Investor Sentiment in the Chinese Stock Market

by

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Contents

List of Figures

List of Tables

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Abstract

The thesis encompasses three essays in empirical asset pricing and focuses on investor sentiment in the Chinese stock markets. Traditional models of asset pricing assume that information is promptly processed and integrated into the prices of asset. In reality, pervasive investor sentiment may distort the assumption. Proponents of the efficient market hypothesis suggest that investor sentiment should not be considered as a pricing factor, since the mispricing caused by sentiment can be eliminated through trades made by rational speculators and arbitraging. However, behavioral finance theory argues that the impact of investor sentiment cannot be disregarded if it leads to uninformed demand shock and the cost of arbitrage is high. The three essays specifically explore whether the pricing effect of sentiment exists in Chinese stock markets.

In Chapter 2, we focus on market-, survey-, text- and search-based investor sentiment proxies and the impact of aggregate sentiment extracted from them in the Chinese stock market. Using data from 2008 to 2019, we find that individual sentiment proxies have limited return predictability, while the aggregate sentiment measures extracted from the four types of sentiment proxies show significant positive predictability both in- and out-of-sample. Moreover, the aggregate sentiment measures can deliver sizable economic gains to a mean-variance utility investor in an asset allocation exercise. This study advances our understanding of investor sentiment and its asset pricing and prediction implications in China.

In Chapter 3, we construct a text-based measure of investor sentiment by extracting the comments from individual investors on stock message boards in China. Using data from 2008 to 2020, we provide extensive evidence that the investor sentiment captured by our measure positively predicts cross-sectional stock returns in

the following ten months. The text-based sentiment reveals that investor trading behaviors are influenced by online messages posted by individual investors. By longing the stocks with high sentiment and shorting the stocks with low sentiment, this long-short strategy based on textual sentiment measure produces significant economic value. In addition, we perform a range of robustness tests and confirm that the return predictability is not due to firm characteristics, common risk factors, investor attention, or alternative sentiment indicators.

In Chapter 4, we introduce disaster-induced sentiment measures derived from disaster-related search terms based on the Baidu Index and Google Trends to characterize investors' responses to disaster events. In particular, we study how disaster-induced sentiment affects stock returns in the Chinese and the US stock markets. Using data from 2007 to 2021, we find that disaster-induced sentiment measures negatively predict country-level market returns in the short term. The sentiment based on Baidu index increases the explanatory power of the return variation in predicting the Chinese stock market in comparison with Googling sentiment used in the literature. In China, the coastal provinces and provinces with high GDP are more heavily influenced by disaster-induced sentiment. Based on disaster-related internet search data, this study promotes our understanding of the impact of disaster-induced sentiment on the performance of stock markets.

Chapter 1

Introduction

This thesis comprises five chapters with a focus on studying the influence of investor sentiment on Chinese stock markets. Specifically, the second chapter explores the market return predictability of collective Chinese investor sentiment based on various types of individual sentiment measures in the time series. The third chapter examines the effect of textual investor sentiment in the cross section based on investors' comments on individual stocks. The fourth chapter constructs disaster-induced sentiment measures based on search data from the Baidu index in China and explores the effect on stock returns from different regions.

Investor sentiment in the stock market pertains to the general emotional state, mood, belief, or anticipation of the future value of assets. As suggested by Baker and Wurgler (2006), it is an emotional factor that can significantly influence investors' trading decisions. Investor sentiment can be triggered by several factors, including noisy information, limited trading experience, knowledge, or skills, and it may stimulate investors to trade at illogical times, leading to either over- or underestimation of stock performance. As a result, investors influenced by irrational sentiment may impact the prices of the stocks they trade, ultimately leading to market mispricing.

Previous literature investigating the effect of investor sentiment on the stock market mainly focuses on developed markets, such as the US and the UK markets (Lemmon and Portniaguina, 2006; Schmeling, 2009). For example, Lemmon and Portniaguina (2006) and Baker and Wurgler (2007) show that sentiment based on survey and market data can negatively predict market returns in the US. In comparison to developed markets, emerging markets are considered to exhibit lower efficiency in pricing stocks due to a large number of unsophisticated investor investors and incomplete regulatory systems, (Kling and Gao, 2008). This thesis intends to contribute further empirical evidence to this area by examining the impact of investor sentiment on the Chinese stock market, which is the largest emerging market globally. Chinese individual investors are heavily influenced by noisy information and seldom conduct fundamental stock valuation research before making investment decisions. Therefore, the impact of investor sentiment on the Chinese stock market is expected to differ from that of developed markets (Bennet et al., 2012; Chen et al., 2014; Chi et al., 2012).

More precisely, the second chapter collects four types of investor sentiment measures based on market, survey, text and search data to predict the aggregate market returns in China. According to classical finance theory, the risk posed by investor sentiment on individual stocks is considered an idiosyncratic type of risk that only affects specific stocks, rather than the entire market. In contrast, De Long et al. (1990) and Baker and Wurgler (2006) propose that if a common noisy signal in the market, such as rumors, triggers investor sentiment, investors may overreact or underreact to the existing information in the stock market. In such cases, investor sentiment may act as a systematic pricing factor that can create deviations in stock prices from their equilibrium levels, particularly when arbitrage is limited or costly.

Previous literature constructs sentiment measures generally based on one type of data (see Kling and Gao, 2008; Chen et al., 2014; Han and Li, 2017). However, Zhou (2018) suggests that using one type of sentiment measure is not sufficient to capture the true investor sentiment. For examples, sentiment measures based on market data come from investors' trading behaviors according to their expectations on the stock market; survey-based sentiment measures investigate the view of investors, which tends to be biased by the design and target of the questionnaire. The investors' views and behaviors are inconsistent sometimes, indicating that both of them contain useful information to predict the market returns. Motivated by these, we aggregate four types of indicators based on market, survey, text and search data into a collective sentiment measure by well extracting their common component in forecasting market returns.

Empirically, this study reveals a host of interesting findings. First, in contrast to the common belief that investor sentiment is a contrarian predictor of market returns across all time horizons, our research provides extensive evidence that in China, investor sentiment serves as a reliable short-term momentum signal on a monthly basis. Second, our newly constructed sentiment measures outperform most of existing sentiment variables in the Chinese stock market, and maintain strong predictability after controlling for economic variables. Third, our research also includes an asset allocation exercise for a mean-variance utility investor, which provides additional evidence supporting our finding that the predictive power of investor sentiment can result in economically significant gains for such kind of investors.

The second chapter also has several notable contributions. First, we develop a new sentiment measure by aggregating different types of investor sentiment indicators. The actual predictive power of sentiment may be underestimated if we only consider individual sentiment measures. Instead, our aggregate sentiment measure encompasses relevant information from all reliable individual proxies, providing a comprehensive measure of market-level sentiment. Second, we show that the effect of investor sentiment in the Chinese stock market differs from previously thought that sentiment is a contrarian predictor. It can positively influence stock prices in the short term.

The third chapter builds upon and contributes to the strand of the literature that explores the impact of firm-specific investor sentiment on cross-sectional asset prices. Existing sentiment variables are mainly available at the market level (Brown and Cliff, 2005; Han and Li, 2017; Schmeling, 2009). These investigations do not fully address whether stocks with different characteristics are disproportionately affected by broad waves of investor sentiment and how individual stock returns are correlated with sentiment, considering the variability of sentiment levels across stocks.

We aim to construct a firm-specific sentiment proxy and examine its effect on stock returns in the cross section from June 2008 to December 2020. This sentiment proxy is measured by differences between the number of positive and negative investor comments on each stock at a monthly frequency. All of the comments are collected from a major online investor forum. Previous studies have examined the forecasting power of investor sentiment on stock returns based on online information with inconsistent results (e.g., Antweiler and Frank, 2004; Tetlock, 2007; Hui et al., 2018). For instance, Antweiler and Frank (2004) find that online messages have the ability to predict market volatility, although the impact on stock returns is statistically significant, it is economically small according to high frequency data in 2000. Furthermore, they document that increased trading volume is linked to disagreement among the posted messages. However, Hui et al. (2018) suggest that the investor sentiment derived from online information is not effective in predicting stock returns.

Considering the inconclusive findings presented in the literature, we tend to investigate the predictive power of investor sentiment based on the online information released by individual investors in China. This motivates the study to present extensive evidence on whether the online comments posted by individuals on stocks can predict future stock returns. Empirically, in asset pricing examinations, we first follow Antweiler and Frank's (2004) method to construct firm-specific sentiment of each stock based on the differences between the number of positive comments and negative comments at monthly frequency. Next, we explore the impact on cross-sectional stock returns and find that equal-weighted portfolios with high sentiment significantly outperform portfolios with low sentiment. The return differential shows significantly positive in the following ten months. Adopting the value-weighted scheme and using well-documented risk factor models like the Carhart four-factor model (Carhart, 1997) and Fama-French five-factor model (Fama and French, 2015) lead to qualitatively the same results. In addition, we document the profitability of a trading strategy with a long position in stocks with high sentiment and a short position in stocks with low sentiment after considering short-selling restrictions and transaction costs.

The third chapter has two main contributions. First, we measure investor sentiment for individual stocks based on text data, it is possible to yield sizable economic gains based on long-short trading strategy in the cross section. This is in contrast to existing articles, which mainly use market sentiment to predict stock returns. Second, we find that the views of investors towards individual stocks can influence stock prices in the Chinese market. Stocks with more positive comments tend to perform better in the short term compared to other stocks.

The fourth chapter constructs disaster-induced sentiment measures based on search data in China and the US to explore the impact on stock returns in different regions during the sample period between 2007 and 2021. Natural disasters can be regarded as non-financial, exogenous shocks to the economy. In addition to exerting an influence on multiple macroeconomic indicators, disasters also have a direct impact on domestic stock markets, with potential spillover effects across stock markets in different countries (Teitler-Regev and Tavor, 2019; Berkman et al., 2011).

Traditional studies normally employ intervention analysis and event study to examine the effect of disaster events on the stock market (Bai et al., 2019; Lee et al., 2018). Search data provides a new way to capture the specific disasters to which people pay attention at anytime, because searching behaviours of the majority of people encompass information related to their sentiment, and the people's concern about potential disasters influences their financial decisions. As yet, research about disasters based on search data has received limited attention. Gao et al. (2020) develop finance- and economics- unrelated sentiment measures relying on search terms from six categories (including disaster) and reveal that their sentiment measures negatively predict market returns across 36 countries.

Motivated by the Googling sentiment measures of Gao et al. (2020), we first construct a global disaster sentiment measure and a US disaster sentiment measure by aggregating search volume of terms related to disaster events in Google search engine. Then we form a Chinese disaster sentiment measure based on search volume of these terms in Baidu search engine, which is the most widely used search engine in China. Our disaster-induced sentiment mainly captures people's negative mood and anxiety since all of search terms related to disaster events are identified with negative sentiment in the dictionary (Hu and Liu, 2004).

In empirical analyses, we conduct a baseline regression to explore the predictability of disaster-induced sentiment measures on excess stock returns in the US and Chinese stock markets. Notably, both measures from different countries have significantly negative predictability on market excess returns in subsequent one month. The economic significance is well addressed by both the t-values of slope coefficient and R^2 statistic. After controlling for the effect of economic variables and the frequency of real disasters, the negative predictive power of disaster-induced sentiment measures is not subsumed. We further document that the predictability of disaster-induced sentiment for returns is pervasive across different sectors.

Since disaster events may elicit different reactions from investors in various regions (Kaplanski and Levy, 2010), we investigate investors' reaction to disasters in different provinces in China. By constructing stock portfolios for each province based on the location of firms' headquarters in China, we find that the disaster-induced sentiment in coastal provinces has stronger negative impact on stock returns than that in inland provinces. This might be due to the geographical distribution of the disaster, since coastal areas face more sea-related disaster threats than inland areas (Kron, 2013), indicating that investors in coastal regions are more sensitive to these kinds of disasters.

The fourth chapter makes two major contributions to the literature. First, our findings indicate that disaster-related search data can gauge the negative sentiment, which signifies the concern about potential disasters from investors. It can be used to examine the impact of negative sentiment in many contexts, such as in any region where the disaster-related search data can be collected. Second, our research demonstrates that constructing search-based sentiment measures using data from Baidu is more suitable than Google in China. This is in contrast to previous studies, which normally rely on Google search engine data to predict Chinese stock markets (Choi et al., 2020; Gao et al., 2020).

In the fourth chapter, the predictive power of sentiment on subsequent stock returns is significantly negative, revealing the opposite direction compared with sentiment measures as the positive predictor in the second and third chapters. The main reason is that the second and third chapters take into account of both positive and negative sentiment since investors' opinions and beliefs on future movement of stock returns can be optimistic or pessimistic. While disaster-induced sentiment in the fourth chapter mainly covers investors' fear and anxiety provoked by unforeseen disaster events, stock prices are negatively affected by the reduced willingness of investors to take risks when fear and anxiety increase. More specifically, stock-specific (disaster-induced) sentiment in the third (fourth) chapter positively (negatively) correlates with contemporaneous returns and leads to higher (lower) returns in the short term, indicating that investor sentiment in China is a convincible momentum factor at monthly frequency.

To summarize, this thesis provides extensive evidence that supports investor sentiment playing a crucial role in the asset pricing area of the Chinese market during the relatively long sample period. As Zhou (2018) documents that exploring sentiment measures over diverse sources and different time horizons is becoming more and more important, we devote to using novel data and quantifying investor sentiment by applying different types of measures to generate more comprehensive and more accurate investor sentiment in China.

Chapter 2

Investor sentiment and market returns: Evidence from China

2.1 Introduction

Investor sentiment refers to a belief formed by investors based on the expectation of future value of stocks, while this belief is not fully explained by existing factors (Baker and Wurgler, 2006). It is important to note that sentiment can be influenced by noise information, which leads to irrational trading behavior and market inefficiencies. The conjecture from De Long et al. (1990) suggests that stocks are held by noise traders, who are not driven by fundamental information rather by their own emotions and beliefs. Shleifer and Vishny (1997) further show that rational investors are limited by arbitrage constraints, which prevent them from correcting market mispricing caused by noise traders. Baker and Wurgler (2006) and Baker et al. (2012) test this conjecture empirically by constructing a composite sentiment index and documenting its return prediction in the U.S. and five non-U.S. developed markets.

There is a growing consensus in the literature that investor sentiment can serve as a contrarian predictor of stock market returns in the long term. High sentiment links to low market returns with the market revision over time (Baker and Stein, 2004; Baker et al., 2012). Nevertheless, the impact of investor sentiment on short-term market returns remains uncertain, as the existing evidence has failed to provide a conclusive answer. For instance, Brown and Cliff (2004) discover that the effect of investor sentiment on the following monthly market returns in the United States is insignificant by using technical indicators and investor survey data. In contrast, Huang et al. (2015) show that their collective sentiment measure based on market data can negatively predict the US stock market on a monthly basis.

