literature (see, e.g., Andrada-Félix et al., 2018; Audrino and Tetereva, 2019). Nevertheless, to ensure that our results are robust, we employ alternative rolling window lengths, i.e., 150 and 250-day windows. Appendix IV reports these results. As expected, the dynamic total connectedness is more persistent for longer windows. The three graphs show a similar pattern with an average correlation of 0.88, indicating that the total connectedness increases in turbulent periods regardless of the rolling window lengths.

5.5.3 Sentiment and volatility net connectedness over time

With the dynamical characteristics that systematic connectedness exhibits, we wonder whether each index has variant features across time and contributes differently during different events. Next, we examine the net directional connectedness of each sentiment and volatility index. In Figure 5.4.a., we show that the net directional connectedness varies over time, where each index plays a different role (net transmitter or net receiver) at different periods. For example, we observe that *StockSentiment* was a net spillover transmitter during the 2018 US-China trade war and the COVID-19 pandemic at the start of 2020 but a net receiver during other times. Similarly, *EuroSentiment,* generally a net receiver, was a net spillover transmitter during the Euro debt crisis in the middle of 2010. In Figure 5.4.b., we observe that volatility indices demonstrate different roles over time. For instance, the VIX tends to be a constant net transmitter for 96% of the time. However, the net directional connectedness of the other indices varies over time with switching role between a net spillover transmitter and receiver. For example, we observe that the EVZ, which is generally a net transmitter, was a net spillover receiver in 2010 during the European debt crisis and in 2020 during the COVID-19 pandemic.

Figure 5. 4. Sentiment and volatility net connectedness over time

This figure plots the net connectedness of each sentiment and volatility index from August 1, 2008, to May 15, 2020.