The motivation behind this study is the ambiguous empirical evidence on the predictability of short-term returns based on investor sentiment. While investor sentiment is widely believed to possess contrarian predictability over the long term, this predictive power does not necessarily extend to the short term. Additionally, compared to developed markets, emerging markets have more binding arbitrage constraints, prevalent local retail investors, and limited openness to international investors. As the largest emerging market, the Chinese stock market is renowned for its unique characteristics compared to the US and other developed markets. First, it is typically regarded as a highly speculative market dominated by individual investors, who are more susceptible to their own emotions (Cheema et al., 2020). Second, due to its stringent institutional settings, such as strong short-selling constraints, the Chinese stock market is highly restrictive and less openness to the international investors. All of these distinctive features seem to increase the possibility that irrational sentiment exerts a greater impact on future returns in the short term.

Recently, some literature studies the effect of investor sentiment on the Chinese stock market by using different measures. Due to the unique characteristics of the Chinese market, Han and Li (2017) find that investor sentiment has the potential power to positively forecast market returns. However, they only use the market data to construct investor sentiment, and Cheema et al. (2020) show that this predictive power is insignificant after excluding the bubble period (2006-2008). In addition, Li et al. (2019) use individual investor comments construct daily textual investor sentiment measure in China, and they find that the text-based sentiment can positively predict future stock market. In contrast, Gao et al. (2020)'s search-based sentiment shows a negative predictive power on a weekly basis in China. According to these evidence, the effect of investor sentiment on market movements in China seems to be ambiguous. Zhou (2018) reviews different measures of investor sentiment based on market, survey, text and media data, and finds that different measures affect stock returns in various degrees. Therefore, one clear limitation of the above research is that they only use one type of indicators to measure sentiment in which the results for predictive power of sentiment may be inaccurate.

In this chapter, we first aim to investigate the forecasting power of aggregate sentiment on stock returns in the Chinese market. To measure the investor sentiment more accurately, we collect four different types of (market-, survey-, text- and search-based) sentiment-related data. Market-based data are commonly used to proxy sentiment related to investors' behavior in the literature, we use five major market-based measures of investor sentiment from the literature: value-weighted price-earnings ratio of the market (Han and Li, 2017), close-end fund discount (Neal and Wheatley, 1998), initial public offerings first-day returns (Baker and Wurgler, 2006), market turnover (Chen et al., 2014) and number of new opened investor accounts in Shanghai Stock Exchange (Chen et al., 2010).

Survey and text data are also important because such data provide unique perspectives on how investors form their beliefs (Zhou, 2018; Li et al., 2019). It is interesting to examine whether sentiment measures based on investors' behavior are consistent with investors' beliefs. Surveys tend to collect opinion polls from market participants to infer their views (Schmeling, 2009). Greenwood and Shleifer (2014) find that there is a strong positive correlation between survey-based measures and past stock returns. We collect three survey-based measures to proxy investor sentiment in China: consumer confidence index (Fisher and Statman, 2003), investor confidence index (Brown and Cliff, 2004) and bullish-bearish market index. Further, sentiment measures extracted from textual data are fueled by increasingly available computer technology, learning algorithms, and dictionaries. Following Antweiler and Frank (2004), we construct textual measure for investor sentiment by using investor comments in the largest Chinese investor online forum. With the rapid development of the Internet, it is necessary to explore search data in financial markets since more and more investors tend to search information and trade stocks online. Additionally, we construct an economics- and finance-related search-based sentiment measure according to Baidu index by using the method from Gao et al. (2020).[1]

Second, we find that more than half of individual sentiment proxies in China

[1]Baidu index collects search volume of various keywords in Baidu search engine, which has the largest search engine market share in China.

have limited predictability of market returns. Only market-wide price-earning ratio (PE), investor confidence index (ICI), comments of investors in Internet (COM) and Baidu Index (BI) have significant positive predictability of market returns, and these four proxies are collected from market-, survey-, text- and search-based data, respectively. In addition, we piece these four sentiment proxies together and extract their common component to form aggregate sentiment measures based on equal-weighted, principal component analysis (PCA), scaled-principal component analysis (SPCA) and partial least square method (PLS). The sample period of aggregate sentiment measures spans a period of 11 years (2008-2019). We find that all of these aggregate measures can significantly and positively predict the monthly market excess returns after controlling for macroeconomic variables which is consistent with Han and Li (2017)'s findings. Besides, the sentiment measure based on the equal-weighted method shows the best forecasting performance, which also performs better than other existing sentiment measures in the Chinese stock market at the monthly horizon. Extending the prediction horizon, we find that predictive abilities of all three aggregate sentiment measures weaken largely after one month and diminish completely in six months.

Third, on the out-of-sample assessment, we employ two evaluation metrics, Campbell and Thompson (2008)'s out-of-sample R^2 statistics and McCracken (2007)'s out-of-sample F-statistics, following studies in the predictability literature (see Chen et al. (2019)). Basically, we start estimation with an initialization period and recursively construct the monthly out-of-sample forecasts for the following periods, until we reach the end of the sample periods. The results show that all of aggregate sentiment measures deliver statistically significant R^2_{OOS} in the evaluation period from January 2017 to November 2019. By contrast, all of the individual proxies generate smaller R^2_{OOS} at a less significant level compared with aggregate sentiment measures. Especially, PE as a market-based measure has a negative value, indicating that it fails to beat the historical sample average in predicting the stock market. Moreover, the strong predictability of aggregate sentiment measures also leads to significant investment profits for mean-variance investors in asset allocation. The annualized certainty equivalent return gains of S^{naive} and S^{pca} are 2.38% and 2.42%, respectively, when the investor with a risk aversion degree of 5 allocates investments between the market and risk-free rate. Moreover, both investment portfolios based on S^{naive} and S^{pca} have large annualized Sharpe ratios, 0.47 and 0.48, respectively. Our results are robust to a transaction cost of 0.50% and other degrees of risk aversion.

Our empirical findings contribute to the literature in two ways. For the first time, we show that aggregate investor sentiment combined different types of data have a better performance in forecasting the market returns compared with other existing sentiment in the Chinese stock market, rather than Han and Li (2017)'s and Chen et al. (2014)'s sentiment measures which use market data, Kling and Gao (2008)'s and Li et al. (2019)'s sentiment measures which focus on survey data and text data, respectively. From different angles, we can measure investor sentiment more comprehensively. Second, For emerging markets (e.g. China) with pervasive irrational speculation and binding arbitrage constraints, investor sentiment tends to positively forecast market returns in the short run, while the effect fades away in six months. The positive sign may be due to, one of the most pronounced behavioral patterns - chasing the trend (Shleifer and Summers, 1990).

This chapter proceeds as follows. Section 2.2 reviews relevant literature. Section 2.3 describes the data and explains the methods. Section 2.4 provides empirical results of return predictability and portfolio exercise. Finally, Section 2.5 concludes.

2.2 Literature review

2.2.1 Investor sentiment in behavioral finance theory

The proposition that investor sentiment plays a significant role in explaining the variation of stock returns has been a longstanding topic of discussion in the literature theoretically and empirically (Stickel, 1985; Baker and Wurgler, 2000; Zhou, 2018). Early theoretical models incorporate the impact of noise traders into the framework of equilibrium asset pricing (e.g., Black, 1986). Stock market participants can be empirically classified into noise traders and rational traders. De Long et al. (1990) argue that limits of arbitrage are responsible for noise traders and give rise to the deviation of stock returns. By affecting noise traders' beliefs, the sentiment of investors exerts greater effect on asset mispricing. Furthermore, Brown and Cliff (2004) research that the sentiment of investors, stemming from investors' subjective visions, exerts an influence on stock valuation and engenders biased expectations, such as a proclivity towards speculation and unreasonable optimistic or pessimistic investment view. The above information reveals that irrational investors' different perspectives about the asset value tend to distort efficient pricing. By using a suitable model, investor sentiment can also have explanatory power for cross-sectional stock returns (Baker and Wurgler, 2006) and market anomalies (Stambaugh et al., 2012). The stronger investor sentiment may bring the greater deviations from fundamental values of asset.

2.2.2 Investor sentiment measures

The methods to measure investor sentiment mainly include single sentiment proxy description and composite measure construction, which rely on market transaction data, investor survey data, text data and search data (Zhou, 2018). Baker and Wurgler (2007) introduce two approaches to describing investor sentiment: bottom-up and top-down. The former is based on biases in market participants' psychology to explain how investors make irrational movements on fundamentals, which is associated with survey data. Investor surveys are generally in the form of questionnaires that institutions or individual investors return about their future market expectations, which are subjective measures of sentiment. The latter top-down approach traces sentiment measure to market transaction data. Investor sentiment measures are obtained objectively based on public transaction data from the capital market. Zhou (2018) documents that the text- and meida-based data, where opinions are extracted from texts, publications, and various Internet activities, can also describe investor sentiment.

<u>Market-based sentiment measures</u>

Closed-end fund discount (CEFD): The closed-end fund discount is the average difference between the market-based net asset value of the funds and the fund's market price. De Long et al. (1990) and Lee et al. (1991) attribute the CEFD to the fact that discounts of closed-end funds have high correlation with small stocks performance, which is subject to the impact of individual investor sentiment. In addition, Neal and Wheatley (1998) find that fund discounts as investor sentiment measure can predict the size premium, i.e., the difference between returns to small and large firms. Huang (2015) also suggests that close-end fund discount is a proxy of individual sentiment proxy since individual investors act as noise traders and destabilize the market by trading close-end funds.

IPO related data (IPOR): Substantial studies indicate that IPO event is related to investors sentiment. In particular, both the volumes of the IPO and IPO first-day returns can be recognized as measures of investor sentiment. Initial public offerings sometimes generate remarkable earnings in the first trading day, reflecting the enthusiasm of the investors (Baker and Wurgler, 2007). For instance, Netscape experienced a 108 percent return on the day of its IPO in August 1995. Ljungqvist et al. (2006) elucidate that irrational sentiment investors create the initial price run-up and produce abnormal positive first-day return. Interestingly, average first-day returns are significantly correlated with IPO volume. It is commonly asserted that the fundamental demand for initial public offerings is highly responsive to fluctuations in investor sentiment. For example, Lee et al. (1991) demonstrate that there is a positive correlation between investor sentiment and a high frequency of IPOs. Besides, Brown and Cliff (2005) find the volume of the IPOs can negatively predict long-term returns of small stocks.

Market turnover (MT): Market turnover, or more generally liquidity, has developed a reputation as investor sentiment measure. Market turnover is a simple proxy of liquidity that can serve as investor sentiment (Baker and Wurgler, 2006). Karpoff (1987) proposes that the market turnover increases in the bullish market; while it will decrease during the bearish periods. Furthermore, Baker and Stein (2004) find that liquidity provides informative evidence that the irrational investors facing short-sale constraints tend to trade when they show optimism and invest in rising stocks, instead of betting on falling stocks when they feel pessimistic. Trading volume also indicates underlying differences of opinion, which in turn, are correlated with the valuation levels with short selling limitations (Scheinkman and Xiong, 2003). The proportion of small trading volume and the proportion of large trading volume can represent sentiment of individual investors and institutional investors, respectively, based on different transaction amounts (Bradley et al., 2009). The rationale is that individual investors have less money to invest, and their investment in the stock market is scattered; whereas institutional investors have a large total capital pool, the funds of investment in the stock market are relatively concentrated and the institutional ownership of some stocks is high.

Price-earning ratios (PE): Numerous papers document that investor sentiment can be captured by mutual fund flow (Ben-Rephael et al., 2012; Frazzini and Lamont, 2008; Indro, 2004). Frazzini and Lamont (2008) provide evidence by using fund flows to measure the sentiment of individual stocks. They find that huge cash inflow into the stocks leading to poor subsequent performance. Han and Li (2017) suggest that market PE ratios can be a substitute proxy for mutual fund flow to estimate the rise in capital inflows to the market. As long as there is a increase in market inflows, the valuation ratio will be likely to rise.

New investor accounts (NIA): New investor accounts in the stock market is indicative of the demand for trading among investors, which can serve as a direct reflection of their willingness to participate in the stock market. Chen et al. (2014) argue that retail investors incline to trade when the number of new accounts increases. Moreover, the number of net added accounts can serve as a distinctive measure for investor sentiment in Chinese stock markets (Chu et al., 2016), and a bi-directional nonlinear casual relation exists between investor sentiment and stock returns at different timescales.

Survey-based sentiment measures

Investor confidence index (ICI): Yale-CCER Chinese investor confidence index (ICI) is based on questionnaire conducted by Yale university and the China Center for Economic Research (CCER), which aims to ask investors from China about their attitudes towards China's future investment prospects. Since June 2005, the China Center for Economic Research (CCER) has designed a survey per month, for studying possible directions covering "up", "down", or "flat" of the stock market. The data are collected from individual and institutional investors in China. CCER compiles the results per month, followed by marking them bearish, bullish, or neutral. The investor confidence index is computed as the spread between the percentage of optimistic investors and pessimistic investors. Fisher and Statman (2000) point out that investor confidence is a powerful predictor of stock market returns. In the US market, investor confidence is measured by Investor Intelligence index (II) and American Association of Individual Investors index (AAII). Brown and Cliff (2004) argue that market returns are positively related to contemporaneous sentiment of American investors both in levels and changes, and returns have strong predictive power for future investor sentiment while sentiment cannot predict subsequent returns.

Consumer confidence index (CCI): As an indicator reflecting general expectations on the overall economic prospects, the consumer confidence index (CCI) also has stock return predictability. Lemmon and Portniaguina (2006) point out a positive relation between ICI and CCI. Qiu and Welch (2004) suggest that CCI as investor sentiment measure has better performance to explain the small-firm return spread than closed-end fund discount. Furthermore, Fisher and Statman (2003) document that consumer confidence is a proxy of individual investor sentiment, which can negatively forecast future stock returns in the US stock market.

Bullish-Bearish Market index (BBM): In the Chinese stock market, the Bullish-Bearish Market index (BBM) is based on the degree of investor optimism on the buy-sell suggestions. It is collected by the magazine Stock Market Dynamic Analysis, which investigates the Chinese individual investors' opinion on the future perspective of the Chinese stock market. The investor sentiment index is constructed in a similar way as the ICI by calculating the difference between the percentage of bullish and bearish investors. Cheng and Liu (2005) take BBM as the Chinese investor sentiment and decompose it into short-term and medium-term elements, and the results reveal that the medium-term sentiment has a significant stronger effect on stock market returns than short-term sentiment.

<u>Text-based sentiment measures</u>

Comments of stocks (COM): Many investors devote a large amount of time and effort to post and read the comments on Internet stock message boards. Through observing more than 1.5 million samples, Antweiler and Frank (2004) find that the stock information from the Internet can forecast the market volatility. Individual investors are prone to collect the opinions from other investors who share the similar signal with them. Positive comments are considered as positive expectations from posters, while the negative comments are opposite. The aggregate sentiment is measured by the spread between the number of positive comments and negative comments. In addition, Guo et al. (2017) collect investors' comment data from Xueqiu - a widely-used professional social network website in the Chinese securities market and obtain an investor sentiment index through semantic analysis. The results reveal that sentiment data can be used to price stocks when investors pay high attention to the stock markets.

Search-based sentiment measures

Baidu Index (BI): A vast number of studies have explored the predictive power of search data on market returns (e.g., Da et al., 2011; Bollen et al., 2011; Bank et al., 2011; Bordino et al., 2012). Gao et al. (2020) construct global investor sentiment by using Google Trends and show that the sentiment measure is a contrarian predictor of global market returns. Besides, Shen et al. (2017) and Fang et al. (2020) show that the search volume of finance-related key words from Baidu Index improves stock return and volatility forecasting in Chinese stock markets. However, the chosen keywords in above two papers include a small part of informtion related to economics and finance, which are insufficient to measure the overall performance of market in China.

In general, the above sentiment proxies obtained by market, survey, text and search data can reflect the investor sentiment intuitively. However, market data represent people's trading decision, which can not reveal the thoughts in investors' mind. As survey-based measures, the concern on divergence of investor perceptions and investors' behaviors cannot be ignored, which indicates the respondents may not act in the same way they indicate in the surveys (Han and Li, 2017). Besides, under textual analysis approaches, since text and search data collected from media and Internet and are not readily available from standard databases, it is difficult to eliminate the noises while processing those massive datasets (Li et al., 2019). Therefore, we need to combine those measures and describe investor sentiment collectively.

2.2.3 Investor sentiment and stock returns

Baker et al. (2012) construct a global investor sentiment from six developed countries (Canada, France, Germany, Japan, the United Kingdom, and the United States), and measure the respective local sentiment. They find that all of sentiment indices have a negative impact on market returns within individual country, and it is noteworthy that international capital flows play a role in influencing global sentiment contagions. Meanwhile, Schmeling (2009) takes the consumer confidence as a measure of retail investor sentiment across 18 developed countries, and shows that it negatively predicts market returns. The results in these studies show that investor sentiment is prevalent in international stock markets.

Some empirical evidence shows that the U.S. investor sentiment can be the bellwether of international stock markets. Verma and Soydemir (2006) suggest that stock market returns of the U.K., Mexico, and Brazil are more likely to be affected by the U.S. investor sentiment. Concetto et al. (2019) document that the U.S. sentiment has a significant spillover effect on the European stock markets, which constitutes a priced risk factor and should be accounted for accordingly in international asset pricing model. In short, the investor sentiment captures broad waves of the global stock markets and provides a significant predictive power of the return-generating process.

There is growing evidence indicating the time-series effect of sentiment on the Chinese stock market from different horizons (e.g. long, medium and short terms) in the literature. As investor sentiment is often portrayed as prime evidence of irrational traders, Han and Li (2017) document that investor sentiment in the Chinese stock market is a significant momentum predictor on a monthly basis. Based on daily survey data on Chinese institutional investors, Kling and Gao (2008) also state that there is a positive short-run relationship between previous stock returns and current institutional investor sentiment. Moreover, Chen et al. (2014) divide the Chinese stock market into three regimes, i.e. a high-return regime, a low-return regime, and a neutral regime. The out-of-sample results reveal that investor sentiment has substantial forecasting performance. In a nutshell, investor sentiment appears to be one driving factor behind price movements in the Chinese stock market.

The effect of investor sentiment on the market can be manifested in various aspects. In recent years, some studies measure the market predictability of investor sentiment from different perspectives. Jiang et al. (2019) aggregate the useful information related to sentiment in corporate financial disclosures and explore the negative predictive power on market returns. Edmans et al. (2022) develop the novel music sentiment, which is derived from data reflecting whether the music melodies investors usually listen to are negative or positive. They find that this music sentiment measure can predict market returns positively in the current week, while it reverses to a negative prediction in the following week. In addition, Mai et al. (2022) suggest that sentiment measures based on investors' trading behaviors exhibit superior predictive power regarding market returns as compared to the sentiment measures predicated on investors' perspectives.

The above literature describes the reasonable mechanisms by which different kinds of proxies can measure investor sentiment. In addition, the lack of collective investor sentiment from different types of measures motivates our study, as the widely accepted individual sentiment measures may not accurately gauge the true sentiment in the Chinese market.

2.3 Data and methodology

2.3.1 Market returns and investor sentiment measures

This chapter covers the sample period with 14 years from 2005 to 2019. Following the convention, the market return of CSI 300 index from CSMAR database is obtained to describe the overall performance of the Chinese stock market, and we use the monthly one-year bank deposit interest rate in China as the risk-free rate. The excess market return is the spread between the market return and the risk-free rate.

We use ten sentiment proxies collected from different types of (market-, survey-

, text- and search-based) data sources to measure the investor sentiment in the Chinese stock market. There are five market-based measures: value-weighted price-earnings ratio of the market (PE), close-end fund discount (CEFD), initial public offerings first-day returns (IPOR), market turnover (MT), number of new opened investor accounts in Shanghai Stock Exchange (NIA). All of them are collected from China Stock Market & Accounting Research (CSMAR) database. As survey-based measure, Investor confidence index (ICI), consumer confidence index (CCI) and bullish-bearish market index (BBM) is designed to investigate domestic investors' potential expectations on the future Chinese stock market, which are obtained from the CEIC Incorporated Company (CEIC) database.

Based on the investor comments in Eastmoney - the largest online investor forum in China, we collected the number of positive, negative and neutral comments on individual stocks from Chinese Research Data Services (CNRDS) database. In addition, we follow Antweiler and Frank (2004)'s method to construct text-based market sentiment measure by extracting information from the investor commments (COM) with Equation 2.1 below:

$$COM_t = \frac{COM_t^{pos} - COM_t^{neg}}{COM_t^{pos} + COM_t^{neg} + COM_t^{neu}} \tag{2.1}$$

where COM_t^{pos}, COM_t^{neg} and COM_t^{neu} represent that the number of positive, negative and neutral comments on all of stocks in CSI300 posted in Eastmoney at the month t, respectively. Furthermore, COM_t is bounded by -1 and +1.

For collecting search data in Baidu Index, we choose the set of finance-related search terms by using 1877 terms from the Chinese sentiment dictionary in finance (Yao et al., 2021). We use Chinese instead of English dictionary for two reasons. First, as commonly used English dictionary in the text analytics literature, Harvard IV-4 Dictionary only contains 149 words in finance labeled with the "positive" or "negative" tag (Gao et al., 2020). Because a single English word can be reflective of multiple Chinese words in different translation contexts. For instance, "profit" can be translated into " 利润", " 盈利", " 利益" in Chinese. Second, it is more appropriate to use Chinese to collect our search data because the target users of Baidu search engine are Chinese investors. Next, we input these 1877 words into Baidu Index and download the monthly search volume of terms. We eventually obtain 657 time series of positive terms and 684 time series of negative terms.[2]

To identify the historical relation between the search volume index and market returns, we regress each of time series of search volume index on the contemporaneous market returns from July 2008 to November 2019. Our monthly data provide 109 (and 279) search terms with significant positive (and negative) t-statistics. We keep the top 100 positive and top 100 negative search terms as the chosen terms to construct the search-based sentiment measure from Baidu Index (BI):

$$BI_t = \sum_{i=1}^{100} R_+^i\left(ST_{i,t}\right) - \sum_{i=1}^{100} R_-^i\left(ST_{i,t}\right) \tag{2.2}$$

where $\sum_{i=1}^{100} R_\pm^i\left(ST_{i,t}\right)$ is the simple average of the top 100 positive (negative) search terms at the month t.[3] Given the disagreement from investors' expectations, BI aims to measure the net effect of market sentiment.

The sample period for market- and survey-based sentiment measures extends from June 2005 to November 2019 covering a total of 174 months, including the global financial crisis in 2008 and the Chinese stock market disaster in 2015. Since the online investor forum of Eastmoney is opened in 2008, and Baidu Index starts to provide the search records from 2007. The sample period for text- and search-based measures spans 138 months from July 2008 to November 2019.

2.3.2 Aggregate sentiment index construction

To construct aggregate sentiment measures in the Chinese stock market, we employ several statistical procedures. Investor sentiment proxies contain both rational and irrational components, and rational factors are normally associated with shifts in macro fundamentals since investor mood can be affected by signals about the economic development (Verma and Soydemir, 2006). In order to remove the exposure to macroeconomic variables, we first follow the orthogonalization procedure

[2] There are 533 terms not included in the Baidu Index, possibly because their historical search volume is not enough to be recorded.

[3] In Table 2.A1, we list the top 10 positive and negative search terms in Baidu Index, respectively.

as suggested in (Baker and Wurgler, 2007) by regressing each individual measure on a group of macroeconomic variables in Equation 2.3,

$$S_{it} = \gamma_0 + \gamma_j \sum_{j=1}^{4} Fund_{jt} + \varepsilon_t \tag{2.3}$$

where S_{it} represents individual indicator of investor sentiment i at time t. $Fund_{jt}$ is the set of fundamentals representing rational expectations, j indicates the macroeconomic climate index (MCI), growth of money supply (MS), short-term interest rates (IR) and foreign exchange rates (EX) documented in Han and Li (2017). The residuals of the orthogonalization procedure (ε_t) are then the measures for the irrational parts of investor sentiment. We take the residuals as the following individual sentiment proxies. Besides, instead of using all of ten individual sentiment proxies, four proxies (price-earnings ratio (PE), investor confidence index (ICI), investor comments (COM) and Baidu Index (BI)) are applied to construct composite sentiment measures.[4] Although other six proxies used in the previous literature somewhat describe investor sentiment, they do not contain useful information in predicting Chinese stock market.

Second, we adopt several econometric approaches to form the aggregating investor sentiment measures. One straightforward approach is to use the simple average of the sentiment proxies, which implies using equal weights (Huang and Lee, 2010).

$$S^{naive} = w_1 S_1 + w_2 S_2 + w_3 S_3 + \cdots + w_n S_n \tag{2.4}$$

where $S_1, S_2, S_3, \cdots, S_n$ are the sentiment proxies and $w_1 = w_2 = w_3 = \cdots = w_n = 1/n$ indicates the equal weights. Then we followed Baker and Wurgler (2006) to use principal component approach (PCA), which extracts the rst principal component from the individual sentiment measures as the composite investor sentiment index.

$$S^{pca} = w_1^{pca} S_1 + w_2^{pca} S_2 + w_3^{pca} S_3 + \cdots + w_n^{pca} S_n \tag{2.5}$$

where $w_1^{pca}, w_2^{pca}, w_3^{pca}, \cdots, w_n^{pca}$ are the optimal choice of weights depends on the

[4]In Panel A of Table 2.2, COM, BI, PE_{sub} and ICI_{sub} individually predict market returns significantly from July 2008 to November 2019. Besides, they are collected based on market, survey, text and search data, respectively.

PCA. In principle, PCA is an objective method removed from the correlation between indicators of the impact. The first principal component maximally captures the common information of the individual measures, which describe the fluctuation of investor sentiment over time.

Although PCA is capable of capturing the variation of the proxies, it may not necessarily be the most relevent information for accurately predicting returns. Hence, Huang (2015) advocates the use of the partial least square (PLS) approach, which employs stock returns to regulate the dimension reduction process in order to extract a composite sentiment measure that is pertinent for forecasting, and discards any idiosyncratic irrelevant components. The implementation of this method involves two steps of ordinary least squares (OLS) regressions. In the first step, a time-series regression is conducted for each individual sentiment proxy at month t on the subsequent market excess return, R_{t+1}.

$$S_{jt} = \pi_0 + \pi_j R_{t+1} + \mu_{jt} \tag{2.6}$$

where S_{jt} is the j-th individual sentiment proxy. The coefficient of π_j in the first-step time-series regression (2.6) captures the sensitivity of the sentiment proxy S_{jt} to the future stock return R_{t+1}. Because R_{t+1} is driven by S_{jt}, authentic investor sentiment is associated with the predictable component of stock returns and exhibits no correlation with the unpredictable errors. As a result, the coefficient π_j delineates the degree of dependence of each sentiment proxy on true investor sentiment. The second-step regression involves a cross-sectional analysis for each period t.

$$S_{jt} = c_t + S_t^{PLS} \hat{\pi}_j + \epsilon_{jt} \tag{2.7}$$

where $\hat{\pi}_j$ is the loading estimated in regression (2.6) and S_t^{PLS} the regression slope, is the PLS sentiment measure at time t. In the regression (2.7), the loading from the first-stage regression is utilized as the independent variable, while S_t^{PLS} represents the regression slope that needs to be estimated.

In addition to the PCA and PLS approaches, we follow Huang et al. (2019) to use a new method, Scaled-PCA (SPCA), which aims to employ the target information for guiding the process of dimension reduction. SPCA is implemented in two steps. First, individual scaled sentiment indicators are constructed, where the scaled coefficient is the slope from the predictive regression of the market excess returns R_{t+1} on the j-th sentiment proxy S_{it}.

$$R_{t+1} = \alpha_i + \beta_i S_{it} + \epsilon_{t+1} \tag{2.8}$$

In the second step, SPCA performs principal component approach on the scaled sentiment proxies ($\beta_i S_{it}$). Then, the first principal component is the SPCA-based composite investor sentiment. In essence, the rescaled series indicates the predictive ability of the j-th sentiment proxy on the future returns. A proxy that exhibits a robust forecasting ability is assigned a higher weight, while a proxy with a weaker forecasting ability is assigned a lower weight. In principle, the logic behind these methods is to aggregate the common variation of the various individual measures and obtain more informative and accurate sentiment measures.

2.3.3 Descriptive statistics

Table 2.1 provides the descriptive statistics for the sentiment measures. Individual sentiment measures are all standardized before the orthogonalization procedure, which facilitates the comparison of their economic significance in the empirical analyses below. In Panel A, we find that PCA and SPCA methods produce essentially similar aggregate investor sentiment measure (S^{pca} and S^{spca}), and standard deviations of S^{pca} and S^{spca} are twice as large as that of S^{naive}, which indicates that sentiment measures constructed by PCA and SPCA appear to be more volatile than equal-weighted aggregate sentiment. Panel B presents that there are significant correlations between contemporaneous market excess return and four individual investor sentiment measures which are used to construct aggregate sentiment. It is obvious to note that individual sentiment proxies do not have significant correlation with each other, which lends further support for the four types of sentiment measure containing different dimensions of information to predict the stock market.