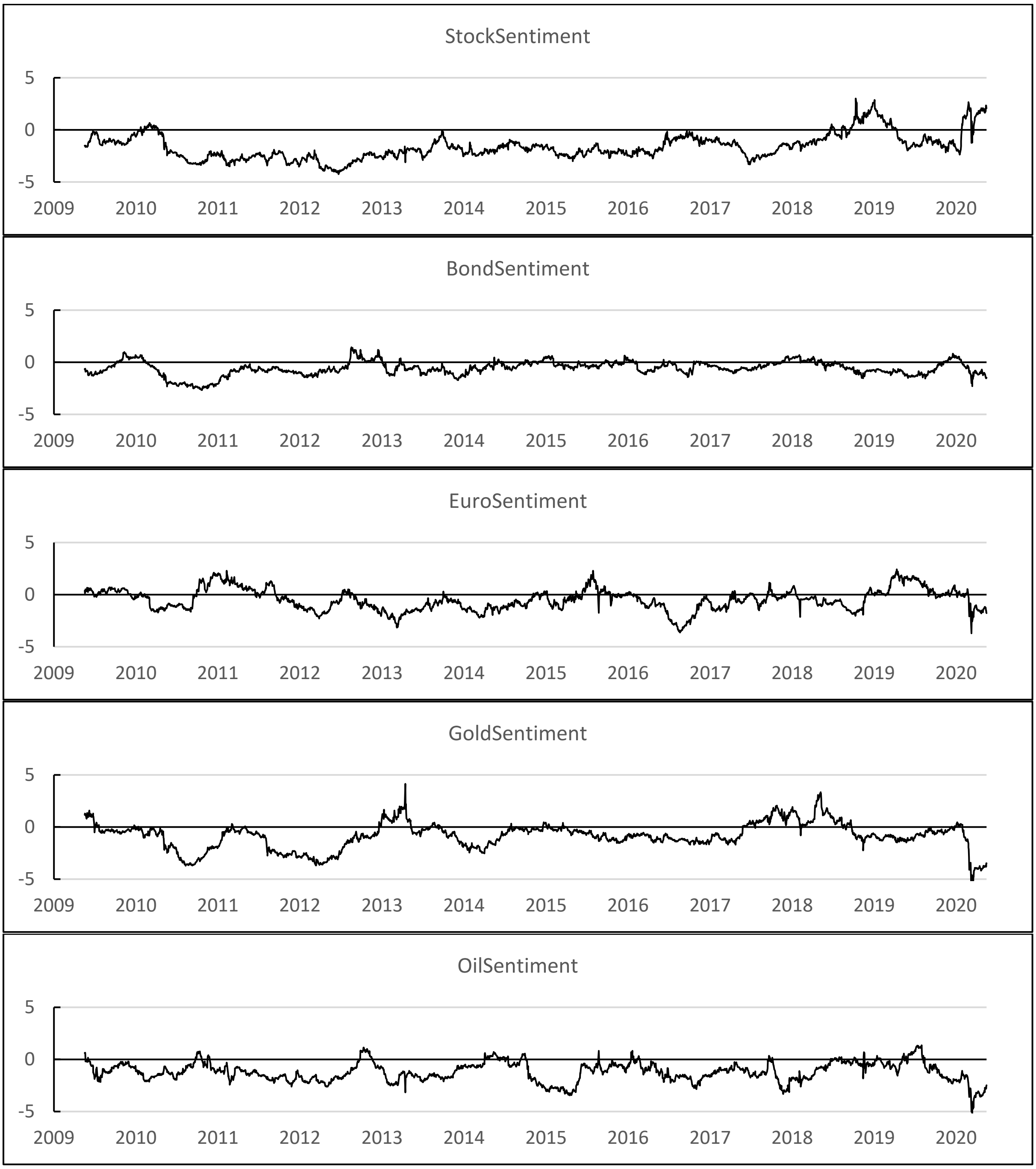


Figure 5.4.a. Sentiment Connectedness

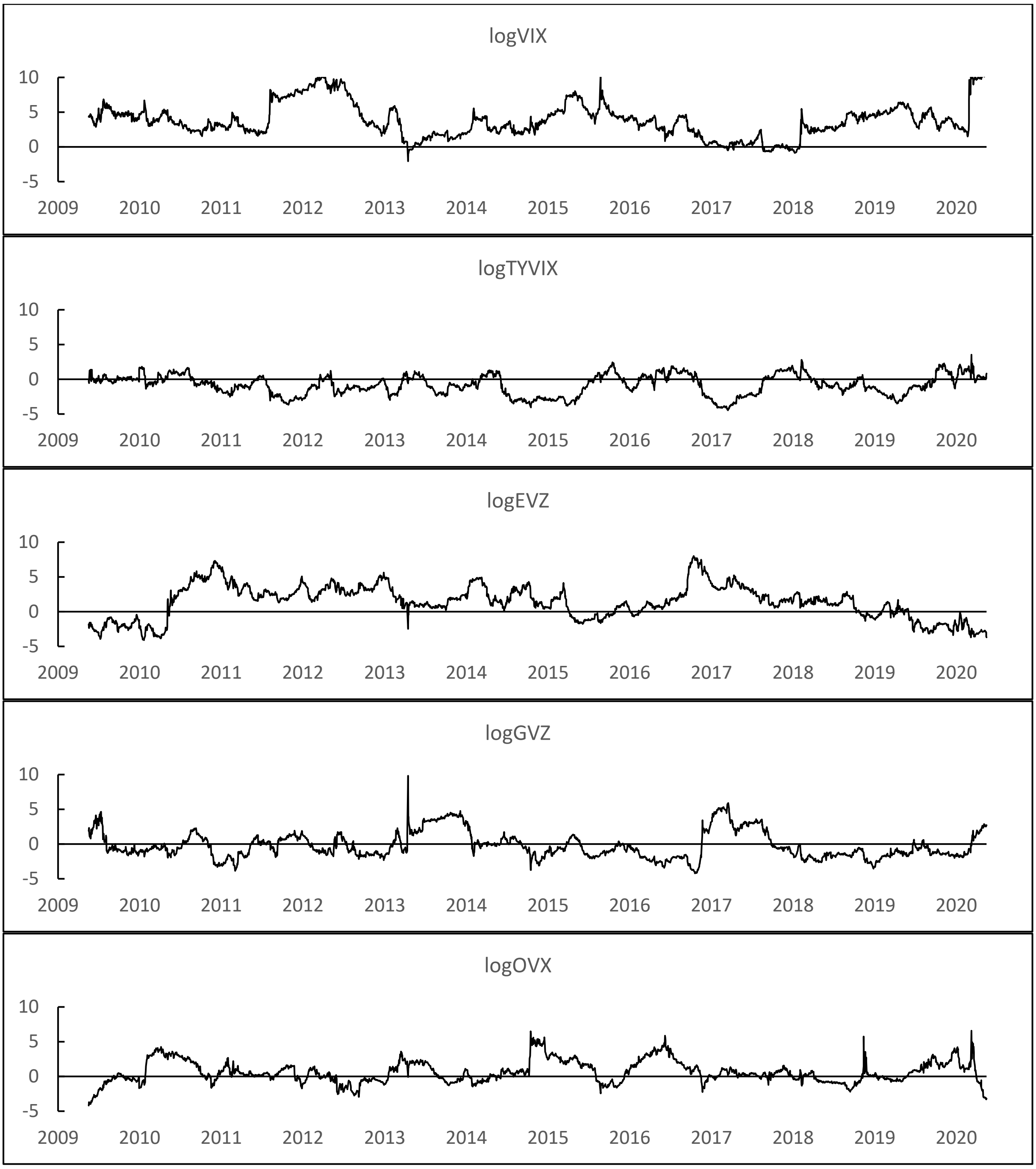


Figure 5.4.b. Volatility Connectedness

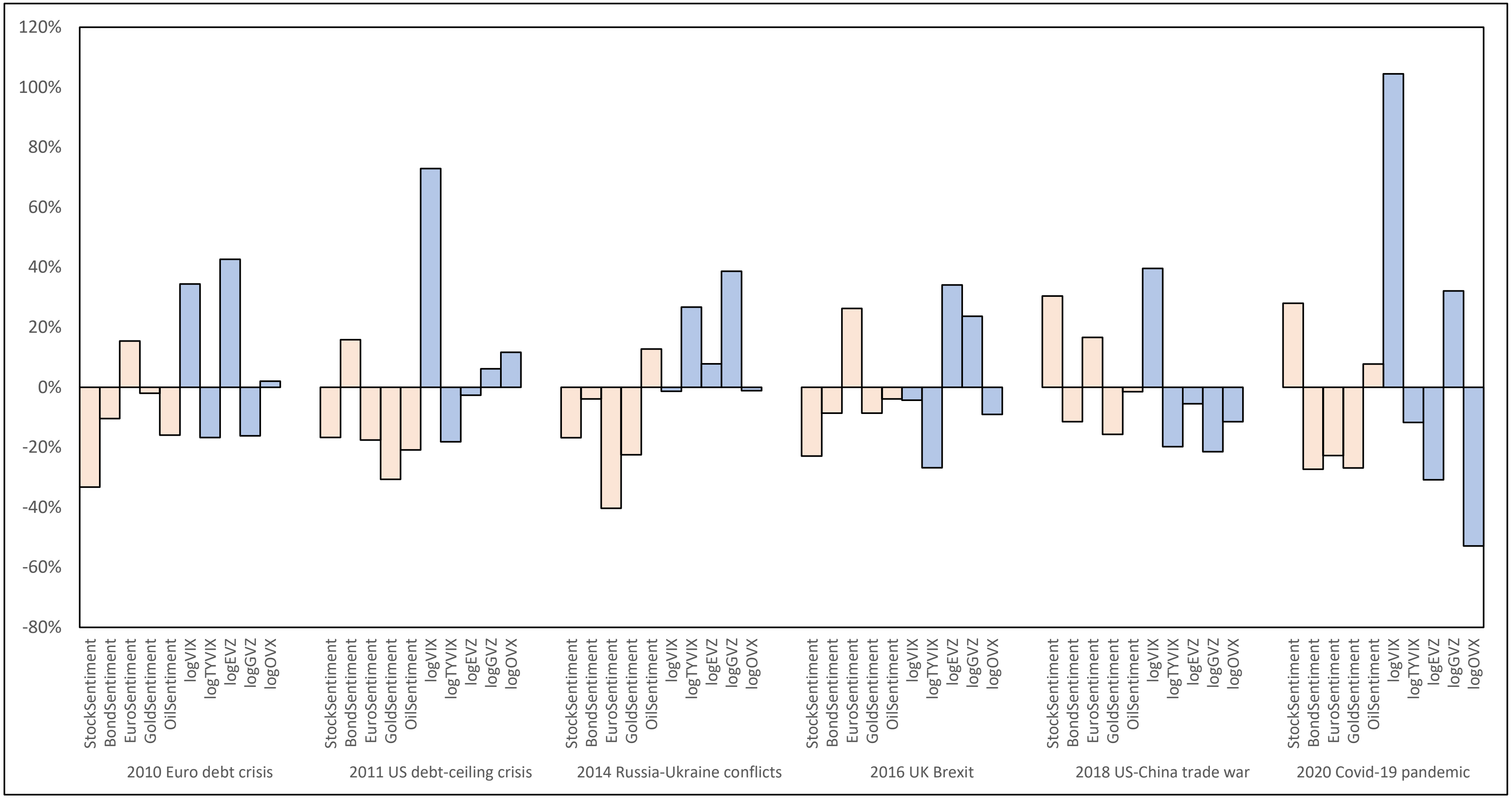
We further investigate how the variables in our system are interconnected during some turbulent periods by examining the net directional connectedness. We study six turbulent periods: (a) Euro Debt crisis (April 2010 – February 2011); (b) US debt-ceiling crisis (May 2011- August 2011); (c) Russia-Ukraine conflict (February 2014 - May 2014); (d) Brexit (June 2016 – November 2016); (e) US-China trade war (May 2018 – December 2018); (f) COVID-19 pandemic (December 2019 – May 2020).[56] Our benchmark for comparison is the result in last row of Table 5.3 where all volatility indices show positive net connectedness and the sentiment indices show negative net connectedness. This suggests that social media sentiments are generally net receivers of shocks over the sample period.

Figure 5.5 shows the bar plot of the net directional connectedness for each sentiment and volatility indices during the different turbulent periods. As can be seen, sentiment indices play a transmitter role during these turbulent periods. Strikingly, *EuroSentiment* is a net spillover transmitter during the Euro debt crisis, the UK Brexit, and the US-China trade war. The European debt crisis undermined investor confidence in the Euro/dollar foreign exchange market, transmitting Euro sentiment and uncertainty to other markets' sentiment and volatility indices. Similarly, Brexit destabilized the EU economy and increased the uncertainty about the stability of the Euro. *EuroSentiment* was also a net transmitter during the US-China trade war. This can be explained by international trade between these two countries, with the US being the main export partner and China being the main import partner for the EU.[57] The US-China trade war affected the global growth prospects, with the EU being one of the main casualties of this event.

[56] We provide more details for these events in Appendix III.
[57] The EU is the third major economic region in the world after US and China. US-China economy constitutes about 40% of the global GDP.

Figure 5. 5. Net total directional connectedness during various crises

This figure plots the net total directional connectedness during various crises: (a) Euro Debt crisis (Apr 2010 – Feb 2011); (b) US debt-ceiling crisis (May 2011- Aug 2011); (c) Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) UK Brexit (Jun 2016 – Nov 2016); (e) US-China trade war (May 2018 – Dec 2018); (f) COVID-19 pandemic (Dec 2019 – May 2020).



We also observe other sentiment indices were net transmitters in turbulent periods. For example, during the 2011 US debt-ceiling crisis, *BondSentiment* was a net transmitter to the other markets. The potential of a US default crisis originated from the US sovereign bond market impacted bond market sentiment, which generated uncertainty in other asset classes. *OilSentiment* was the net transmitter during the 2014 Russia-Ukraine conflict. This can be explained by Russia being one of the world's leading oil and gas producers and exporters. The geopolitical crisis generated by the conflict increased uncertainty among investors due to the potential effect of the energy crisis on the global economy (Gao et al., 2022).

Finally, *Stocksentiment* was the largest sentiment net transmitter during the 2018 US-China trade war. The continuous rounds of retaliatory tariffs between the US and China led to high uncertainty in the financial markets. China’s countermeasure tariffs on US products led to a decline in US exports to China and caused slumps in many US sectors. *Stocksentiment* and *Oilsentiment* were also net spillover transmitters during the COVID-19 pandemic. Lockdowns and border closures during the pandemic strongly affected the stock and oil markets and lowered overall business confidence.

In terms of volatility, the VIX was the most dominant transmitter in many turbulent periods, including the US debt-ceiling crisis, the US-China trade war, and the COVID-19 pandemic. This is consistent with Greenwood-Nimmo et al. (2021), who document that, during high connectedness periods, world trade flows and GDP growth are influenced by the spillover originating from the equity market. The EVZ is another important net spillover transmitter, particularly during the Euro debt crisis, The Russia-Ukraine conflict, and the UK Brexit.[58]

[58] We also visualised a net pairwise directional connectedness map for detailed spillovers across various indices in Appendix VI.

However, there is a possibility that both social media sentiment and implied volatility are driven by the state of the business cycles and market conditions, which may affect our outcomes. To ensure that our results are not driven by market fundamentals, we orthogonalize all ten indices using a set of business cycle proxies. More specifically, we control for the term spread (calculated as the difference between the 10-year and 2-year Treasure Bonds), the 3-month Treasury Bill, the credit spread (calculated as the difference between Moody's Baa corporate bond yield and the 10-year Treasure Bond rate), and the TED spread which is a proxy of funding liquidity. All these business cycle variables are downloaded from Federal Reserve Bank of St. Louis. We also control for the Pástor and Stambaugh's (2003) liquidity factor as a proxy of market liquidity.[59] First, we regress each sentiment and implied volatility series against the above five business cycle proxies, and take residual series. We then use the orthogonalized series to compute the static and dynamics connectedness tables during various crises.

The results reported in Appendix V suggest that our main result that sentiment indices are net triggers of shocks during turbulent times hold after controlling for the state of the business cycle and market conditions. All the patterns are consistent with those reported in Figure 5.5, except for the 2014 Ukraine-Russia conflict and the UK Brexit where the effect of the sentiments turned weaker.

5.5.4 Social media turning from net receiver to net transmitter of shocks

Our findings so far show that most volatilities are net transmitters while most sentiments are net receivers of shocks. However, social media sentiment still matters as its role can switch from net receiver to net transmitter during turbulent periods. We further explore

[59] Source: https://finance.wharton.upenn.edu/~stambaug/.

why that is the case. More specifically, we test for the social media "echo chamber" channel (Jiao et al., 2020). The echo chamber effect suggests that while social media often repeat existing news, some investors interpret repeated signals as genuinely new information. Hence, it is possible that the spillover effect from sentiment to volatility is driven by news media, rather than social media content itself.

To test this, we use sentiment indices from the RMA *News*, as well as the *News&Social* categories. While the *Social* category we employed in our main specification is based on social media outlets, the *News* category is based on news media outlets. *News&Social* combines both groups. We present the results for the two additional groups in Table 5.5.

Panel A reports the static connectedness for the *News* category. Consistent with our main finding, market-specific sentiments and volatilities are interconnected. The stock market volatility remains the most significant net transmitter. It is worth mentioning that the static total connectedness for the *News* category is around 40%, while the static total connectedness for the *Social* category is around 30% (see Table 5.3). This indicates that while traditional news media (online in digital form) remains one of the main sources of information for financial markets, social media sentiment also provides a substantial new information. However, when we consider both *News&Social* (Panel B), we observe that total connectedness only increased from 40.62% to 40.82% with the addition of social media signals. This points toward social media adding little information to the market.

To further examine whether social media is less-informativeness than news and the "echo chamber" theory. We further control for the effect of news sentiment by orthogonalizing each social media sentiment with the sentiment from the *News* category. More specifically, we regress each social media sentiment series on its respective news sentiment. The residual from this regression is the orthogonalized social media sentiment series, which we then use to recompute the connectedness results during the various turbulent periods.

Table 5. 5. Full sample connectedness for the *News* category

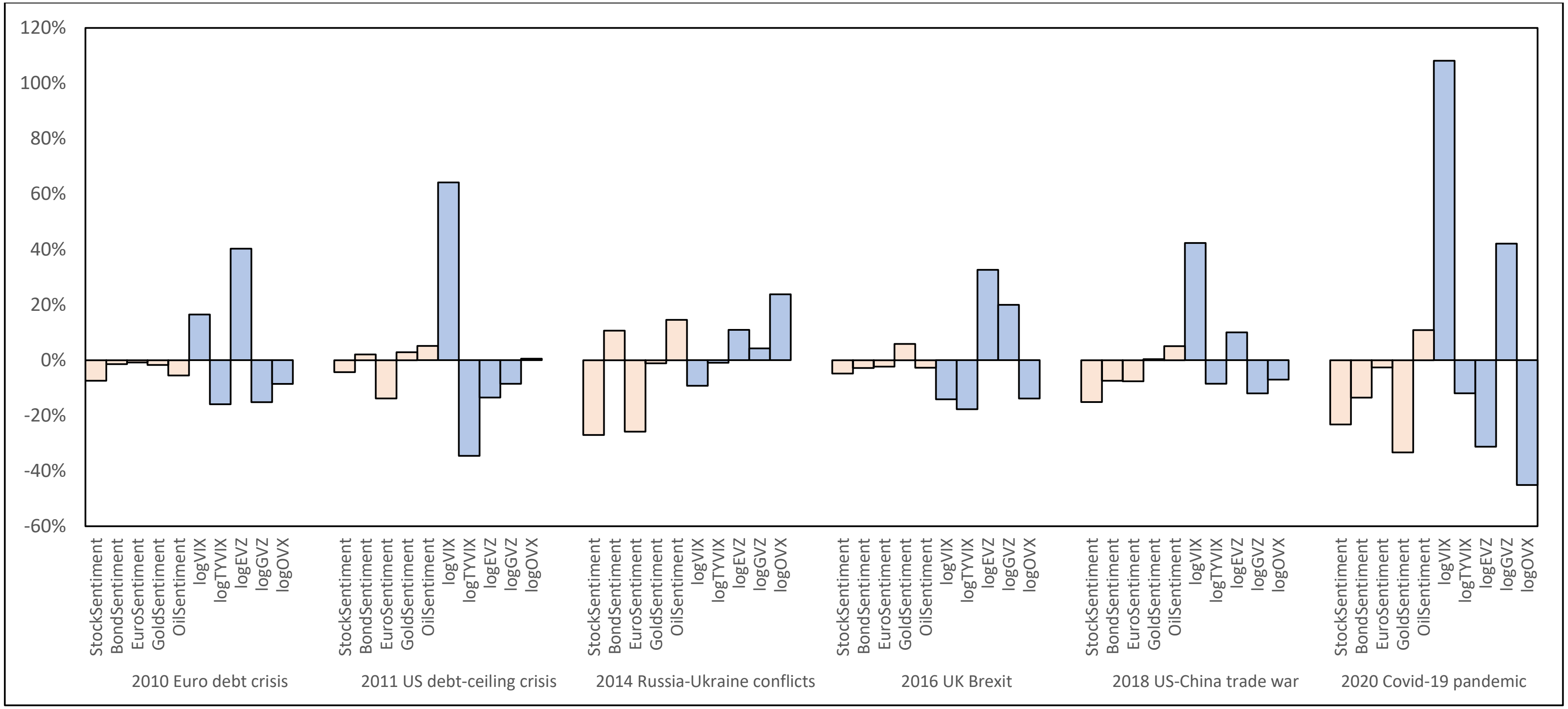
This table reports the full-sample GVD connectedness for sentiment and volatility indices using RMA *News* sentiment (Panel A) and *News&Social* sentiment (Panel B), and CBOE volatility indices from August 1, 2008, to May 15, 2020. The diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness either between the sentiment indices (upper-left grey shade), between the implied volatility indices (bottom-right grey shade), or between the sentiment indices and implied volatility indices. All results are based on VARs of order two and GVDs of 10-day ahead forecast errors. The ijth entry of the upper left 10×10 submatrix is the estimated ijth pairwise directional connectedness contribution to the forecast-error variance of market i's sentiment (or implied volatility) rising from sentiment (or implied volatility) shocks to market j. The off-diagonal row sums (last column) and column sums (second last row) are the total directional connectedness from all others (different markets' sentiment or implied volatility) to i and to all others (different markets' sentiment or implied volatility) from i.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*	from others
Panel A: News											
StockSentiment	42.05	0.42	4.00	4.47	12.00	22.18	2.49	3.07	3.82	5.48	57.95
BondSentiment	2.07	84.45	0.21	0.66	1.76	5.75	2.17	0.23	1.24	1.46	15.55
EuroSentiment	5.43	0.23	72.75	1.91	5.65	5.32	0.28	4.37	2.56	1.50	27.25
GoldSentiment	7.25	0.58	1.90	60.85	9.88	8.23	1.34	1.78	6.27	1.91	39.15
OilSentiment	11.62	0.61	4.71	6.81	50.14	11.65	1.32	1.10	3.00	9.04	49.86
VIX	4.31	0.31	1.20	1.35	4.05	52.45	9.63	7.06	10.10	9.53	47.55
TYVIX	1.67	0.51	0.35	0.22	1.52	14.03	58.88	9.04	8.45	5.33	41.12
EVZ	1.43	0.22	1.27	0.55	0.96	10.28	9.94	59.12	10.83	5.41	40.88
GVZ	2.11	0.35	1.08	2.03	2.11	14.32	7.94	9.00	54.58	6.48	45.42
OVX	2.49	0.19	0.97	0.76	5.34	14.85	6.84	4.05	6.01	58.50	41.50
to others	38.37	3.43	15.68	18.76	43.27	106.61	41.93	39.71	52.29	46.15	Total
Net (To-From)	-19.57	-12.11	-11.58	-20.39	-6.58	59.07	0.81	-1.16	6.87	4.65	40.62
Panel B: News&Social											
StockSentiment	43.70	0.45	4.60	4.39	12.49	21.23	1.80	2.60	3.21	5.52	56.30
BondSentiment	2.22	83.52	0.21	0.57	1.91	6.07	2.42	0.26	1.39	1.44	16.48
EuroSentiment	5.86	0.17	71.97	1.93	5.57	5.34	0.29	4.84	2.67	1.35	28.03
GoldSentiment	6.89	0.49	2.08	60.19	9.38	8.50	1.57	2.16	7.08	1.65	39.81
OilSentiment	11.85	0.65	4.67	6.50	49.49	11.76	1.45	1.12	2.87	9.63	50.51
VIX	4.17	0.39	1.36	1.20	4.36	52.21	9.67	7.05	10.09	9.50	47.79
TYVIX	1.55	0.62	0.38	0.17	1.75	14.18	58.49	9.07	8.48	5.33	41.51
EVZ	1.11	0.30	1.43	0.55	1.07	10.24	9.95	59.13	10.84	5.38	40.87
GVZ	1.70	0.42	1.24	2.18	2.14	14.25	7.95	9.02	54.63	6.48	45.37
OVX	2.39	0.21	0.91	0.55	5.71	14.84	6.85	4.04	6.03	58.48	41.52
to others	37.73	3.70	16.88	18.05	44.37	106.41	41.96	40.15	52.65	46.29	Total
Net (To-From)	-18.57	-12.79	-11.15	-21.76	-6.14	58.62	0.45	-0.72	7.28	4.77	40.82

The plots in Figure 5.6 show that after controlling for news sentiment, many of the social media sentiments are no longer being the net transmitter of shocks. While *OilSentiment* remains an important net transmitter of shocks during the Russia-Ukraine conflicts and the COVID-19 pandemic, the importance of *EuroSentiment* during the Euro debt crisis and the UK Brexit disappears. Similarly, the importance of *StockSentiment* during the US-China trade war and the COVID-19 pandemic also recedes. These results suggest that periods of high social media coverage are associated with higher volatility, primarily because social media posts repeat (e.g., reshare) existing news. Therefore, we attribute the echo chamber effect as the explanation as to why social media sentiment may turn into a net trigger of connectedness during turbulent times.

Figure 5. 6. Net total directional connectedness during various crises (controlling for news sentiment)

This figure plots the net total directional connectedness during various crises after orthogonalizing the social media sentiment with the news sentiment: (a) Euro Debt crisis (Apr 2010 – Feb 2011); (b) US debt-ceiling crisis (May 2011- Aug 2011); (c) Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) UK Brexit (Jun 2016 – Nov 2016); (e) US-China trade war (May 2018 – Dec 2018); (f) COVID-19 pandemic (Dec 2019 – May 2020).



5.6 Conclusions

We examine the connectedness between social media sentiment and market-implied volatility indices across various asset classes, such as stock, bond, foreign exchange, precious metals, and energy. Using data from August 2008 to May 2020, we find that social media sentiment and market volatility indices are weakly connected. There is a strong spillover from volatility to the sentiment index of the same market, but not the opposite direction. In particular, the VIX is the major net spillover transmitter. Second, the informational spillover comes mainly from the market volatility block to the market sentiment block, further confirming the importance of volatility indices. Third, the connectedness between market sentiment and volatility indices increases in turbulent economic periods, and sentiment indices can switch from being a net receiver to a net transmitter during such times. This can be explained by the “echo chamber” effect where social media repeat existing news media signals, but some investors interpret repeated signals as genuinely new information.