Figure 2.1 shows the fluctuation of S^{naive} and S^{pca} together with the market excess returns in the sample periods. It is obvious to note that both of sentiment measures move simultaneously with the market excess return for most of the time, indicating a high correlation between the investor sentiment and excess return. For example, the largest price crash (the post 2015 period) is in line with the wave of negative sentiment that prevailed from June 2015 to January 2016. The spike in February 2019 is possibly a response to the information that a rise in US tariffs on Chinese goods will be delayed, indicating the ease of China-US trade friction.

2.4 Empirical results

2.4.1 Short-term return predictability

Based on the available data, the baseline predictive regressions are as follows:

$$R_{t+1} = \alpha + \beta S_t + \varepsilon_{t+1} \tag{2.9}$$

where R_{t+1} is the market excess return in month $t+1$, S_t represents one of sentiment proxy measures in month t. We test the in-sample predictive ability of S_t by estimating Regression 2.9. For example, S^{naive} is the composite sentiment measure constructed by equal-weighted method. We evaluate the slope coefficient to test the null hypothesis that investor sentiment has no predictive power, i.e., $\beta = 0$. If the slope coefficient β is statistically significant and different from zero under the alternative hypothesis, then the sentiment variable S_t contains valuable information for predicting future returns.

The results of Regression 2.9 are presented in Table 2.2. Panel A shows the forecasting power for each individual sentiment proxy. In contrast to the common belief that sentiment serves as a contrarian predictor, we observe that nine of ten individual proxies can positively forecast future market excess returns, while only PE, ICI, COM and BI differ meaningfully from zero at the 5% level. Market-wide PE ratio has the strongest predictive power with the β estimates of 0.024. In addition, the in-sample R^2s of PE and ICI equal 7% and 4.5% in the sample period from June 2005 to November 2019, which are economically large. For the subsample period from July 2008 to November 2019, we find the significance of β estimates of PE_{sub} and NIA_{sub} decreases, which is consistent with Cheema et al. (2020)'s fingdings. They argure that the positive predictive power of market-based investor sentiment in the Chinese stock market is limited to the bubble period (2006-2008). While the predictability of ICI remains in the subsample period with R^2 of 4.4%. Our results in Panel A imply limited predictability of individual sentiment proxies when they are used individually. The noises in measuring the market sentiment are likely to impair their ability to predict the market. It is reasonable to choose better candidates as investor sentiment to remove noises from individual proxies by extracting the common component.

We then select four sentiment proxies (PE, ICI, COM and BI) to construct our aggregate sentiment measure since they have stronger predictive power based on the results in Panel A of Table 2.2.[5] Besides, they are collected from various types of data sources (market, survey, text and search data). Therefore, we take the equal-weighted, PCA, SPCA, and PLS approaches to collect the common information from the individual sentiment proxies. Panel B of Table 2.2 reports the forecasting results for the aggregate investor sentiment measures. We observe that all of them have positive predictability for future market excess returns. They have R^2s ranging from 5.9% to 7.2%, which are larger than those of individual sentiment proxies. Among the four measures, we note that S^{naive} has the largest significant β (0.034) estimate at the 1% level, which suggests that a one-standard deviation increase in S^{naive} leads to a 2.2% increase in the next month's expected market return. In addition, S^{pca} and S^{spca} show the same effect on future market returns. In Panel C, we show that the predictability of aggregate investor sentiment remains after excluding the bubble periods (2006-2008 and 2014-2015), and decreases of significance can be attributed to the relatively short sample periods.

In Table 2.3, we conduct following multivariate regressions to test whether the predictive power of investor sentiment measures still remain after controlling

[5]NIA is not included because its predictive power does not exist in the subsample period from July 2008 to November 2019.

macroeconomic variables.

$$R_{t+1} = \alpha + \beta S_t + \varphi_i Econ_t + \varepsilon_{t+1} \tag{2.10}$$

where $Econ_t$ represents one of the nine economic variables in Goyal and Welch (2008). Table 2.3 reports the estimation results for four individual sentiment proxies and four aggregate sentiment measures. Our findings indicate that after considering economic variables, the regression slopes of all sentiment measures remain statistically significant. This suggests that the influence of investor sentiment on the overall stock market cannot be attributed to economic fundamentals. Besides, the β estimates are much larger than the results from Table 2.2. All of the R^2s generated by aggregate sentiment measures are larger than R^2s generated by individual sentiment proxies in Table 2.3. Our results demonstrate that by using individual sentiment proxies collectively, the equal-weighted aggregate sentiment measure performs better than other aggregate sentiment measures constructed by PCA, SPCA and PLS. In addition, S^{pca} and S^{spca} are exactly the identical time series which show the same performance in Table 2.2 and 2.3.[6] For control variables, industrial growth (IND), long-term bill return (LBR) and stock return variance (SRV) exhibit negative predictive power for the market at the 10% significance levels. Only dividend-price ratio (DP) shows the positive predictability.

The capacity of short-term predictive regressions is restricted to indicating a statistical association, without the ability to deduce causality. The presence of feedback between market returns and sentiment measures adds complexity to the causal relations (Chu et al., 2016). Therefore, the Vector Autoregressive (VAR) method are conducted to examine the causal relation between investor sentiment and market returns. The stability condition of the VAR model is tested first, followed by the examination of Granger-causality based on the VAR model. This approach offers a potential mechanism for estimating the dependence between market returns and sentiment measures. The results are presented in Table 2.4. We find all of aggregate sentiment measures can reject the null hypothesis at the 1% significant level in line (2), (4) and (6), respectively, which means that there is a one-directional linear

[6] In the following empirical parts, we only report the results of S^{pca}.

causality from investor sentiment to stock returns. In addition, we observe that market returns also have Granger causality for investor sentiment at 10% significant level, which is consistent with the findings of Kling and Gao (2008). The finding implies that the performance of the stock market also has an impact on investor sentiment. Because Chinese individual investors tend to adopt a simple passive trading strategy, which involves purchasing stocks with good performance and selling those with poor performance in the past.

We next compare the aggregate investor sentiment measure with other existing sentiment predictors in the Chinese stock market in terms of forecasting power for market returns. We use three investor sentiment measures, including Chinese Investor Composite Sentiment Index (S^{CISCI}) constructed by Yi and Mao (2009), Investor Sentiment Index (S^{ISI}) constructed by Ma and Zhang (2015) and market-based sentiment measure (S^{HL}) constructed by Han and Li (2017). Then we investigate the additional predictability of our aggregate sentiment measures by conducting a predictive regression analysis that controls for existing sentiment measures:

$$R_{t+1} = \alpha + \beta S_t + \phi S_t^{other} + \varphi_i Econ_t + \varepsilon_{t+1} \tag{2.11}$$

where S_t is one of the aggregate sentiment measures S^{naive}, S^{pca} and S^{pls}. Panels A, B and C of Table 2.5 report the estimation results for Regression 2.11 based on S^{naive}, S^{pca} and S^{pls}, respectively. We find that the β estimates of all of three aggregate sentiment measures remain statistically significant after considering for existing sentiment variables, and S^{naive} still possesses the strongest predicting power. Additionally, we find that the slope estimates of S^{CISCI}, S^{ISI} and S^{HL} are statistically insignificant at the 10% level, indicating that their explanatory power is subsumed by our aggregate sentiment predictors. Thus, we conclude that our investor sentiment measures contain sizable and unique information in forecasting the stock market.

2.4.2 Long-term return predictability

Given the strong one month ahead predictive power of aggregate sentiment measures, we next investigate their performances for longer prediction horizons. To explore whether S^{naive}, S^{pca} and S^{pls} have varying degrees of forecasting power, we use the following predictive regression for long-horizon market returns,

$$R_{t \to t+h} = \alpha + \beta S_t + \varphi_i Econ_t + \varepsilon_{t \to t+h} \tag{2.12}$$

where $R_{t \to t+h}$ is the average stock market excess return over the prediction horizon, $h = 1$, 2, 3, 6, 9, 12 and 24 months, and S_t represents one of the individual or aggregate sentiment measures. Panel A of Table 2.6 reports the forecasting results for PE, ICI, COM and BI, respectively. We find that PE and COM have significant predictability for the longer horizons up to 6 and 12 months, respectively. Besides, ICI and BI contain short-term forecasting power, and especially ICI can only predict market returns one month ahead. It may be attributed that the part of expectation on long-term trend of market movements measured by ICI is largely ignored by Chinese individual investors. Consistent with Han and Li (2017)'s findings, PE, as the sentiment index based on market data, experiences a shift from a momentum predictor in the short term to a contrarian predictor in the long term at 24-month lag. However, there is no clear evidence indicating that the negative predictive power of sentiment indexes based on survey, text and search data carries over to the long horizon.

In Panel B, S^{naive} has positive forecasting power from one month up to three months. In particular, the β estimates at two-month horizon and three-month horizon are 50% smaller than that in the one-month horizon. In addition, the R^2 also decreases from 22.7% to 19.5%. We observe qualitatively similar results for S^{pca} and S^{pls}. Many studies document that the predictability of sentiment is more pronounced in the short term (Zhou, 2018; Baker and Stein, 2004; Ben-Rephael et al., 2012), while it is worth noting that aggregate sentiment measures can not negatively predict market returns in the long run, implying that there is no signal for the market revision after sentiment retreats. Compared with PE and COM, the weaker performance for aggregate sentiment after three months is possibly because the sentiment indexes measuring investors' belief (ICI and BI) have little forecasting power for market returns in the long term .

2.4.3 Forecasting asymmetry of aggregate investor sentiment

In this subsection, we run the predictive regressions separately for different market states. Shen et al. (2017) find that the predictive power of Baker and Wurgler (2006)'s sentiment measure is significantly different during high- and low-sentiment periods, and we follow Stambaugh et al. (2012) and define the high (low) sentiment period when the sentiment in the previous month is above (below) its median value in the sample period. To explore whether the aggregate investor sentiment measures have symmetric predictability in different sentiment states, we estimate the following regressions,

$$R_{t+1} = \alpha + \beta^{high} S_t I_t^{high} + \beta^{low} S_t I_t^{low} + \varphi_i Econ_t + \varepsilon_{t+1} \tag{2.13}$$

where S_t represents one of the aggregate sentiment measures, S^{naive}, S^{pca} and S^{pls}, $I_t^{high}(I_t^{low})$ is an indicator that assumes a value of one during high (low) sentiment periods in month t and zero other wise.

As shown in Table 2.7, equal-weighted sentiment measures S^{naive} can positively predict subsequent stock returns over both high and low sentiment periods, indicating strong predictive abilities of aggregate investor sentiment in different sentiment states. In particular, we find asymmetric predictive power of investor sentiment in the Chinese stock market. All of regression slopes β^{high} have clearly larger values and t-statistics than β^{low}. For example, the β^{high} is 0.038 and significant at 1% level for S^{naive}, while the β^{low} is 0.035 and significant at 10% level. This finding suggests that aggregate investor sentiment tends to exert greater positive effect on future stock returns when investors are enthusiastic. Intuitively, when sentiment level is high, individual investors tend to trade irrationally and drive the prices deviate from fundamentals, which results in a short-term positive price pressure and raises stock prices subsequently.

In summary, the increased likelihood of misperception regarding future market movements indicates that in the short term, investor sentiment exhibits momentum predictability for the following returns. Specifically, a high level of sentiment tends to be associated with higher stock returns in the following periods.

2.4.4 Out-of-sample performance

In this subsection, we aim to tackle the prominent challenge raised by Goyal and Welch (2008). The primary focus is to examine whether the robust predictability of monthly returns observed within the sample analysis can be extended to the out-of-sample period. They argue that an over-fitted predictive model exhibits superior forecasting capabilitie by using in-sample data. However, this ability to predict future returns might not be consistently maintained out of sample. Thus, Goyal and Welch (2008) suggest that the most appropriate method for evaluating actual return predictability in real-time is through out-of-sample testing.

To conduct the out-of-sample analysis, this study allocates the period from July 2008 to December 2016 as the in-sample period for parameterizing our model, then the following three-year period is utilized as the out-of-sample period for the purpose of assessing the forecasting performance. In the estimation process of the in-sample model, a recursive estimation approach is adopted. For forecasting the next period $t + 1$ in the out-of-sample period, we employ a single-factor predictive model:

$$\hat{R}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t S_t \tag{2.14}$$

where $\hat{R}_{t+1}$ and $\hat{\alpha}_t$ represent the OLS estimates obtained from Regression 2.9 based on data from period 1 to period t. The estimation process follows a recursive approach, where Regression 2.9 is estimated recursively and out-of-sample forecasts are constructed for the subsequent periods based on Regression 2.14 repeatedly until the end of the sample period.

After conducting a comparison between the out-of-sample predictions produced by the predictive model based on Regression 2.14 and the historical average used as the benchmark, it is expected that the benchmark model will exhibit a higher mean squared forecast error (MSFE) compared to the developed predictive model.

This hypothesis suggests that our predictive model, which incorporates investor sentiment, surpasses the benchmark in terms of performance. To appropriately assess the performance of the out-of-sample predictions, this study calculates the out-of-sample R^2 statistics introduced by Campbell and Thompson (2008), as well as the out-of-sample F-statistics proposed by McCracken (2007). The out-of-sample R^2 statistic quantifies the proportional decrease in MSFE achieved by the predictive regression forecast compared with the historical average benchmark. This measure is calculated using the following equation:

$$R^2_{OOS} = 1 - \frac{\Sigma_{t=n}^{T-1}(R_{t+1} - \hat{R}_{t+1})^2}{\Sigma_{t=n}^{T-1}(R_{t+1} - \bar{R}_{t+1})^2} \tag{2.15}$$

where the range of the R^2_{OOS} statistic is $(-\infty, 1]$. The expression R_{t+1} refers to the realized excess market return in period $t+1$, while $\bar{R}_{t+1}$ represents the historical average, and $\hat{R}_{t+1}$ denotes the forecasted stock return. The presence of a positive R^2_{OOS} value signifies the forecast $\hat{R}_{t+1}$ has better performance than the benchmark $\bar{R}_{t+1}$ when considering MSFE. To assess whether two predictions possess similar levels of forecasting accuracy, the out-of-sample F-statistics is adopted. In this context, we examine the null hypothesis that the MSFE of the predictive regression model is higher than that of the historical average.

Table 2.8 presents the performance of the out-of-sample predictions based on individual and aggregate sentiment measures using Regression 2.14. Panel A presents the out-of-sample results for the four proxies of individual sentiment. Among them, ICI, COM and BI produce positive R^2_{OOS} statistic with values of 2.57%, 2.81% and 2.66%, respectively, but they are only significant at 10% level. According to the OOS-F statistics. Our result indicates that the PE does not outperform the historical sample average in predicting the market returns in the out-of-sample period. In contrast, in the case of S^{naive}, S^{pca} and S^{pls} in Panel B, the OLS forecast models generate positive R^2_{OOS} statistics of 5.50%, 5.44% and 5.67%, respectively, implying that all of models are successfully to beat the historical sample average in predicting the stock market. Thus, consistent with our in-sample findings, relying on a single proxy results in an underestimation of the out-of-sample predictablity of investor sentiment for the future market returns. Aggregate sentiment measures outperform all of individual sentiment variables out of sample.