Our study has several implications. For market participants, they may face a challenge to hedge asset-specific uncertainty in turbulent periods. Thus, diversification benefits could be impaired at times when it is most needed. Market regulators may also consider monitoring social media trends, particularly during turbulent times, since they can influence investors' expectations for various assets. If left unchecked, social media activities have the potential to destabilize markets.

Chapter 6

Concluding Remarks

This thesis investigates the effects of social media on different aspects of financial markets. As a vital element of digitization in the last decades, the rise of social media has profoundly reformed how people obtain and exchange information and become one of the leading news channels. Given that investors make decisions based on their information set, understanding this new information channel's impact on investors and financial markets is paramount. Such knowledge can benefit market participants and regulators in terms of recognising the role of social media and monitoring its impacts on the quality and stability of financial markets. In that matter, the findings and implications of this thesis might be of interest to investors, scholars and policymakers.

Chapter 2 offers a comprehensive view of the rationales and frameworks covered in this thesis. Starting with investor sentiment and media effects, it explains why investor sentiment influences investors' decision-making process and the connections between media coverage, investor sentiment and impacts on financial markets. In addition, we depict the process of capturing investor sentiment and summarise the commonly used methodologies for sentiment identification and reasons why social media sentiment is the premium choice of the research. The chapter then discusses the necessity of conducting research on social media from a regulatory perspective, especially for market stability, market quality and investor protection standpoint.

We finally synthesize and demonstrate that prior studies have shown the association between social media and financial markets, especially for its predictability on asset returns and volatilities. They do not, however, explore the mechanism by which social media sentiment transmits to the movements in security prices and affects investor behaviours in one or multiple financial markets. Thus, this motivates us to address literature gaps and uncover the reasons behind the documented social media sentiment effects. In order to lay the ground for the empirical chapters, we present the relevant literature and frameworks in market microstructure, such as price discovery, market quality, and market dynamics of spillover effect.

Chapters 3 to 5 are the empirical chapters. Chapter 3 assesses the impact of Twitter feeds on stock returns from August 2012 to December 2018 at the intraday level. Specifically, we employ Twitter feeds to construct a proxy for social media sentiment and focus on tweets related to the SPDR S&P 500 ETF (SPY) as a representation of the US stock market. We modify the Hasbrouck's (1991) informativeness of trades model by interacting Twitter sentiment with the trades in the vector autoregression (VAR) model. This modified VAR model allows us to measure the price impact of social media sentiment through its impact on trades.

Our findings suggest that trades have a greater price impact when there is an increase in the number of tweets and sentiment even after controlling for volatility, liquidity shocks, and limit-order activity. Both bullish and bearish tweets amplify the impact of trades on returns. The impact of Twitter sentiment on prices causes a permanent price movement, indicating that Twitter sentiment contains information. The smart and astute intraday investors can trade on it and facilitate price discovery. This chapter makes a significant contribution to the fast-growing literature on the impact of social media on financial markets by interpreting the channel of how social media affects prices. It has important implications for investors and market officials seeking to understand and better regulate the markets in consideration of information disseminated via social media.

Chapter 4 examines the impact of social media sentiment on market quality such as informational efficiency from August 2012 to March 2022. It reveals the relationship between Twitter sentiment, investor herding and informational efficiency. Precisely, we extract sentiment from tweets and analyse its impact on SPY price efficiency. We employ two commonly used informational efficiency measures, the autocorrelation and variance ratio, to capture the price efficiency of SPY.

Our findings reveal that higher sentiment leads to higher return autocorrelation and variance ratio the following day, indicating a decrease in informational efficiency. Delving into the underlying transmission channel, Chapter 4 also shows that the impact of social media sentiment on informational efficiency stems from the emergence of herding behaviours among traders the following day. Heightened sentiment leads to collective one-sided buying or selling actions, and such herding behaviour acts as an obstacle to the efficient dissemination of information and diminishes informational efficiency. It confirms that social media sentiment can become noisy and misleading for unsophisticated investors at daily or lower frequencies.

This chapter provides another explanation for a long-standing anomaly in financial markets, which is the existence of market inefficiency. Therefore, considering social media sentiment as a crucial factor is essential in devising investment strategies for market participants. More importantly, recognizing the influence of social media sentiment can help the oversight to monitor and manage potential market risks and disruptions effectively. As such, social media can be an additional surveillance tool for policymakers within the market regulatory framework.

Chapter 5 expands research boundaries of social media sentiment's impact beyond the linkages within single markets. It assesses the spillover effects between social media sentiments and market-implied volatilities among stock, bond, foreign exchange, and commodity markets. The investigation period ranges from August 2008 to May 2020 by leveraging the Refinitiv MarketPsych Analytics social media sentiment data. We consider investor sentiment specific to each asset class and employ a connectedness measure to capture the shares of forecast-error variation in an asset due to shocks arising elsewhere.

We find that informational spillover comes mainly from volatility indices to sentiment indices, with the VIX being the most significant net transmitter. Within each asset class, there is a stronger spillover from volatility to the sentiment, but a marginal effect for the opposite direction. The connectedness between sentiment and volatility increases in turbulent economic periods, such as the Global Financial Crisis, Brexit, the US-China trade war, and the COVID-19 pandemic. Furthermore, sentiment indices can switch from being a net receiver to a net transmitter of shocks during turbulent periods. This can be explained by the "echo chamber" effect, where social media repeat existing news media signals, but some investors interpret repeated signals as genuinely new information.

The findings of Chapter 5 further corroborate the results observed in Chapters 3 and 4 that social media sentiment contains information at intraday high frequency and creates market inefficiency the following day. Social media sentiment disseminates rapidly, and its contained information is incorporated into prices within intraday. In other words, prices can converge value-relevant information in a timely manner. However, investors still translate the signal as new and valuable information, trading collectively and resulting in inefficiency, while it is just a repeated signal with few economic values the following day.

Overall, this thesis studies social media sentiment effects on various important but oversight aspects of financial markets. It adds empirical evidence on how social media influences financial markets and market participants at different levels. It also provides a behavioural perspective to interpret financial markets connections and illustrates the process of how social media sentiment evolves over time. This is among the first to comprehensively understand social media sentiment while considering the complexity of the market structure and dynamics in reality. This thesis contributes to existing literature in behavioural finance, information theory, financial econometrics, and computational linguistics in finance with multidisciplinary implications.

The potential areas for future research may encompass disciplines such as social media sentiment analysis and natural language processing (NLP). Given the unique characteristics of social media networks, using sentiment analysis tools tailored for social media messages, such as Valence Aware Dictionary and Sentiment Reasoner (VADER), could be an improvement for sentiment detection. Because VADER provides a sophisticated method for analyzing sentiment on social media by considering the language patterns commonly found in social media platforms. It assesses the strength of sentiments expressed and adapts sentiment scores based on stylistic features, such as multiple exclamation points or emojis, which can convey stronger emotions. These elements have a notable influence on the sentiment scores assigned to each message. More importantly, the rapid progress in natural language processing (NLP) and sentiment analysis outpaces the timeline for conceptualizing, researching, and completing this PhD thesis. The sentiment analysis in NLP has evolved rapidly, moving to machine learning techniques, such as pre-trained language model Bidirectional Encoder Representations from Transformers (BERT), which can analyze sentiment at contextual level. Notably, the cutting-edge large language models such as GPT or Gemini represent the latest advancements in this field. These methodologies offer sophisticated means of understanding the context and nuanced sentiment, thereby improving accuracy and reliability in sentiment analysis. This presents a potential pathway for further exploration and future research in this fast-changing field.

Reference List

Agrawal, S., Azar, P. D., Lo, A. W., & Singh, T. (2018). Momentum, mean-reversion, and social media: Evidence from StockTwits and twitter. *Journal of Portfolio Management*, *44*(7), 85-95.

Akhtar, S., Faff, R., Oliver, B., & Subrahmanyam, A. (2011). The power of bad: The negativity bias in Australian consumer sentiment announcements on stock returns. *Journal of Banking & Finance*, *35*(5), 1239-1249.

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

AlMousa, M., Benlamri, R., & Khoury, R. (2021). Exploiting non-taxonomic relations for measuring semantic similarity and relatedness in WordNet. *Knowledge-Based Systems*, 212, 106565.

Al-Nasseri, A., Ali, F. M., & Tucker, A. (2021). Investor sentiment and the dispersion of stock returns: Evidence based on the social network of investors. *International Review of Financial Analysis*, *78*, 101910.

Alomari, M., Al Rababa'a, A. R., El-Nader, G., Alkhataybeh, A., & Rehman, M. U. (2021). Examining the effects of news and media sentiments on volatility and correlation: Evidence from the UK. *The Quarterly Review of Economics and Finance*, *82*, 280-297.

Amihud, Y., & Mendelson, H. (1980). Dealership market: Market-making with inventory. *Journal of Financial Economics*, 8(1), 31-53.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31-56.

Andrada-Félix, J., Fernandez-Perez, A., & Sosvilla-Rivero, S. (2018). Fear connectedness among asset classes. *Applied Economics*, *50*(39), 4234-4249.

Antonakakis, N. (2012). Exchange return co-movements and volatility spillovers before and after the introduction of euro. *Journal of International Financial Markets, Institutions and Money*, *22*(5), 1091-1109.

Antonakakis, N., & Kizys, R. (2015). Dynamic spillovers between commodity and currency markets. *International Review of Financial Analysis*, *41*, 303-319.

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

Audrino, F., & Tetereva, A. (2019). Sentiment spillover effects for US and European companies. *Journal of Banking & Finance*, *106*, 542-567.