2.4.5 Asset allocation analysis

In this subsection, we provide further understanding by employing the traditional approach of asset allocation method for a mean-variance utility investor (DeMiguel et al., 2009). To be specific, a mean-variance utility investor actively makes adjustments for their portfolios between the risky asset and the risk-free asset. These adjustments are determined by considering the excess return expected for the next period, as indicated by Regression 2.14. At the end of period t, the investor distributes a portion w_t of their portfolio to the market portfolio, while the remaining (1 - w_t) is allocated to the risk-free asset. The allocation of market portfolios, represented as w_t, is determined by two key factors. First, it considers the market price of risk, which is computed by dividing the predicted excess return of the market portfolio $\hat{R}_{t+1}$ by its corresponding variance $\hat{\sigma}^2_{t+1}$. The expected variance is evaluated using a five-year rolling period of monthly excess returns. Second, it exhibits an inverse relationship with the risk aversion coefficient, γ. The weights of equities are determined by

$$w_t = \frac{1}{\gamma}\frac{\hat{R}_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{2.16}$$

To address practical issues, we set two boundaries on the allocation of weight to market portfolios: w_t must have a value greater than zero, and its maximum value is set to 1.5. These limits correspond to short-selling and leverage constraints, repectively. The realized return of the portfolio R^P_{t+1} is then computed as:

$$R^P_{t+1} = w_t R_{t+1} + R^f_{t+1} \tag{2.17}$$

where R^f_{t+1} refers to the risk-free returns. In order to investigate the performance of the portfolio, we calculate the certainty equivalent return (CER) of the portfolio is

$$CER_P = \hat{\mu}_P - 0.5\gamma\hat{\sigma}^2_P \tag{2.18}$$

where $\hat{\mu}_P$ and $\hat{\sigma}^2_P$ represent the average and variance of the excess returns of the portfolio, respectively, while γ represents the coefficient of risk aversion. For the aim of assessing the economic significance of the enhanced out-of-sample predictive power resulting from investor sentiment, we proceed to calculate the disparity in Sharpe ratios and the CER gain between an investor who utilizes the benchmark portfolio strategy solely based on historical averages and another investor who employs the portfolio strategy on the basis of the predictive Regression 2.14. To obtain the annual portfolio excess return, the disparity is multiplied by 12. Additionally, a transaction cost of 50 basis points is considered to check the robustness of asset allocation outcomes. This approach allows us to evaluate the direct economic significance of return predictability.

Table 2.9 presents the findings of asset allocation for S^{naive}, S^{pca} and S^{pls} in the evaluation period of January 2017 to November 2019. We find that the return forecasting power of all aggregate sentiment measures generates large investment profit across both degrees of risk aversion in Panels A and B. For example, in Panel A, in which the risk aversion coefficient is 5, the CER gains of S^{naive} and S^{pca} equal 2.38% and 2.42%, respectively. The large magnitude of the CER gains implies that an investor displaying a risk aversion level of 5, will consent to pay an annual charge as high as 238 basis points for predictive regression forecasts of S^{naive} and 242 basis points for those of S^{pca}. These findings remain consistent after considering transaction cost of 0.5%. Both S^{naive} and S^{pca} demonstrate significant net gains with returns of 1.75% and 1.73% after deducting transaction costs, respectively, which are still sizable. Besides, the investment portfolio based on S^{naive} and S^{pca} generates large Sharpe ratios. As Panel A shows, when $\gamma = 5$, the annualized Sharpe ratios are 0.47 and 0.48 for S^{naive} and S^{pca}, respectively. The asset allocation results are robust to the risk aversion of 3 in Panel B. Thus, our results suggest that aggregate investor sentiment has the potential to generate significant investment profits.

2.4.6 Economic explanation

Inspired by Chen et al. (2019), the positive predictive power of our investor sentiment measures may stem from the net buying performance of individual investors. High sentiment results in small order imbalance, which pushes up the price in the short term. Price pressure tends to persist for an extended period and stock returns may not reverse at the subsequent month. We use change in small order flow on a monthly basis, denoted as ΔSOF reflect the trading behavior of individual investors (orders valued below 40,000 RMB are considered small). In Table 2.10, we find that individual investors are more inclined to continue buying after high sentiment drives up stock prices, thereby causing consistent increasing in stock prices, and this pattern will last for up to 6 months. Besides, small order reversals emerge at the 12-month horizon.

To get insight into sentiment predictability, it is necessary to investigate the driving force of it. Since existing pricing models suggest that stock prices are determined by both future expected cash flow and discount rate, we further analyze whether investor sentiment can forecast aggregate stock market returns by anticipating either cash flow or discount rate (Baker and Wurgler, 2006). We choose the aggregate dividend price ratio as the discount rate proxy, since the volatility in aggregate dividend price ratio is primarily driven by discount rate (Cochrane, 2008), and the aggregate dividend growth is adopted as the cash flow proxy.

Table 2.11 reports the results. Our investor sentiment measures display different effect between cash flow and discount rate. The slope of S^{pls} for D/P_{t+1} is virtually equal to zero and statistically insignificant. However, the coefficient of S^{pls} for DG_{t+1} is 2.436 at 1% significant level. The significant positive effect of investor sentiment for dividend growth rate and no impact for dividend price ratio indicate that sentiment presents significantly predictive power for market returns by cash flow channel at the monthly frequency. In addition, the long-term negative predictive power of investor sentiment for dividend growth is consistent with Han and Li (2017), implying that sentiment is a contrarain predictor for stock returns over longer horizons in the Chinese stock market.

2.5 Conclusion

This chapter investigates the collective predictive power of investor sentiment measures for the Chinese stock market by employing different types of data (market, survey, text and search data). This is in contrast to existing studies, which mainly use one type of sentiment measure to construct composite investor sentiment. We employ four different methods, equal-weighted, PLS, PCA, and an enhanced PCA technique called SPCA, to combine various proxies of individual investor sentiment. Our findings demonstrate a strong and significantly positive predictive power of the aggregate investor sentiment on market returns in the short term. As the prediction horizons extend, the level of predictability weakens and completely diminishes in the 6 months. The predictive power of our sentiment measures is still present after excluding the bubble periods and controlling for macroeconomic variables in the Chinese stock market. In addition, aggregate investor sentiment demonstrates strong performance in out-of-sample prediction, leading to substantial economic benefits for mean-variance utility investors in asset allocation.

Table 2.1: Descriptive statistics of Chapter 2

In Panel A, we report the summary statistics for the monthly excess returns of the CSI 300 market index (R_{CSI}), ten individual sentiment proxies (all orthogonalized to macro effects): value-weighted price-earnings ratio of the market (PE), close-end fund discount (CEFD), initial public offerings first-day returns (IPOR), market turnover (MT), number of new opened investor accounts in Shanghai Stock Exchange (NIA), consumer confidence index (CCI), investor confidence index (ICI), Bullish-Bearish Market index (BBM), investor comments (COM) and Baidu Index (BI), and four aggregate investor sentiment measures: equal-weighted sentiment measure (S^{naive}), aggregate sentiment based on PCA method (S^{pca}), aggregate sentiment based on Scaled-PCA method (S^{spca}) and aggregate sentiment based on PLS method (S^{pls}) . The sample period is provided in the last column. Panel B reports cross-correlation coefficients between market return and three individual investor sentiment measures selected for constructing aggregate sentiment measure. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A	N	Mean	Median	Std. dev.	Max	Min	Sample period
R_{CSI}	174	0.010	0.009	0.087	0.277	-0.262	2005:06-2019:11
PE	174	0.063	0.087	1.004	3.340	-2.723	2005:06-2019:11
IPOR	174	0.026	-0.206	1.052	6.176	-1.319	2005:06-2019:11
CEFD	174	0.065	0.248	0.823	1.206	-2.734	2005:06-2019:11
MT	174	-0.005	-0.166	0.868	3.085	-1.494	2005:06-2019:11
NIA	174	0.049	-0.187	1.016	5.809	-1.277	2005:06-2019:11
CCI	174	-0.002	-0.268	0.875	2.409	-1.235	2005:06-2019:11
BBM	174	0.002	0.007	0.807	2.393	-4.799	2005:06-2019:11
ICI	174	0.014	0.013	0.961	2.179	-2.478	2005:06-2019:11
COM	138	0.001	-0.019	0.997	2.481	-2.270	2008:07-2019:11
BI	138	0.003	0.006	0.823	2.576	-2.320	2008:07-2019:11
S^{naive}	138	-0.012	0.048	0.657	1.811	-2.062	2008:07-2019:11
S^{pca}	138	0.000	0.118	1.209	3.302	-3.728	2008:07-2019:11
S^{spca}	138	0.000	0.118	1.209	3.302	-3.728	2008:07-2019:11
S^{pls}	138	-0.018	0.087	1.150	3.056	-3.753	2008:07-2019:11

Panel B	R_{CSI}	PE	ICI	COM	BI
R_{CSI}	1				
PE	0.66***	1			
ICI	0.16**	0.06	1		
COM	0.43***	0.26*	0.19*	1	
BI	0.24***	0.14	0.05	0.21*	1

Table 2.2: Single-factor predictive regression

This table reports the estimation results of the following predictive regression,

$$R_{t+1} = \alpha + \beta S_t + \varepsilon_{t+1},$$

where R_{t+1} denotes the CSI300 market index excess return ($\mathrm{R}_{\mathrm{CSI}}$) at time $t+1$, and S_t denotes one of the ten sentiment proxies and four aggregate investor sentiment measures in Panel A of Table 2.1. The sample period is provided in the last column. In following three panels, we present the estimates of regression slope coefficients, Newey and West (1987) t-statistics (with a lag of 4) , and R^2 statistics of regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

		$t-stat$	R^2	Sample period
Panel A: Individual sentiment proxies				
PE	0.024***	[2.74]	0.070	2005:06-2019:11
IPOR	-0.002	[-0.41]	0.001	2005:06-2019:11
CEFD	0.010	[1.27]	0.008	2005:06-2019:11
NIA	0.012*	[1.74]	0.018	2005:06-2019:11
MT	0.004	[0.68]	0.002	2005:06-2019:11
ICI	0.019***	[3.30]	0.045	2005:06-2019:11
BBM	0.011	[1.44]	0.020	2005:06-2019:11
CCI	0.005	[1.02]	0.003	2005:06-2019:11
COM	0.012**	[2.17]	0.025	2008:07-2019:11
BI	0.023***	[3.01]	0.052	2008:07-2019:11
$\mathrm{PE}_{\mathrm{sub}}$	0.016*	[1.77]	0.021	2008:07-2019:11
$\mathrm{ICI}_{\mathrm{sub}}$	0.017***	[3.11]	0.044	2008:07-2019:11
$\mathrm{NIA}_{\mathrm{sub}}$	0.006	[0.73]	0.009	2008:07-2019:11
Panel B: Aggregate sentiment proxies				
S^{naive}	0.034***	[3.23]	0.072	2008:07-2019:11
S^{pca}	0.024***	[3.04]	0.064	2008:07-2019:11
S^{spca}	0.024***	[3.04]	0.064	2008:07-2019:11
S^{pls}	0.022***	[2.98]	0.059	2008:07-2019:11
Panel C: Aggregate sentiment proxies (excluding the bubble period)				
S^{naive}	0.015*	[1.70]	0.022	2016:01-2019:11
S^{pca}	0.008*	[1.74]	0.021	2016:01-2019:11
S^{spca}	0.008*	[1.74]	0.021	2016:01-2019:11
S^{pls}	0.010*	[1.88]	0.027	2016:01-2019:11

Table 2.3: Predictive regressions with economic variables

This table reports the estimation results of the following predictive regression,

$$R_{t+1} = \alpha + \beta S_t + \varphi_i Econ_t + \varepsilon_{t+1},$$

where R_{t+1} denotes the market index excess return (R_{CSI}) and at time $t+1$, S_t denotes one of sentiment measure at time t. $Econ_t$ represents the 9 economic variables in Goyal and Welch (2008): Inflation (INF), Industrial growth (IND), Book-to-Market ratio (BM), Dividend-price ratio (DP), Dividend yield (DY), Long-term bill return (LBR), Term spread (TS), Consumption Growth (CG), Stock return variance (SRV). We present the estimates of regression slope coefficients, Newey and West (1987) t-statistics (with a lag of 4) , and R^2 statistics of regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period for all of sentiment measures extends from July 2008 to November 2019.

	PE	ICI	COM	BI	S^{naive}	S^{pca}	S^{spca}	S^{pls}
S_t	0.024**	0.019***	0.018*	0.019**	0.044***	0.027***	0.027***	0.025***
	[2.17]	[3.12]	[1.67]	[2.30]	[3.16]	[3.12]	[3.12]	[3.26]
INF	0.010	0.015*	0.006	0.003	0.009	0.007	0.007	0.008
	[1.13]	[1.77]	[0.84]	[0.40]	[1.07]	[1.04]	[1.04]	[1.12]
IND	-0.016***	-0.017***	-0.014**	-0.011*	-0.017***	-0.016***	-0.016***	-0.016***
	[-3.19]	[-3.57]	[-2.52]	[-1.73]	[-3.01]	[-2.99]	[-2.99]	[-2.85]
BM	0.003	0.007	-0.007	0.002	0.003	0.003	0.003	0.003
	[0.24]	[0.59]	[-0.14]	[0.07]	[0.08]	[0.08]	[0.08]	[0.09]
DP	0.131	0.034	0.261**	0.211**	0.329***	0.341***	0.341***	0.338***
	[1.60]	[0.45]	[2.48]	[2.29]	[3.78]	[3.75]	[3.75]	[3.96]
DY	-0.107	-0.020	-0.146	-0.074	-0.225**	-0.227**	-0.227**	-0.217**
	[-1.38]	[-0.30]	[-1.33]	[-1.13]	[-2.50]	[-2.50]	[-2.50]	[-2.53]
LBR	-0.015**	-0.019**	-0.017***	-0.014*	-0.019***	-0.020***	-0.020***	-0.017***
	[-2.13]	[-2.31]	[-2.82]	[-1.98]	[-3.56]	[-3.58]	[-3.58]	[-3.25]
TS	-0.002	-0.005	-0.007	-0.005	-0.006	-0.008	-0.008	-0.007
	[-0.32]	[-0.57]	[-0.59]	[-0.56]	[-0.75]	[-0.76]	[-0.76]	[-0.65]
CG	-0.011*	-0.011*	-0.009	-0.010	-0.007	-0.006	-0.006	-0.007
	[-1.70]	[-1.78]	[-1.27]	[-1.33]	[-1.07]	[-1.05]	[-1.05]	[-1.13]
SRV	-0.011	-0.012	-0.019***	-0.017**	-0.019***	-0.019***	-0.019***	-0.017***
	[-1.26]	[-1.63]	[-2.77]	[-2.17]	[-2.93]	[-2.91]	[-2.91]	[-2.73]
R^2	0.188	0.192	0.180	0.190	0.227	0.221	0.221	0.224

Table 2.4: Granger-causality test

This table reports pairwise Granger causality tests for aggregate sentiment measure (S^{naive}, S^{pca}, S^{pls}) and market excess returns (R_{CSI}). Since S^{pca} and S^{spca} are identical time series constructed by PCA and SPCA method, respectively, we only report results for S^{pca}. All lag lengths are chosen by the minimizing SIC. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from July 2008 to November 2019.

Null Hypothesis:	F-statistic	Prob.
(1) R_{CSI} does not Granger Cause S^{naive}	5.3	0.070*
(2) S^{naive} does not Granger Cause R_{CSI}	10.1	0.006***
(3) R_{CSI} does not Granger Cause S^{pca}	5.1	0.077*
(4) S^{pca} does not Granger Cause R_{CSI}	9.8	0.007***
(5) R_{CSI} does not Granger Cause S^{pls}	6.2	0.045**
(6) S^{pls} does not Granger Cause R_{CSI}	12.3	0.002***

Table 2.5: Comparison with other investor sentiment proxies

This table reports results from following predictive regression,

$$R_{t+1} = \alpha + \beta S_t + \phi S_t^{other} + \varphi_i Econ_t + \varepsilon_{t+1},$$

where R_{t+1}) denotes the market index excess return ($\mathrm{R_{CSI}}$) at time $t+1$, S_t is one of the composite sentiment measures S^{naive}, S^{pca} and S^{pls} constructed by the equal-weighted, principal component analysis and partial least square approaches, respectively. S^{other} represents other investor sentiment measures in the Chinese stock market, including Chinese Investor Composite Sentiment Index (S^{CICSI}) constructed by Yi and Mao (2009), Investor Sentiment Index (S^{ISI}) constructed by Wei et al. (2014) and market-based sentiment measure (S^{HL}) constructed by Han and Li (2017). We present the estimates of regression slope coefficients, Newey and West (1987) t-statistics (with a lag of 4) , and R^2 statistics of regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period extends from July 2008 to November 2019.

	S^{ISI}	S^{CICSI}	S^{HL}
Panel A: Results for S^{naive}			
S^{naive}	0.039***	0.039***	0.041***
	[2.94]	[2.90]	[3.61]
S^{other}	-0.011	-0.010	0.007
	[-1.03]	[-1.07]	[1.30]
Control	Yes	Yes	Yes
R^2	0.217	0.213	0.219
Panel B: Results for S^{pca}			
S^{pca}	0.025***	0.025***	0.029***
	[2.90]	[2.86]	[3.59]
S^{other}	-0.011	-0.010	0.008
	[-1.04]	[-1.08]	[1.34]
Control	Yes	Yes	Yes
R^2	0.208	0.202	0.209
Panel C: Results for S^{pls}			
S^{pls}	0.022***	0.021***	0.024***
	[3.02]	[2.97]	[3.59]
S^{other}	-0.011	-0.010	0.008
	[-1.05]	[-1.10]	[1.24]
Control	Yes	Yes	Yes
R^2	0.207	0.214	0.217

Table 2.6: Long-term predictability

Panel A reports the estimation results of following bivariate predictive regression,

$$R_{t\to t+h} = \alpha + \beta S_t + \varphi_i Econ_t + \varepsilon_{t\to t+h}$$

where $R_{t\to t+h}$ is the average stock market excess return over the prediction horizon, h = 1, 2, 3, 6, 9, 12 and 24 months, S_t denotes one of sentiment measures in Table 2.3 at month t, respectively. In each panel, we present the estimates of regression slope coefficients, Newey and West (1987) t-statistics (with a lag of 4), and R^2 statistics of regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period extends from July 2008 to November 2019.

	h = 1	h = 2	h = 3	h = 6	h = 9	h = 12	h=24
Panel A: Results for PE, ICI, COM and BI							
PE	0.024**	0.020**	0.019*	0.013*	0.006	0.000	-0.004*
	[2.17]	[2.01]	[1.83]	[1.71]	[0.84]	[0.03]	[-1.74]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.188	0.176	0.169	0.162	0.153	0.151	0.159
ICI	0.019***	0.001	0.001	0.001	0.001	0.001	0.001
	[3.12]	[0.30]	[0.39]	[0.22]	[0.42]	[0.69]	[0.45]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.192	0.152	0.151	0.151	0.151	0.151	0.151
COM	0.018*	0.012*	0.010*	0.008*	0.008*	0.007*	0.004
	[1.67]	[1.88]	[1.91]	[1.78]	[1.75]	[1.70]	[1.40]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.180	0.184	0.182	0.175	0.170	0.162	0.156
BI	0.019**	0.015*	0.008	0.005	0.004	0.002	0.002
	[2.30]	[1.92]	[1.50]	[1.38]	[1.25]	[1.02]	[0.78]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.190	0.186	0.163	0.158	0.155	0.152	0.151
Panel B: Results for S^{naive}, S^{pca} and S^{pls}							
S^{naive}	0.044***	0.022*	0.022*	0.006	0.003	0.002	0.001
	[3.16]	[1.83]	[1.72]	[1.03]	[0.61]	[0.48]	[0.39]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.227	0.206	0.195	0.165	0.159	0.153	0.152
S^{pca}	0.027***	0.014*	0.013*	0.005	0.003	0.003	0.001
	[3.12]	[1.86]	[1.76]	[1.06]	[0.62]	[0.49]	[0.43]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.221	0.185	0.179	0.160	0.155	0.152	0.151
S^{pls}	0.025***	0.011*	0.011*	0.004	0.001	0.001	-0.001
	[3.26]	[1.89]	[1.75]	[0.67]	[0.18]	[0.20]	[-0.50]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.224	0.179	0.170	0.156	0.155	0.151	0.153

Table 2.7: Forecasting results for different market states

This table reports results from following predictive regressions,

$$R_{t+1} = \alpha + \beta^{high} S_t I_t^{high} + \beta^{low} S_t I_t^{low} + \varphi_i Econ_t + \varepsilon_{t+1}$$

where R_{t+1} is the market excess return at time t+1, S_t represents one of the aggregate sentiment measures, S^{naive}, S^{pca} and S^{pls}, I_t^{high}(I_t^{low})is an indicator that takes a value of one when month t is in a high (low) sentiment period and zero other wise. We follow Stambaugh et al. (2012) and define the high (low) sentiment period when the sentiment at previous month is above (below) its median value of the sample period. In each panel, we present the estimates of regression slope coefficients, Newey and West (1987) t-statistics (with a lag of 3), and R^2 statistics of regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	High	Low
S^{naive}	0.038***	0.035*
	[3.04]	[1.67]
Control	Yes	Yes
R^2	0.238	0.195
S^{pca}	0.021***	0.019*
	[2.77]	[1.70]
Control	Yes	Yes
R^2	0.217	0.190
S^{pls}	0.022**	0.018*
	[2.53]	[1.91]
Control	Yes	Yes
R^2	0.216	0.186

Table 2.8: Out-of-sample forecasting results

This table reports the Campbell and Thompson (2008)'s out-of-sample R^2 statistics and McCracken (2007)'s out-of-sample F-statistics for predicting the average stock market returns at time $t + 1$ based on the sentiment measures in Table 2.3. All of the predictors and regression slopes are estimated recursively using the data available at the forecasting formation time t. The out-of-sample period is from July 2008 to November 2019. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	OOS-R^2	OOS-F	Initial window size	Evaluation period
Panel A: Results for individual sentiment proxies				
PE	-1.87%	-0.641	2008:07 –2016:12	2017:01 –2019:11
ICI	2.57%*	0.922	2008:07 –2016:12	2017:01 –2019:11
COM	2.81%*	1.014	2008:07 –2016:12	2017:01 –2019:11
BI	2.66%*	0.934	2008:07 –2016:12	2017:01 –2019:11
Panel B: Results for aggregate sentiment proxies				
S^{naive}	5.50%***	2.036	2008:07 –2016:12	2017:01 –2019:11
S^{pca}	5.44%***	2.013	2008:07 –2016:12	2017:01 –2019:11
S^{pls}	5.67%***	2.103	2008:07 –2016:12	2017:01 –2019:11

Table 2.9: Asset allocation performance

This table reports the portfolio performance measures for a mean-variance utility investor with a risk-aversion coefficient (γ) of 3 or 5, who allocates monthly between equities and risk-free bills using the out-of-sample forecasts of the stock market excess returns based on the aggregate investor sentiment S^{naive}, S^{pca} and S^{pls}. Panels A and B report the asset allocation results for risk aversions of 3 and 5, respectively. In each panel, we present the annualized CER gain and annualized Sharpe ratio. In addition, we consider a proportional transaction cost of 50 basis points per transaction and show the net-of-transactions-costs CER gain and Sharpe ratio. The out-of-sample evaluation period extends from January 2017 through November 2019.

	No Transaction Cost		50 pbs Transaction Cost	
	CER Gain (%)	Sharpe Ratio	CER Gain (%)	Sharpe Ratio
Panel A: Risk Aversion = 5				
S^{naive}	2.38%	0.47	1.75%	0.39
S^{pca}	2.42%	0.48	1.73%	0.39
S^{pls}	2.28%	0.43	1.60%	0.36
Panel B: Risk Aversion = 3				
S^{naive}	2.33%	0.57	1.55%	0.42
S^{pca}	2.44%	0.59	1.78%	0.43
S^{pls}	2.17%	0.54	1.45%	0.40

Table 2.10: Relation with small order imbalance

This table reports results from following predictive regressions,

$$\Delta SOF_{t+h} = \alpha + \beta_1 S_t + \varphi_i Control + \varepsilon_{t+h}$$

where ΔSOF_{t+h} is s the change in small order flow over the period h, where $h = 1$, 6, and 12 months. S_t represents one of the aggregate sentiment measures, S^{naive}, S^{pca} and S^{pls}. Control variables include market returns at time t, $t-1$, and $t-2$. In each panel, we present the estimates of regression slope coefficients, Newey and West (1987) t-statistics (with a lag of 3), and R^2 statistics of regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period extends from July 2008 to November 2019.

	h=1	h=6	h=12
Panel A: Results for S^{naive}			
S^{naive}	0.15***	0.08**	-0.01
	(3.01)	(2.29)	(-0.89)
Control	Yes	Yes	Yes
R^2	0.219	0.134	0.075
Panel B: Results for S^{pca}			
S^{pca}	0.13***	0.07*	-0.02
	(2.83)	(1.81)	(-1.01)
Control	Yes	Yes	Yes
R^2	0.205	0.128	0.074
Panel C: Results for S^{pls}			
S^{pls}	0.13***	0.07**	-0.02
	(2.95)	(2.01)	(-0.67)
Control	Yes	Yes	Yes
R^2	0.209	0.138	0.075

Table 2.11: Forecasting cash flow and discount rate with investor sentiment

This table reports the estimation results for the regressions,

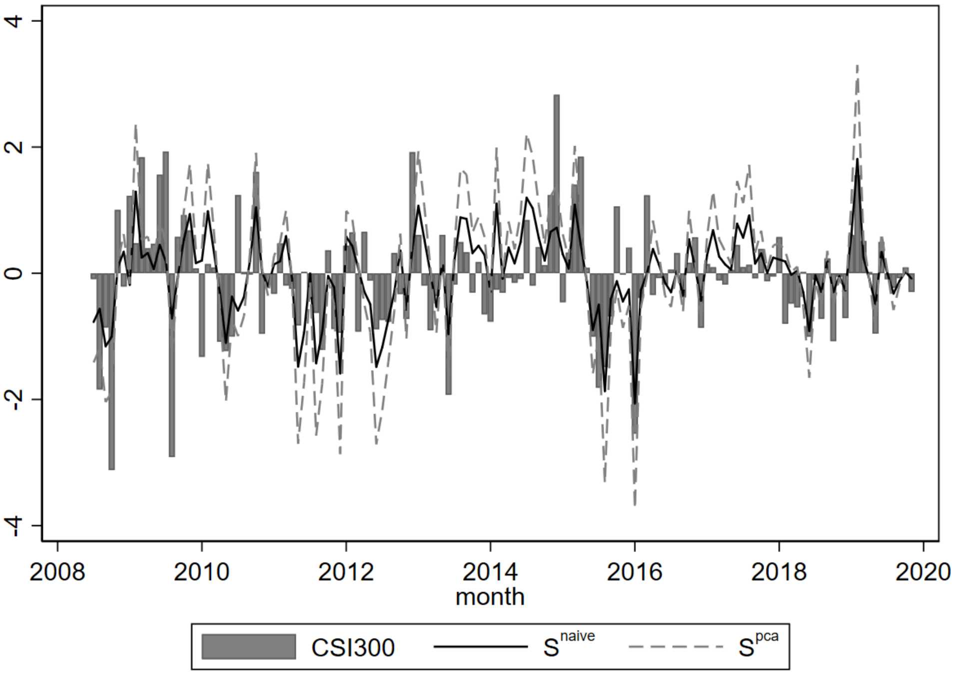
$$Y_{t+h} = \alpha + bS_t + cD/P_t + \varepsilon_{t+h}, Y = D/P, DG$$

where D/P_{t+h} is the log of a twelve-month moving sum of dividend price ratio on the whole stock market of month $t+h$, DG_{t+h} is the log of a twelve-month moving sum of aggregate dividend growth rate on the whole market of month $t+h$, $h=1$, 6, and 12 months. S_t represents one of the aggregate sentiment measures, S^{naive}, S^{pca} and S^{pls}. In each panel, we present the estimates of regression slope coefficients, Newey and West (1987) t-statistics (with a lag of 3), and R^2 statistics of regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period extends from July 2008 to November 2019.

Predictor	DG_{t+1}		D/P_{t+1}		DG_{t+6}		D/P_{t+6}		DG_{t+12}		D/P_{t+12}	
	b	R^2	b	R^2	b	R^2	b	R^2	b	R^2	b	R^2
S^{naive}	2.561**	0.126	0.343	0.251	1.211*	0.109	0.233	0.195	-1.211	0.109	0.233	0.173
S^{pca}	2.359**	0.141	0.391	0.268	1.342*	0.112	0.257	0.208	-1.339*	0.112	0.257	0.192
S^{pls}	2.436***	0.146	0.415	0.271	1.487*	0.126	0.244	0.217	-1.362*	0.126	0.244	0.184

Figure 2.1: Investor sentiment and market excess returns

The solid and dashed line depict the aggregate investor sentiment index obtained from the equal-weighted (S^{naive}) and PCA method (S^{pca}), respectively. The gray bar depicts the monthly market excess returns (R_{CSI}).