Audrino, F., Sigrist, F., & Ballinari, D. (2020). The impact of sentiment and attention measures on stock market volatility. *International Journal of Forecasting*, *36*(2), 334-357.

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

Bae, K. H., Ozoguz, A., Tan, H., & Wirjanto, T. S. (2012). Do foreigners facilitate information transmission in emerging markets?. *Journal of Financial Economics*, 105(1), 209-227.

Bagehot, W. (1971). The only game in town. *Financial Analysts Journal*, 27(2), 12-14.

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271-299.

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

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129-151.

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, 104(2), 272-287.

Bali, T. G., Peng, L., Shen, Y., & Tang, Y. (2014). Liquidity shocks and stock market reactions. *Review of Financial Studies*, *27*(5), 1434-1485.

Banerjee, S., & Kremer, I. (2010). Disagreement and learning: Dynamic patterns of trade. *Journal of Finance*, 65(4), 1269-1302.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2), 785-818.

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

Baur, D. G., & McDermott, T. K. (2016). Why is gold a safe haven? *Journal of Behavioral and Experimental Finance*, *10*, 63-71.

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

Bennani, H. (2020). Central bank communication in the media and investor sentiment. *Journal of Economic Behavior & Organization*, *176*, 431-444.

Benston, G. J., & Hagerman, R. L. (1974). Determinants of bid-asked spreads in the over-the-counter market. *Journal of Financial Economics*, 1(4), 353-364.

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

Birru, J., & Young, T. (2022). Sentiment and uncertainty. *Journal of Financial Economics*, 146(3), 1148-1169.

Blasco, N., Corredor, P., & Ferreruela, S. (2012). Market sentiment: a key factor of investors' imitative behaviour. *Accounting & Finance*, 52(3), 663-689.

Blair, B. J., Poon, S. H., & Taylor, S. J. (2001). Modelling S&P 100 volatility: The information content of stock returns. *Journal of Banking & Finance*, 25, 1665-1679.

Boehmer, E., & Kelley, E. K. (2009). Institutional investors and the informational efficiency of prices. *Review of Financial Studies*, 22(9), 3563-3594.

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

Bouri, E., Cepni, O., Gabauer, D., & Gupta, R. (2021). Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis*, *73*, 101646.

Breugem, M., & Buss, A. (2019). Institutional investors and information acquisition: Implications for asset prices and informational efficiency. *Review of Financial Studies*, 32(6), 2260-2301.

Broadstock, D. C., & Zhang, D. (2019). Social-media and intraday stock returns: The pricing power of sentiment. *Finance Research Letters*, *30*, 116-123.

Brogaard, J., Hagströmer, B., Nordén, L., & Riordan, R. (2015). Trading fast and slow: Colocation and liquidity. *Review of Financial Studies*, *28*(12), 3407-3443.

Brogaard, J., Hendershott, T., & Riordan, R. (2019). Price discovery without trading: Evidence from limit orders. *Journal of Finance*, *74*(4), 1621-1658.

Brown, P., Walsh, D., & Yuen, A. (1997). The interaction between order imbalance and stock price. *Pacific-Basin Finance Journal*, *5*(5), 539-557.

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

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

Busse, J. A., & Green, T. C. (2002). Market efficiency in real time. *Journal of Financial Economics*, 65(3), 415-437.

Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. *Journal of International Money and Finance*, *42*, 38-70.

Cai, F., Han, S., Li, D., & Li, Y. (2019). Institutional herding and its price impact: Evidence from the corporate bond market. *Journal of Financial Economics*, 131(1), 139-167.

Cepoi, C. O. (2020). Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil. *Finance Research Letters*, 36, 101658.

Chalmers, J., Kaul, A., & Phillips, B. (2013). The wisdom of crowds: Mutual fund investors' aggregate asset allocation decisions. *Journal of Banking & Finance*, *37*(9), 3318-3333.

Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10), 1651-1679.

Chau, F., Deesomsak, R., & Lau, M. C. (2011). Investor sentiment and feedback trading: Evidence from the exchange-traded fund markets. *International Review of Financial Analysis*, 20(5), 292-305.

Chen, H., Noronha, G., & Singal, V. (2004). The price response to S&P 500 index additions and deletions: Evidence of asymmetry and a new explanation. *Journal of Finance*, *59*(4), 1901-1930.

Chen, H., De, P., Hu, Y., & Hwang, B. H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies*, 27(5), 1367-1403.

Chen, W. P., Chung, H., & Lien, D. (2016). Price discovery in the S&P 500 index derivatives markets. *International Review of Economics & Finance*, 45, 438-452.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *Journal of Finance*, *56*(2), 501-530.

Chordia, T., Roll, R., & Subrahmanyam, A. (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics*, *76*(2), 271-292.

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: do individual returns herd around the market? *Financial Analysts Journal*, 51(4), 31-37.

Christoffersen, P., & Pan, X. N. (2018). Oil volatility risk and expected stock returns. *Journal of Banking & Finance*, *95*, 5-26.

Clement, M. B., & Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance*, 60(1), 307-341.

Comerton-Forde, C., & Putniņš, T. J. (2015). Dark trading and price discovery. *Journal of Financial Economics*, 118(1), 70-92.

Conrad, F. G., Gagnon-Bartsch, J. A., Ferg, R. A., Schober, M. F., Pasek, J., & Hou, E. (2021). Social media as an alternative to surveys of opinions about the economy. *Social Science Computer Review*, *39*(4), 489-508.

Cookson, J. A., Engelberg, J. E., & Mullins, W. (2023). Echo chambers. *Review of Financial Studies*, *36*(2), 450-500.

Cornelli, F., Goldreich, D., & Ljungqvist, A. (2006). Investor sentiment and pre-IPO markets. *Journal of Finance*, 61(3), 1187-1216.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance*, 66(5), 1461-1499.

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies*, *28*(1), 1-32.

Danbolt, J., Siganos, A., & Vagenas-Nanos, E. (2015). Investor sentiment and bidder announcement abnormal returns. *Journal of Corporate Finance*, *33*, 164-179.

Dávila, E., & Parlatore, C. (2021). Trading costs and informational efficiency. *Journal of Finance*, 76(3), 1471-1539.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance*, 40(3), 793-805.

De Jong, P., Elfayoumy, S., & Schnusenberg, O. (2017). From returns to tweets and back: An investigation of the stocks in the Dow Jones industrial average. *Journal of Behavioral Finance*, 18(1), 54-64.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance*, 45(2), 379-395.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting*, *28*(1), 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119-134.

Dougal, C., Engelberg, J., Garcia, D., & Parsons, C. A. (2012). Journalists and the stock market. *Review of Financial Studies*, 25(3), 639-679.

Dufour, A., & Engle, R. F. (2000). Time and the price impact of a trade. *Journal of Finance*, *55*(6), 2467-2498.

Dumas, B., Kurshev, A., & Uppal, R. (2009). Equilibrium portfolio strategies in the presence of sentiment risk and excess volatility. *Journal of Finance*, *64*(2), 579-629.

Duz Tan, S., & Tas, O. (2021). Social media sentiment in international stock returns and trading activity. *Journal of Behavioral Finance*, 22(2), 221-234.

Edmans, A., Garcia, D., & Norli, Ø. (2007). Sports sentiment and stock returns. *Journal of Finance*, 62(4), 1967-1998.

Edmans, A., Fernandez-Perez, A., Garel, A., & Indriawan, I. (2022). Music sentiment and stock returns around the world. *Journal of Financial Economics*, 145(2), 234-254.

Elder, J., & Serletis, A. (2010). Oil price uncertainty. *Journal of Money, Credit and Banking*, *42*(6), 1137-1159.

Engelberg, J. E., & Parsons, C. A. (2011). The causal impact of media in financial markets. *Journal of Finance*, *66*(1), 67-97.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2), 383-417.

Fan, J. H., Binnewies, S., & De Silva, S. (2023). Wisdom of crowds and commodity pricing. *Journal of Futures Markets*, *43*(8), 1040-1068.

Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *Journal of Finance*, *64*(5), 2023-2052.

Federal Reserve Board (2023). *Silicon Valley Bank Review–Supervisory Materials*. https://www.federalreserve.gov/supervisionreg/silicon-valley-bank-review-supervisory-materials.htm

Fenzl, T., & Pelzmann, L. (2012). Psychological and social forces behind aggregate financial market behavior. *Journal of Behavioral Finance*, 13(1), 56-65.

Fernandez-Perez, A., Fuertes, A. M., Gonzalez-Fernandez, M., & Miffre, J. (2020). Fear of hazards in commodity futures markets. *Journal of Banking & Finance*, *119*, 105902.

Filip, A. M., & Pochea, M. M. (2023). Intentional and spurious herding behavior: A sentiment driven analysis. *Journal of Behavioral and Experimental Finance*, 100810.

Foucault, T., Hombert, J., & Roşu, I. (2016). News trading and speed. *Journal of Finance*, 71(1), 335-382.

French, K. R., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, 17(1), 5-26.

Frijns, B., Indriawan, I., Tourani-Rad, A., & Zhang, H. (2023). The effect of equity market uncertainty on informational efficiency: Cross-sectional evidence. *Global Finance Journal*, 100854.

Gan, B., Alexeev, V., Bird, R., & Yeung, D. (2020). Sensitivity to sentiment: News vs social media. *International Review of Financial Analysis*, 67, 101390.

Gao, L., Hitzemann, S., Shaliastovich, I., & Xu, L. (2022). Oil volatility risk. *Journal of Financial Economics*, *144*(2), 456-491.

Gao, L., & Süss, S. (2015). Market sentiment in commodity futures returns. *Journal of Empirical Finance*, *33*, 84-103.

Giannini, R., Irvine, P., & Shu, T. (2019). The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. *Journal of Financial Markets*, *42*, 94-120.

Goddard, J., Kita, A., & Wang, Q. (2015). Investor attention and FX market volatility. *Journal of International Financial Markets, Institutions and Money*, *38*, 79-96.

Goettler, R. L., Parlour, C. A., & Rajan, U. (2009). Informed traders and limit order markets. *Journal of Financial Economics*, *93*(1), 67-87.

Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies*, *28*(1), 73-111.

Greenwood-Nimmo, M., Nguyen, V. H., & Rafferty, B. (2016). Risk and return spillovers among the G10 currencies. *Journal of Financial Markets*, *31*, 43-62.

Greenwood-Nimmo, M., Nguyen, V. H., & Shin, Y. (2021). Measuring the connectedness of the global economy. *International Journal of Forecasting*, *37*(2), 899-919.

Grinblatt, M., Keloharju, M., & Linnainmaa, J. T. (2012). IQ, trading behavior, and performance. *Journal of Financial Economics*, 104(2), 339-362.

Gu, C., & Kurov, A. (2020). Informational role of social media: Evidence from Twitter sentiment. *Journal of Banking & Finance*, 121, 105969.

Guégan, D., & Renault, T. (2021). Does investor sentiment on social media provide robust information for Bitcoin returns predictability? *Finance Research Letters*, 38, 101494.

Han, L., Li, Z., & Yin, L. (2017). The effects of investor attention on commodity futures markets. *Journal of Futures Markets*, *37*(10), 1031-1049.

Hasbrouck, J. (1988). Trades, quotes, inventories, and information. *Journal of Financial Economics*, 22(2), 229-252.

Hasbrouck, J. (1991). Measuring the information content of stock trades. *Journal of Finance*, 46(1), 179-207.

He, W., & Shen, J. (2014). Do foreign investors improve informational efficiency of stock prices? Evidence from Japan. *Pacific-Basin Finance Journal*, 27, 32-48.

Hendershott, T., & Jones, C. M. (2005). Island goes dark: Transparency, fragmentation, and regulation. *Review of Financial Studies*, 18(3), 743-793.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *Journal of Finance*, *66*(1), 1-33.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance*, 58(3), 1009-1032.

Hirshleifer, D., Jiang, D., & DiGiovanni, Y. M. (2020). Mood beta and seasonalities in stock returns. *Journal of Financial Economics*, *137*(1), 272-295.

Hoffmann, P. (2014). A dynamic limit order market with fast and slow traders. *Journal of Financial Economics*, *113*(1), 156-169.

Huang, H. G., Tsai, W. C., Weng, P. S., & Wu, M. H. (2021). Volatility of order imbalance of institutional traders and expected asset returns: Evidence from Taiwan. *Journal of Financial Markets*, *52*, 100546.

Huberman, G., & Regev, T. (2001). Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. *Journal of Finance*, *56*(1), 387-396.

Indriawan, I. (2020). Market quality around macroeconomic news announcements: Evidence from the Australian stock market. *Pacific-Basin Finance Journal*, 61, 101071.

Jiang, G. J., & Tian, Y. S. (2005). The model-free implied volatility and its information content. *Review of Financial Studies*, *18*(4), 1305-1342.

Jiao, P., Veiga, A., & Walther, A. (2020). Social media, news media and the stock market. *Journal of Economic Behavior & Organization*, 176, 63-90.

Jones, C. M., Kaul, G., & Lipson, M. L. (1994). Transactions, volume, and volatility. *Review of Financial Studies*, 7(4), 631-651.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2000). Losing sleep at the market: The daylight saving anomaly. *American Economic Review*, *90*(4), 1005-1011.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review*, *93*(1), 324-343.

Kaplanski, G., & Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics*, 95(2), 174-201.

Kaplanski, G., & Levy, H. (2014). Sentiment, irrationality and market efficiency: The case of the 2010 FIFA World Cup. *Journal of Behavioral and Experimental Economics*, 49, 35-43.

Karagozoglu, A. K., & Fabozzi, F. J. (2017). Volatility wisdom of social media crowds. *Journal of Portfolio Management*, *43*(2), 136-151.

Karampatsas, N., Malekpour, S., Mason, A., & Mavis, C. P. (2023). Twitter investor sentiment and corporate earnings announcements. *European Financial Management*, 29(3), 953-986.

Kim, J. S., Ryu, D., & Seo, S. W. (2014). Investor sentiment and return predictability of disagreement. *Journal of Banking & Finance*, 42, 166-178.

Kocaaslan, O. K. (2019). Oil price uncertainty and unemployment. *Energy Economics*, *81*, 577-583.

Kocoń, J., & Maziarz, M. (2021). Mapping WordNet onto human brain connectome in emotion processing and semantic similarity recognition. *Information Processing & Management*, *58*(3), 102530.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, *74*(1), 119-147.

Kumar, A., & Lee, C. M. (2006). Retail investor sentiment and return comovements. *Journal of Finance*, 61(5), 2451-2486.

Kurov, A. (2008). Investor sentiment, trading behavior and informational efficiency in index futures markets. *Financial Review*, 43(1), 107-127.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1), 23-43.

Laborda, R., & Olmo, J. (2014). Investor sentiment and bond risk premia. *Journal of Financial Markets*, *18*, 206-233.

Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. *Journal of Finance*, 46(2), 733-746.

Leitch, D., & Sherif, M. (2017). Twitter mood, CEO succession announcements and stock returns. *Journal of Computational Science*, *21*, 1-10.

Leung, H., & Ton, T. (2015). The impact of internet stock message boards on cross-sectional returns of small-capitalization stocks. *Journal of Banking & Finance*, 55, 37-55.

Li, T., Chen, H., Liu, W., Yu, G., & Yu, Y. (2023). Understanding the role of social media sentiment in identifying irrational herding behavior in the stock market. *International Review of Economics and Finance*, 87, 163-179.

Liang, C., Tang, L., Li, Y., & Wei, Y. (2020). Which sentiment index is more informative to forecast stock market volatility? Evidence from China. *International Review of Financial Analysis*, *71*, 101552.

Liew, J. K. S., & Wang, G. Z. (2016). Twitter sentiment and IPO performance: A cross-sectional examination. *Journal of Portfolio Management*, *42*(4), 129-135.

Liu, S. (2015). Investor sentiment and stock market liquidity. *Journal of Behavioral Finance*, *16*(1), 51-67.

Lo, A., & MacKinlay, C. (1988). Stock market prices do not follow random walks: evidence from a simple specification test. *Review of Financial Studies*, 1,41–66.

Long, S., Lucey, B., Xie, Y., & Yarovaya, L. (2023). "I just like the stock": The role of Reddit sentiment in the GameStop share rally. *Financial Review*, 58(1), 19-37.

Loughran, T., & McDonald, B. (2014). Measuring readability in financial disclosures. *Journal of Finance*, 69(4), 1643-1671.

Madhavan, A., & Smidt, S. (1991). A Bayesian model of intraday specialist pricing. *Journal of Financial Economics*, 30(1), 99-134.

Mangee, N. (2018). Stock returns and the tone of marketplace information: does context matter?. *Journal of Behavioral Finance*, *19*(4), 396-406.

McKenzie, M. D., & Faff, R. W. (2003). The determinants of conditional autocorrelation in stock returns. *Journal of Financial Research*, 26(2), 259-274.

McKenzie, M. D., & Kim, S. J. (2007). Evidence of an asymmetry in the relationship between volatility and autocorrelation. *International Review of Financial Analysis*, 16(1), 22-40.

Menkhoff, L., & Nikiforow, M. (2009). Professionals' endorsement of behavioral finance: does it impact their perception of markets and themselves? *Journal of Economic Behavior & Organization*, 71(2), 318-329.

Mensi, W., Al Rababa'a, A. R., Vo, X. V., & Kang, S. H. (2021). Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. *Energy Economics*, *98*, 105262.

Michaelides, A., Milidonis, A., & Nishiotis, G. P. (2019). Private information in currency markets. *Journal of Financial Economics*, *131*(3), 643-665.

Moseki, K. K., & Rao, K. M. (2018). Empirical measures of symmetry of market sentiments. *Cogent Economics & Finance*, *6*(1), 1430113.

Navigli, R. (2009). Word sense disambiguation: A survey. *ACM computing surveys (CSUR)*, 41(2), 1-69.

Newman, N., Fletcher, R., Schulz, A., Andi, S., Robertson, C. T., & Nielsen, R. K. (2021). *Reuters Institute Digital News Report 2021*. https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2021-06/Digital_News_Report_2021_FINAL.pdf

Nofer, M., & Hinz, O. (2015). Using twitter to predict the stock market: Where is the mood effect?. *Business & Information Systems Engineering*, *57*, 229-242.

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *Journal of Finance*, 54(6), 2263-2295.

Nofsinger, J. R. (2005). Social mood and financial economics. *Journal of Behavioral Finance*, 6(3), 144-160.

O'Hara, M., & Ye, M. (2011). Is market fragmentation harming market quality?. *Journal of Financial Economics*, 100(3), 459-474.

Papakyriakou, P., Sakkas, A., & Taoushianis, Z. (2019). The impact of terrorist attacks in G7 countries on international stock markets and the role of investor sentiment. *Journal of International Financial Markets, Institutions and Money*, 61, 143-160.

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642-685.

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563-602.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, *58*(1), 17-29.

Price, S. M., Doran, J. S., Peterson, D. R., & Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance*, *36*(4), 992-1011.

Raddant, M., & Kenett, D. Y. (2021). Interconnectedness in the global financial market. *Journal of International Money and Finance*, *110*, 102280.

Rakowski, D., Shirley, S. E., & Stark, J. R. (2021). Twitter activity, investor attention, and the diffusion of information. *Financial Management*, *50*(1), 3-46.