Appendix

Table 2.A1: Search terms in Baidu Index

We list the top 10 positive and negative terms respectively based on the t-statistics in the regressions in which each term is regressed on the contemporaneous market return.

Positive terms		Negative terms	
BEAUTY	美观	DAMN	该死
GOOD	不错	DECLINE	下降
BUSINESS OPPORTUNITY	商机	FLOOD	淹没
BEST	最好	EXCUSE	宽恕
RUSH	冲锋	CRASH	崩盘
MAKE MONEY	赚钱	SLUMP	暴跌
STRIVE	奋斗	ABNORMAL	变态
LIKE	喜欢	STOCK MARKET DISASTER	股灾
FLUTTER	飞舞	ILLEGAL	非法
DETAIL	详细	NEW LOW	新低

Chapter 3

Textual investor sentiment and cross-sectional stock returns: Evidence from China

3.1 Introduction

Classic asset pricing models can be applied on the highly efficient market. However, since the 1980s, numerous efforts have been made to perform asset pricing research under the assumption that the incorporation of investor sentiment, which potentially breaches the efficient market hypothesis, at least in the short term. Studies from this perspective, including the work of De Long et al. (1990), Black (1986), and Brown and Cliff (2004) suggest a significant role of investor sentiment in predicting stock returns. Prior works uniformly indicate that sentiment serves as a potent long-term contrarian predictor over time (Baker and Stein, 2004; Baker et al., 2012). Furthermore, the predictability of sentiment becomes more evident in cross-sectional analysis (Baker and Wurgler, 2006; Huang, 2015).

The literature related to cross-sectional asset pricing has offered a variety of different sentiment proxies, which are derived from various sources such as investor surveys (Schmeling, 2009; Ilut and Schneider, 2014), market trading information (Baker et al., 2012; Huang et al., 2015), and textual information such as newspapers (Tetlock, 2007; Garcia, 2013), as well as Google search logs (Da et al., 2015). Multiple investor sentiment measures possess strong predictability in explaining portfolio returns, especially in the case of stocks that present valuation difficulties and high arbitrage costs (Baker and Wurgler, 2006). However, the above sentiment proxies generally are obtained based on the data with description of the whole market. The researchers mainly examine the market sentiment effect on stock portfolios with different characteristics. In this chapter, we construct the text-based sentiment of individual stocks by using investor's online comments on each firm and investigate its effect on cross-sectional returns in the Chinese stock market.

Given the restricted availability of data, the market- and survey-based data are typically collected to examine the effect of investor sentiment on market returns within a monthly or quarterly timeframe. The textual data are complementary to show stock specific sentiment in the cross section. Textual measures obtained from social media can be regarded as "more primitive" in comparison to market-based sentiment indicators. This is because they do not depend on equilibrium market quantities such as returns or volume, which can be influenced by numerous market factors, leading to potential confounding effects. Moreover, textual measures tend to be available at a higher frequency, such as daily or even minute-by-minute levels than survey-based indicators. According to the study conducted by Sun et al. (2016), the intraday S&P 500 can be predicted on a half-hour basis by utilizing investor sentiment derived from textual analysis, with a lag of half an hour. In addition, text-based datasets typically contain more fruitful information related to investor sentiment. For example, Twitter - one of the famous social media platforms, has a user base exceeding 350 million individuals. Users actively post their thoughts and opinions on a variety of topics, including stock prices. McGurk et al. (2019) filter sentiment-related information from Twitter and document that textual sentiment measures produce a significantly positive impact on abnormal stock returns.

In this chapter, we employ a distinctive and extensive dataset comprising 68 million text observations extracted from a prominent Chinese online investor forum - Eastmoney. The dataset covers a period of 12 years, ranging from 2008 to 2020. In order to extract textual sentiment, supervised machine-learning methods are employed to classify and label each of text message into positive, negative or neutral textual tone (Goodfellow et al., 2016; Trevor et al., 2009). Zhou (2018) documents that sentiment measures derived from textual analysis demonstrate superior performance in predicting stock market compared to survey- and market-based measures by far, such as the sum of fears based on financial and economic attitudes disclosed by Internet searches (Da et al., 2015) and manager sentiment based on firms' financial disclosures (Jiang et al., 2019). While these measures aggregate all of sentiment-related information from the overall market rather than individual stocks.

Instead of constructing market sentiment, the approach adopted in this study involves utilizing the spread between the number of positive and negative comments to represent the stock-specific sentiment in each month. By employing these textual measures, we can evaluate various hypotheses in the cross section for Chinese stock market. In the previous study conducted by Antweiler and Frank (2004), the message-board dataset utilized contains approximately 1.6 million messages sourced from Yahoo! Finance and Raging Bull. These messages were collected during the year 2000, which coincided with the peak of the dot-com bubble. In comparison, the dataset used in our study encompasses a substantially larger number of observations and covers a much longer and more comprehensive period, which is essential for making robust time-series econometric inferences. Furthermore, the textual sentiment derived from our dataset provides a more direct reflection of the views expressed by a substantial number of individual investors, who play a significant role in behavioral asset-pricing models.

Compared with newspapers and corporate reports, massive comments on stocks belong to informal media, which mainly represent the subjective feelings of the individual investors with larger noise and uncertainty (Antweiler and Frank, 2004). We consider whether these comments comprise information that is financially relevant since retail investors' trading behaviors may be aligned with their own viewpoints. Does the aggregate sentiment from the investor comments have pricing implications for individual stocks? This is the natural research question as a significant percentage of online posts explicitly make assertions that specific stocks have good or bad performance in the future. In addition, according to Shiller (2015), the new and effective interactive communication media can contribute to the expansion of interpersonal contagion of ideas. This phenomenon can result in herding behavior, which amplifies the aggregate impact of noise trading, and subsequently results in more significant patterns of stock mispricing.

Our study focuses on the Chinese stock market, which is recognized as the biggest and most important emerging capital markets in the world. Based on the 2019 annual report of China Securities Depository and Clearing Corporation, retail investors account for over 90% of investor population in China. Although retail investors only represent around 20% of the market value, they are responsible for more than 80% of trade volume. The imbalance is primarily due to the state's ownership of many sizable firms, where governmental agencies retain most of the shareholdings. Meanwhile, it is likely that the representative posters on online investor forums are retail investors. Therefore, we anticipate that the textual information derived from these posts to be a good representation of the investor sentiment that is the main driver of trading in the Chinese stock market. Meanwhile, it is well-documented in financial studies that retail investors are significantly impacted by sentiment (Fang and Peress, 2009). They are more likely to hold portfolios less diversified and trade speculative stocks by adopting basic trading strategies like trend chasing (Kumar and Lee, 2006). In addition, the Chinese stock market imposes stringent constraints on short selling, which adds to the difficulty of arbitraging away the mispricing caused by sentiment (Mei et al., 2009). Those conditions make it perfect to investigate the impact of individual invesotor sentiment on stock returns in the Chinese market.

Our objective is to investigate the cross-sectional relation between investor sentiment based on investor comments and stock returns using all A-share stocks listed on the Shanghai and Shenzhen Stock Exchanges, covering the period from June 2008 to December 2020. Based on the beliefs or expectations conveyed in the posts, investor comments in Eastmoney are classified into three categories: positive, negative, and neutral. A comment with a positive sentiment implies an expectation of the referenced stock price to increase in the forthcoming period or indicates the poster's inclination to purchase the stock. A comment with a negative sentiment suggests an anticipation of the referenced stock price dropping in the forthcoming period or indicates the poster's inclination to sell the stock. A neutral sentiment denotes an expectation for the stock price to stay consistent in the near term without clear expectations, and the poster exhibits no trading inclination.

Following Antweiler and Frank's (2004) method, we construct sentiment measure (Sent) for each stock based on the difference between the number of positive comments and negative comments on a monthly basis. In the asset pricing tests, all of stocks are sorted into five portfolios from high to low value of Sent, we observe that equally-weighted (EW) portfolios that take a long position in stocks with high sentiment and a short position in stocks with low sentiment produce a significant monthly return of 8.37% in the formation month, and the positive returns based on this trading strategy will significantly last in the following ten months from 2.22% to 0.18%. After controlling for the factors in the Carhart four-factor model and the Fama-French five-factor model, the risk-adjusted returns persist significantly and positively for the formation month and subsequent ten months. In contrast to the prior findings of the contrarian predictability in the cross sectional studies (Baker and Wurgler, 2000; Baker et al., 2012), our research uncovers a term structure where sentiment from individual investors consistently exerts a positive effect on cross-sectional stock returns as well as Han and Li's (2017) findings for the overall market. It can be explained by a trend-following pattern as we mentioned in the chapter 1, individual investors are more likely to buy stocks which are praised by other investors. In addition, the value-weighted portfolios basically produce the same results. We also construct changes in sentiment measures, since Brown and Cliff (2004) document that the shifts of sentiment can possibly influence stock returns. However, our results show that long-short portfolios based on changes in sentiment do not offer significant returns in the subsequent months.

Chung et al. (2012) argue that the impact of sentiment is most likely to be evident in expansionary states when investor optimism increases. Cheema et al. (2020) document that in the Chinese stock market, a robust positive correlation between investor sentiment and near-term market returns only exists during bubble periods (2006-2008). We further examine this issue by selecting the two subperiods excluding the bubble periods, which are from January 2010 to December 2014 and January 2017 to December 2020. The same positive pattern is observed consistent with the baseline results when we use the subperiods, while the effect lasts 4 months and 8 months, respectively. Meanwhile, the magnitude and significance of the returns decrease compared with the results of the whole sample.

Since there is growing evidence in the literature suggesting that both of sentiment and attention are strong contrarian predictors (Baker and Stein, 2004; Barber and Odean, 2008; Da et al., 2011). Especially, high sentiment is normally linked with high attention. For example, abnormal trading volume used in Barber and Odean (2008) as a famous attention proxy has a high correlation with abnormal turnover used in Liu et al. (1990) as a sentiment measure. To extend the analysis and ensure that other sentiment or attention variables do not subsume the predictive power of our text-based sentiment measure for stock returns, we adopt double-sorting exercises and find that the positive effect of sentiment remains. Our textual sentiment measure shows a greater effect on future returns for stock with higher investor attention and sentiment. This finding is consistent with the theory of limited attention (Kahneman, 1973), which suggests that stock prices can be influenced by media information when investors actually pay attention to it. In addition, we perform the Fama-MacBeth regressions, which also take account of firm characteristics used in the literature, and examine the marginal effect of sentiment on cross-sectional stock returns.

Next, the economic implications of the sentiment measures' positive predictability in the cross section are investigated. To be specific, this study constructs a strategy that assumes long positions in high sentiment stocks and short positions in low sentiment stocks, given that short selling is permitted only for certain stocks in China since 2010. Notably, an investor can make a quarterly profit of 4.82% by implementing the strategy. We further consider the turnover rate and transaction cost for the strategy. The turnover rate of sentiment-based strategy is similar to the traditional momentum strategy documented in Han et al. (2016). More importantly, the break-even transaction costs per month are as high as 1.97%, which is considerably higher than those in the momentum and trend strategies in Han et al. (2016).

This chapter thus contributes to the existing literature by proposing a text-based sentiment measure in the cross-section to describe the expectations of individual investors towards stocks in the Chinese stock market, as well as providing compelling evidence on the significant positive return predictability of text-based sentiment. Our work has strong ties to the studies of Li et al. (2019) and Guo et al. (2017) as both papers extract information from investor opinions in the Internet. However, we aim to reveal the cross-sectional pricing implication via long-short trading strategies on a monthly basis, stock-specific sentiment is formed by investors' disagreement, whereas Li et al. (2019) and Guo et al. (2017) investigate textual sentiment from the overall market perspective.

This chapter proceeds as follows. Section 3.2 reviews relevant literature. Section 3.3 explains the methods and provides descriptive statistics. Section 3.4 analyzes and discusses empirical results. Finally, Section 3.5 concludes.

3.2 Literature review

The empirical finance literature has indicated a significantly negative relationship between investor sentiment and stock returns in the cross section (Baker and Wurgler, 2006). Discovering reliable proxies for investor sentiment has become the primary focus of the sentiment-related literature. Specifically, there are three potential sources of investor sentiment proxies: market trading data, investor surveys and textual data from traditional and social media (Zhou, 2018).

3.2.1 Comparison of market-, survey- and text-based sentiment measures

Baker and Wurgler (2006) and Huang et al. (2015) generally find that investor sentiment is related to cross sectional returns based on investor sentiment proxies derived from market- and survey-based data. Investor surveys are generally in the form of questionnaires that institutions or individual investors return about their future market expectations, which are the most straightforward, direct indicators of sentiment. Market-based sentiment measures are obtained objectively based on public transaction data from the capital market.

The application of surveys and market data as measures of investor sentiment has kept controversial. Da et al. (2015) point out that the surveys for investors and consumers are unreliable generally since there is little incentive for respondents answer the questions truthfully. In addition, the investor sentiment proxies based on market data normally describe overall market sentiment. If a portion of the market is efficient, investor sentiment tends to have a larger impact on the cross section of stock returns in the short term, while this phenomenon is not able to be observed with applying sentiment to the whole market. Compared to above sources, text-based sentiment analysis on the internet and social media provide targeted assessments of investor sentiment for individual stocks (Sun et al., 2016).

In comparison to the predictive performance based on the market information and survey analysis, Zhou (2018) points out that sentiment measures based on textual analysis forecast the stock returns better, which may show that information from the media-based sentiment measures may be neglected in the stock market. Besides, Wang et al. (2021) suggest that overall market-level investor sentiment tends to drive the systemic mispricing of assets, while stock-specific investor sentiment tends to be a factor in idiosyncratic mispricing (Ding et al., 2023). The construction of individual stock sentiment can reveal whether a specific stock is underpriced during its own high sentiment phases, as there could be instances where a certain stock is experiencing a high sentiment phase while the market is in a low sentiment phase (Yang and Zhou, 2016).