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

Roll, R. (1984). A simple implicit measure of the effective bid-ask in an efficient market. *Journal of Finance*, 39,1127–1139.

Roşu, I. (2019). Fast and slow informed trading. *Journal of Financial Markets*, *43*, 1-30.

Scheinkman, J. A., & Xiong, W. (2003). Overconfidence and speculative bubbles. *Journal of Political Economy*, 111(6), 1183-1220.

Schnaubelt, M., Fischer, T. G., & Krauss, C. (2020). Separating the signal from the noise–financial machine learning for twitter. *Journal of Economic Dynamics and Control*, *114*, 103895.

Schober, M. F., Pasek, J., Guggenheim, L., Lampe, C., & Conrad, F. G. (2016). Social media analyses for social measurement. *Public Opinion Quarterly*, *80*(1), 180-211.

SEC. (2008). *Commission guidance on the use of company web sites*. https://www.sec.gov/rules/interp/2008/34-58288.pdf

SEC. (2012). *Investment adviser use of social media. National examination risk alert. https://www.sec.gov/about/offices/ocie/riskalert-socialmedia.pdf*

SEC. (2013). *SEC says social media ok for company announcements if investors are alerted.* https://www.sec.gov/news/press-release/2013-2013-51htm

SEC (2023). *SEC Charges Eight Social Media Influencers in $100 Million Stock Manipulation Scheme Promoted on Discord and Twitter*. https://www.sec.gov/news/press-release/2022-221

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International review of financial analysis*, *70*, 101496.

Shen, J., Yu, J., & Zhao, S. (2017). Investor sentiment and economic forces. *Journal of Monetary Economics*, 86, 1-21.

Shi, Y., & Ho, K. Y. (2021). News sentiment and states of stock return volatility: Evidence from long memory and discrete choice models. *Finance Research Letters*, 38, 101446.

Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *American Economic Review*, 71, 421–436.

Shu, H. C., & Chang, J. H. (2015). Investor sentiment and financial market volatility. *Journal of Behavioral Finance*, *16*(3), 206-219.

Sibande, X., Gupta, R., Demirer, R., & Bouri, E. (2023). Investor sentiment and (anti) herding in the currency market: evidence from twitter feed data. *Journal of Behavioral Finance*, *24*(1), 56-72.

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

Smales, L. A., & Kininmonth, J. N. (2016). FX market returns and their relationship to investor fear. *International Review of Finance*, *16*(4), 659-675.

Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014). Tweets and trades: The information content of stock microblogs. *European Financial Management*, *20*(5), 926-957.

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

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

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

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of finance*, 62(3), 1139-1168.

Tetlock, P. C., Saar‐Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *Journal of Finance*, 63(3), 1437-1467.

Tetlock, P. C. (2011). All the news that's fit to reprint: Do investors react to stale information? *Review of Financial Studies*, 24(5), 1481-1512.

Triki, M. B., & Maatoug, A. B. (2021). The GOLD market as a safe haven against the stock market uncertainty: evidence from geopolitical risk. *Resources Policy*, 70, 101872.

Umar, Z., Gubareva, M., Yousaf, I., & Ali, S. (2021). A tale of company fundamentals vs. sentiment driven pricing: The case of GameStop. *Journal of Behavioral and Experimental Finance*, 30, 100501.

Valadkhani, A. (2022). Do large-cap exchange-traded funds perform better than their small-cap counterparts in extreme market conditions? *Global Finance Journal*, 53, 100743.

Vidhu Bhala, R. V., & Abirami, S. (2014). Trends in word sense disambiguation. *Artificial Intelligence Review*, 42, 159-171.

Vosen, S., & Schmidt, T. (2011). Forecasting private consumption: survey-based indicators vs. Google trends. *Journal of Forecasting*, *30*(6), 565-578.

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking & Finance*, *41*, 17-35.

Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics*, 58(3), 369-396.

Whaley, R. E. (2009). Understanding the VIX. *Journal of Portfolio Management*, *35*(3), 98-105.

Yousaf, I., Youssef, M., & Goodell, J. W. (2022). Quantile connectedness between sentiment and financial markets: Evidence from the S&P 500 twitter sentiment index. *International Review of Financial Analysis*, *83*, 102322.

Zhang, X. F. (2006). Information uncertainty and stock returns. *Journal of Finance*, 61(1), 105-137.

Zhang, H., Hong, H., Guo, Y., & Yang, C. (2022). Information spillover effects from media coverage to the crude oil, gold, and Bitcoin markets during the COVID-19 pandemic: Evidence from the time and frequency domains. *International Review of Economics & Finance*, *78*, 267-285.

Zhou, G. (2018). Measuring investor sentiment. *Annual Review of Financial Economics*, 10, 239-259.

Appendices

Appendix I. Word cloud for tweets data and tweets sentiment extraction examples

1. The qualitative word cloud below (created based on 7 million tweet messages regarding $SPY) shows the 100 most talked words/topics among the 7 million tweets. The larger the word in this cloud, the more popular (mentioned) the topic is along with $SPY.

2. Classified positive and negative tweets are demonstrated below as examples.

a. 06/02/2018 10:07:22 am EST "I did explain yesterday that a lot of great buying opportunity would come from that dip. It is already happening as we have bounced already 700 points in the $SPY today.

-This single tweet's tone is quantified by WordNet as 0.80 (positive).

b. 30/03/2022 6:17:16 pm EST "$SPY bad day to be an investor."

-This single tweet's tone is quantified by WordNet as -0.70 (Negative).

Appendix II. Block connectedness methodology

Greenwood-Nimmo et al.'s (2016, 2021) developed the block aggregation approach and improved the flexibility of the DY approach. The generalized aggregation approach supports any desired block structure with re-ordered variables, as the GVD method is not order-sensitive.

If we have five different variables for each group or block i $\{v_{it}, w_{it}, x_{it}, y_{it}, z_{it}\}$ in the order $Y_t = (v_{1t}, w_{1t}, x_{1t}, y_{1t}, z_{1t}, \cdots, v_{Nt}, w_{Nt}, x_{Nt}, y_{Nt}, z_{Nt})'$ and we aim to assess the spillover of the two blocks in the model as a whole by considering all five variables in each block. The connectedness matrix D^H can be reformulated in block form as follows, with $g = N$ blocks and each containing m variables ($m = 5$ in this illustration):

$$\mathrm{D}^{\mathrm{H}} = \begin{bmatrix} B_{11}^H & \cdots & B_{1N}^H \\ \vdots & \ddots & \vdots \\ B_{N1}^H & \cdots & B_{N1}^H \end{bmatrix}, \qquad \text{(II.1)}$$

where $B_{ij}^H = \begin{bmatrix} d_{v_i v_i}^H & d_{v_i w_i}^H & d_{v_i x_i}^H & d_{v_i y_i}^H & d_{v_i z_i}^H \\ d_{w_i v_i}^H & d_{w_i w_i}^H & d_{w_i x_i}^H & d_{w_i y_i}^H & d_{w_i z_i}^H \\ d_{x_i v_i}^H & d_{x_i w_i}^H & d_{x_i x_i}^H & d_{x_i y_i}^H & d_{x_i z_i}^H \\ d_{y_i v_i}^H & d_{y_i w_i}^H & d_{y_i x_i}^H & d_{y_i y_i}^H & d_{y_i z_i}^H \\ d_{z_i v_i}^H & d_{z_i w_i}^H & d_{z_i x_i}^H & d_{z_i y_i}^H & d_{z_i z_i}^H \end{bmatrix}$ for $i, j = 1,2, \cdots, N$,

hence, the block B_{ii}^H captures the within-block connectedness for block i while B_{ij}^H captures all spillover effects from block j to block i. Therefore, we can define the total within-block forecast error variance contribution for block i as:

$$W_{ii}^H = \frac{1}{m} e_m' B_{ii}^H e_m, \qquad \text{(II.2)}$$

where m is the number of variables in each block and e_m is an $m \times 1$ vector of ones. Likewise, we define the total pairwise directional spillover from market block j to block i $(i \neq j)$ at horizon H as:

$$P_{ij}^H = \frac{1}{m} e_m' B_{ij}^H e_m. \qquad \text{(II.3)}$$

Finally, the aggregated connectedness matrix by using Greenwood-Nimmo et al. (2021) approach is re-formed as:

$$\mathrm{D^H} = \begin{bmatrix} W_{11}^H & P_{12}^H & \cdots & P_{1N}^H \\ P_{21}^H & W_{22}^H & \cdots & P_{2N}^H \\ \vdots & \vdots & \ddots & \vdots \\ P_{N1}^H & P_{N2}^H & \cdots & W_{NN}^H \end{bmatrix}. \tag{II.4}$$

Based on the above illustration, W_{ii}^H, the total within-block contribution can be decomposed into common-variable forecast error variance contribution within-block i (K_{ii}^H), and cross-variable effects (C_{ii}^H), we define K_{ii}^H and C_{ii}^H as[60]:

$$K_{ii}^H = \frac{1}{m} trace(W_{ii}^H), \tag{II.5}$$

and

$$C_{ii}^H = W_{ii}^H - K_{ii}^H. \tag{II.6}$$

Now, the aggregated connectedness to block i is as follows:

$$P_{i\leftarrow\bullet}^H = \sum_{j=1, j\neq i}^N P_{ij}^H, \tag{II.7}$$

while the aggregated connectedness from block i can be written as:

$$P_{\bullet\leftarrow i}^H = \sum_{j=1, j\neq i}^N P_{ji}^H, \tag{II.8}$$

thus, the net directional spillover from block i to all other blocks is:

$$P^H = P_{\bullet\leftarrow i}^H - P_{i\leftarrow\bullet}^H . \tag{II.9}$$

Finally, the aggregated spillover effect between-block can be expressed as:

$$B\_B^H = \frac{1}{N}\sum_{i=1}^N P_{i\leftarrow\bullet}^H \tag{II.10}$$

and the aggregated spillover effect within-block is:

$$W\_B^H = 100 - {B_B}^H. \tag{II.11}$$

[60] K_{ii}^H is the proportion of forecast error variance of Y_{it} that is not attributable to spillovers among innovations within block i nor to the spillovers from block j with ($i \neq j$). C_{ii}^H is the proportion of forecast error variance of Y_{it} attributable to spillovers among innovations within block i.

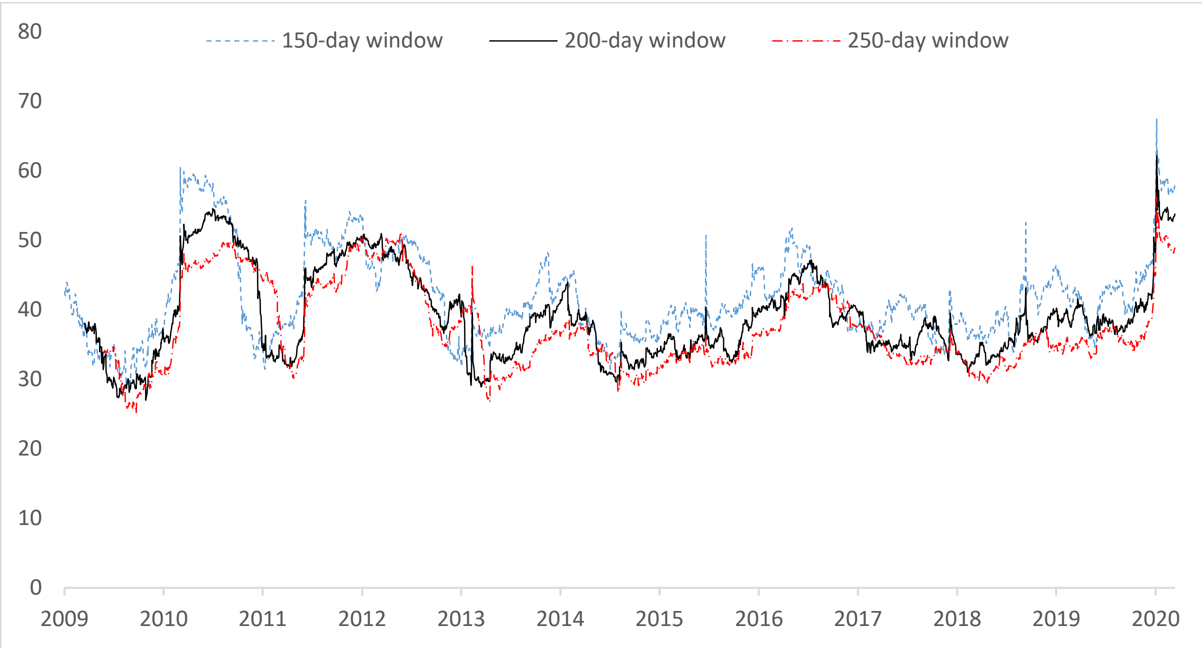
Appendix III. The choices of the time frame for each period

This table lists the six turbulent periods considered in the study and their associated landmark events.

	Phase starts	Associated event(s)	Phase ends	Associated event(s)
Euro debt crisis	April 12, 2010	Greece requested a loan of €45 billion from the EU and the IMF. Standard & Poor's downgraded Greece's sovereign debt rating from BB+ to "junk".	February 28, 2011	The second of Greek bailout. Portugal reached a bailout deal with the EU and the IMF.
US debt ceiling crisis	May 1, 2011	At the end of April 2011, US Congress delayed the approval for the 2011 budget. The US hit the 14.29 trillion debt ceiling in May 2011.	August 31, 2011	Obama signed the debt ceiling bill to avert a financial default.
Russia-Ukraine conflicts	February 20, 2014	Russia began the annexation of Crimea.	May 1, 2014	The Ukrainian parliament declared Crimea a territory temporarily occupied by Russia. Multiple regional conflicts temporarily ended at the end of April.
UK Brexit	June 23, 2016	The referendum result was released. 52% of the UK voters chose to leave the EU.	November 25, 2016	Prime Minister Theresa May seeked negotiations for leaving the EU smoothly.
US-China trade war	May 29, 2018	The White House announced a 25% tariff on $50 billion of Chinese goods. Former US president Donald Trump declared the increased tariff on Twitter the following day.	December 1, 2018	The US and China leaders agreed on a truce for the trade war during the G20 summit in Argentina.
COVID-19 pandemic	December 12, 2019	The National Bureau of Economic Research (NBER) lists the business cycle reference dates with the peak in Q4 2019.	May 15, 2020	The NBER lists business cycle reference dates with the trough in Q2 2020.

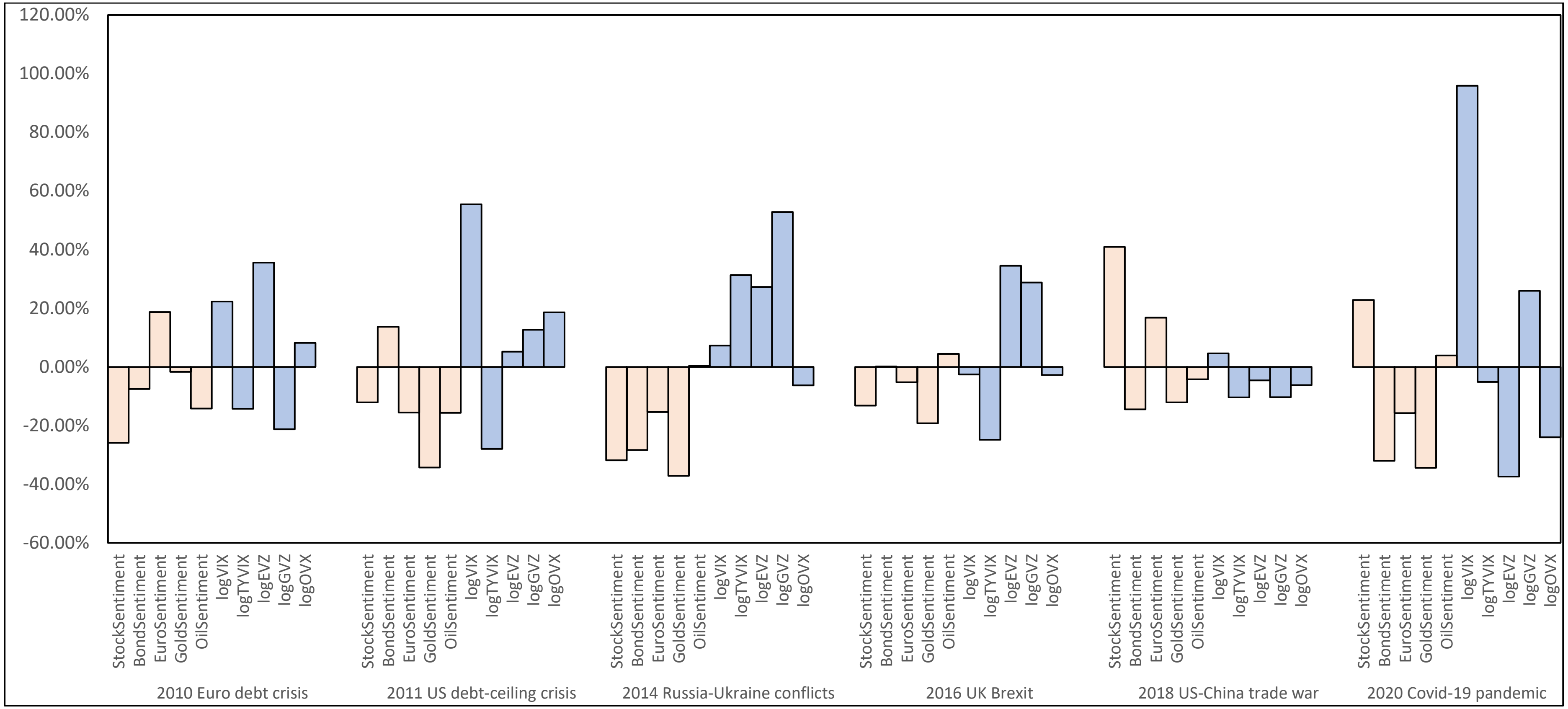
Appendix IV. Dynamic total connectedness using different windows

This figure plots the connectedness value over the sample period using different windows, i.e., 150 days, 200 days, and 250 days.



Appendix V. Net total directional connectedness after controlling for market conditions during various crises

This figure plots the net total directional connectedness for the the orthogonalized sentiment and volatility indices during various crises: (a) Euro Debt crisis (Apr 2010 – Feb 2011); (b) US debt-ceiling crisis (May 2011- Aug 2011); (c) Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) UK Brexit (Jun 2016 – Nov 2016); (e) US-China trade war (May 2018 – Dec 2018); (f) COVID-19 pandemic (Dec 2019 – May 2020). We control for the term spread, the 3-month Treasury Bill rate, the credit spread the TED spread and the Pástor and Stambaugh's (2003) liquidity factor.



Appendix VI. Net pairwise directional connectedness during various crises

This figure plots the net pairwise directional connectedness during six crises: (a) Euro Debt crisis (Apr 2010 – Feb 2011); (b) US debt-ceiling crisis (May 2011- Aug 2011); (c) Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) UK Brexit (Jun 2016 – Nov 2016); (e) US-China trade war (May 2018 – Dec 2018); (f) COVID-19 pandemic (Dec 2019 – May 2020). Arrow width reflects the value in net connectedness. The unidirectional red arrows and turquoise arrows represent the sentiment spillovers and volatility spillovers during various crises, respectively. Gold nodes are those greatest net transmitter sentiments at different turbulent periods.