3.2.2 The effect of text-based sentiment measures on stock returns

With the rapid advancement of information technology and learning algorithms, it is becoming increasingly easy to get access to measure the sentiment via textual analysis and media sources. Tetlock (2007) creates a simple measure to test the media pessimism based on the amounts of negative media content which are collected from "Abreast of the Market" of the Wall Street Journal column, fingering out that the media delivering the more pessimistic market information, can negatively predict market movements. From a sample of S&P 500 companies from over 2005 to 2008, Joseph et al. (2011) find that online search intensity persuasively forecasts abnormal stock returns and trading volumes per week and that the sensitivity of returns to search intensity has positive correlation with the difficulty of arbitrage. Kim et al. (2019) document that the changes of analysts' recommendations significantly influence stock returns and investor sentiment. In terms of the predictability of the stock returns, Garcia (2013) uses New York Times financial news to extract the fraction of positive and negative words and reveals that news content can predict stock returns in recessions. Recently, Jiang et al. (2019) construct a manager sentiment index from conference calls based on the Loughran and McDonald's (2011) financial dictionary, and find that manager sentiment possesses predictive power for stock returns using out-of-sample forecast evaluation.

In the Chinese stock market, Li et al. (2019) developed textual sentiment measures by using an online message dataset and evaluated its impact on future market returns, volatility, and trading volume. Their research indicates that textual sentiment has a greater impact during periods of higher investor attention and increased volatility. While they mainly focus on the influence of text-based sentiment on overall stock market, few research sheds light on cross-sectional implications of textual sentiment in Chinese stock market.

Overall, the investor sentiment measures based on textual analysis are complementary to traditional market-based and survey-based measures, which are also associated with stock returns. However, applying textual approach also has its limitations. One notable limitation is that textual datasets are not readily available from conventional databases, and the cost of collecting these vast datasets is high. On the other hand, the filtered information based on textual analysis may be not correlated with investor sentiment. Besides, textual analysis is adopted in the most of mainstream economics literature based on the English language, it is much more difficult to use other languages to interpret investor sentiment.

3.3 Data description

We collect data on market capitalization, trading volume, returns and the number of news articles for all A-share stocks listed on Shanghai and Shenzhen stock exchanges from the China Stock Market and Accounting Research (CSMAR) database. In addition, the monthly Fama-French five-factor model (FF5F) and Carhart four-Factor model (Carhart) are also obtained from CSMAR. In the Chinese Research Data Services Platform (CNRDS), the number of investor comments in Eastmoney (the largest online investor forum in China) are pre-labeled with positive (Pos), negative (Neg) and neutral (Neu) sentiment on individual stocks at daily frequency from January 2008 to December 2020. Instead of using the conventional dictionary-based method based on the counts of positive and negative words specified by the customized financial dictionary, supervised-learning methods are employed for sentiment-related information extraction in CNRDS. [1] Besides, we also collected the times of read for all of comments in each stock at monthly frequency from CNRDS. The sample period is from June 2008 to December 2020. The main empirical analysis starts from June 2008 to ensure there are enough comments on stock to form reliable sentiment.

The textual sentiment is constructed as follows. Firstly, we delete the comments when the number of reading times is zero because if these comments do not contain useful information if no one pay attention on them, then the number of positive comments and the number of negative comments are winsorized at 99% level to reduce the effect of possibly spurious outliers with 3701 observations deletion. As documented in Antweiler and Frank (2004), excessive optimism and pessimism are more likely to be noise and do not help to predict stock returns. Secondly, we follow Antweiler and Frank's (2004) method to aggregate the comments classifications in order to obtain text-based sentiment for individual stocks in each month with Equation 3.1 below,

$$Sent_{i,t} = \frac{COM_{i,t}^{pos} - COM_{i,t}^{neg}}{COM_{i,t}^{pos} + COM_{i,t}^{neg} + COM_{i,t}^{neu}} \tag{3.1}$$

where $COM_{i,t}^{pos}$, $COM_{i,t}^{neg}$ and $COM_{i,t}^{neu}$ represent that the number of positive, negative and neutral comments on individual stocks i in all A-share stocks posted in Eastmoney at the month t, respectively. Due to the different size of individual stocks, we use the percentage ratios to measure the investor sentiment on individual stocks.

For trading data of stocks, we exclude the stocks with the ST (special treatment) and PT (particular transfer), since the prices of ST and PT stocks are likely to be influenced by mergers and acquisitions due to their shell values (Li et al., 2019),

[1] First, message contents are manually marked to obtain positive, negative and neutral messages, where 1 represents positive, -1 represents negative and 0 represents neutral, then the supervised learning algorithm can automatically be applied to learn the classification model based on the training data set and divided the messages of the whole dataset.

meanwhile ST and PT stocks contain less than 5% of stock market capitalization. Then, we also delete the trading data of each stock for the first month after Initial Public Offerings (IPO) because IPO stocks tend to produce extremely positive returns in the following days (Ljungqvist et al., 2006).

Panel A of Table 3.1 provides the descriptive statistics from June 2008 to December 2020. We can find that the maximum number of comments for three different categories (Pos, Neg and Neu) are much larger than mean value, indicating that a few of stocks attract most of investor attention. The arithmetic mean and standard deviation of the overall sentiment are 0.069 and 0.114, respectively, which indicates that Chinese investors are generally more optimistic and more likely affected by sentiment, consistent with the common perception of a speculative market. Since market turnover is widely used as a sentiment proxy to measure market sentiment, we take abnormal turnover (Aturn) as stock specific sentiment following by Liu et al. (2019), which is calculated as a stock's turnover in the previous month divided by its turnover in the previous year. We also collect three attention proxies in the previous literature. Nearness to 52-week high (52wh) and nearness to historical high (Hish) used by Li and Yu (2012) determined by dividing the stock price at the end of a month by the highest stock price in the previous 52 weeks and the highest historical stock price, respectively. News coverage (Nc) used by Fang and Peress (2009) is calculated as the cumulative number of news articles released regarding a stock during a month. In addition, we also take the number of comments' reading (Read) as an attention variable provided by CNRDS. Because more times investors read, the comments are more likely to cause the shifts of sentiment.

Panel B presents the correlation coefficients of the attention and sentiment variables. Our textual sentiment measure is positively correlated with return-related attention variables (52wh and Hish) while have negative correlations with proxies unrelated with stock returns (Read, Nc and Aturn), indicating that trading tendencies of those retail investors is to chase the trend and buy stocks with better performance in the past, which results in stock prices deviating further from their fundamental level. In addition, the negative correlation with Read also suggests that our textual sentiment contains different information compared with investor attention. Increased times of comments read mean that more people are interested in this message, while the proportion of agreement and disagreement is tested by the level of sentiment.

3.4 Empirical Results

3.4.1 Textual sentiment and stock returns

In this section, we study the effect of textual sentiment on cross-sectional stocks returns. First, in Panel A of Table 3.2, we sort individual stocks into five portfolios based on our textual sentiment in current month, which is portfolio formation month, then we obtain equal-weighted portfolio returns within each decile of the sentiment variable. The returns of the lowest and highest sentiment portfolios are -0.0352 and 0.0485 in month 0, and turn to -0.0047 and 0.0175 in month 1. We find that portfolios with higher textual sentiment produce significant higher returns in the formation month and this pattern persists in the subsequent ten months. The mean values of portfolio returns increase gradually with higher sentiment, indicating that the stocks received more positive comments from investors which are more likely to continually perform better than those with more negative comments. Besides, portfolios (1 and 2) with low textual sentiment have negative returns in the month 1 and 2, but turns significantly positive in month 3.

Panel B and Panel C of Table 3.2 report the equal-weighted and value-weighted monthly returns of long-short portfolios in the formation month and following ten months. A long-short strategy is constructed using the extreme quintiles, 1 and 5, with the long (short) leg being the high (low) -sentiment decile. Notably, the equal-weighted (value-weighted) portfolios that long high-sentiment stocks and short low-sentiment stocks generates a significantly positive return of 0.0837 (0.0893) in the current month and decrease to a return of 0.0222 (0.0202) in month 1. Although the magnitude of profit from long-short portfolios is not large, its significance remains at 1% level until month 10. In addition, we examine αs of the long and short positions based on Carhart four-factor model and Fama-French five-factor model, these translate to 2.04% and 2.08% of risk-adjusted returns in month 1 by applying the equal-weighting scheme. The αs are significantly positive in the future ten (nine) months for equal-weighted (value-weighted) portfolios. Compared with the profit from original high-minus-low αs, the positive impact of textual sentiment on future stock returns is weaker in both magnitudes and t-values.

Han and Li (2017) document two reasons which can explain this pattern. First, one of the most prominent behavioral propensities is the inclination to follow trends. As market sentiment gets higher and new investors pile into the market, trend-following patterns tend to persist for longer horizons as suggested by Burdekin and Redfern (2009). Second, based on the purchasing power in the future from trend-following individual investors as assumed in De Long et al. (1990)'s model, the rational speculator buys before others and makes a profit on the subsequent selling to those individual investors. The essence of this model is that informed rational speculators exploit the systemic biases of others who infer far into the future by buying ahead of trend-following investors, so they trigger anticipated sentiment demands over a longer period of time. As long as rational speculators focus on a long enough investment horizon, they can leverage sentiment factors to reap the profits.

Given the strong predictive power of text-based sentiment measure at the monthly horizon, we next examine the profitability for longer prediction horizons. The formation and holding periods are 1, 3, 6, 9, and 12 months. The differences between equal-weighted (value-weighted) average monthly returns of high-sentiment and low-sentiment portfolios are reported in Table 3.3. We follow Jegadeesh and Titman (1993) use the calendar-time overlapping portfolio approach to calculate the returns in holding periods. As shown in Panel A, the positive effect persists considerably beyond the 1-month horizon, while the coefficients become smaller and some are insignificant when the formation period is 12 months. In addition, the impact of sentiment on future stock returns weakens when the formation and holding periods increase. For example, when the formation and holding month is fixed at 1-month, the return of longing high-sentiment portfolio and short low-sentiment portfolio changes from 0.0222 (significant at 1% level) to 0.0031 (significant at 5% level) when the holding period changes to 12-month, and the value turns to 0.0164 (significant at 1% level) when the formation period changes to 12 months, indicating that the effect of sentiment is more pronounced in the short run. Furthermore, the impact of sentiment on equal-weighted stock returns is higher than value-weighted stock returns both in terms of magnitudes and t-values.

Cheema et al. (2020) document that investor sentiment does not have predictive power excluding the bubble periods in the Chinese stock market. We further consider the issue by using two subperiods from January 2010 to December 2014 and January 2017 to December 2020 without bubble periods during financial crisis and Chinese stock market disaster. The results are reported in Table 3.4. The positive effect of textual sentiment remains in two subperiods. The equal-weighted portfolio of longing high-sentiment stocks and shorting low-sentiment stocks produces significantly positive return of 0.0201 (t=4.73) and 0.0173 (t=6.43) in month 1 in Panel A and Panel B, respectively. While the positive predictability lasts next four months and eight months, relatively shorter than ten months compared with the whole sample period. Besides, The pattern is qualitatively the same when the corresponding abnormal returns estimated from Carhart four factor model and Fama-French five factor model. The results also are less significant in terms of magnitudes and t-values compared with the whole sample.

3.4.2 Double-sort exercise

As shown in the baseline results, our textual sentiment exerts the positive impact on stock returns in the cross section. The previous literature documents that the significant effect of other sentiment measures on future stock returns. For instance, Zhou (2018) reviews fifteen sentiment measures in the US stock market, and find 13 of 15 measures can significantly predict market returns. Hence, another interesting issue is whether the effect of our text-based sentiment is related to existing investor sentiment measures.

We apply double-sort exercise to control for the effect from abnormal turnover (Aturn), which used by Liu et al. (2019a) as a sentiment factor in the cross section to explain the turnover anomalies. In Table 3.5, stocks are grouped into tertiles (low, medium and high group) based on Aturn first, then within each group we divide the stocks into five groups by textual sentiment. In terms of the excess monthly returns between high-sentiment and low-sentiment portfolios, the results show that stocks with high (low) Aturn are likely to offer profits of 0.0247 (0.0215) in month 1. Although the equal-weighted spreads are less significant in low and medium Aturn group, the predictability can last six and eight months, respectively.

While since most of sentiment proxies are constructed in the time series to predict market returns, we also take several cross-sectional attention measures as control variables to examine whether they influence the positive effect of our textual sentiment. Da et al. (2011) suggest that generating sentiment requires the prerequisite of investor attention. Stronger sentiment is normally linked with higher investor attention, especially that originating from noise traders who are susceptible to behavioral biases.

More reading times of a comment mean that the comment receives more attention. We wonder whether the impact of sentiment is limited to stocks that receive a lot of attention. We first sort stocks based on the number of comments' reading (Read), then within each group stocks are divided into five groups by textual sentiment. The results are reported in Table 3.6. The significant profits in all of portfolios indicate that investor attention cannot explain the effect of textual sentiment. In addition, we can find that the difference of monthly returns between high-sentiment portfolio and low-sentiment portfolio and the corresponding αs in high groups of Read are greater than those in low groups in both magnitude and t-values. For example, the positive spreads in month 1 between high-sentiment and low-sentiment portfolio are 0.0255 (0.0180) in high (low) Read group. The predictive power disappears in the sixth (seventh) month in low (meidum) Read group, while it lasts over ten months in high Read group.

Based on evidence in Table 3.6, we also look at whether news media is a potential driving factor behind the predictability of textual sentiment measure. In Table 3.7, stocks are grouped into low, medium and high groups based on the median value of news coverage (Nc) first, within each group we divide stocks into five groups according to the textual sentiment. We observe the same pattern that monthly return differentials between high sentiment and low sentiment portfolios are significantly positive in the longer periods in high Nc group than those in low and medium Nc group. Furthermore, the positive returns in month 1 are the most substantial in the high Nc group at 0.0241. These could be rationalized that individual investors are more likely to be attracted by attention-grabbing stocks. Besides, the magnitude and significance of positive returns in low and meidum Nc group coefficients somewhat weaken but remain significant. In a nutshell, the positive impact of textual sentiment on future stock returns cannot be explained by existing attention measures in the literature.

Table 3.8 presents that portfolio returns from long-short strategy by controlling for volatility (Vol), because higher volatility is highly correlated with investor sentiment (Lee et al., 2002). We further examine the effect of textual sentiment are not driven by this stock characteristic. The positive effect of textual sentiment becomes stronger with the increase of volatility, indicating that Chinese investors are more likely to ignore the risk. For example, the portfolio returns by longing high-sentiment stocks and short low-sentiment stocks in high Vol group are 0.0049 higher than low Vol group in month 1. Taken together, the results are significant in low, medium and high Vol groups, which suggests that the predictive power of textual sentiment is not subsumed by stock volatility.

In the light of the momentum effect documented in the literature, some researchers may suggest that the positive effect of sentiment on stock returns in the cross section is driven by the momentum effect of high past return. For example, Han and Li (2017) document that higher stock returns are positively correlated with previous month's return. We further double sort the stocks by stock returns in the previous month (Pr) and sentiment to control for the momentum effect. Table 3.9 shows that the return diffrences and corresponding risk-adjusted ones between high-sentiment and low-sentiment portfolios remain significantly positive in all Pr groups. For example, the spread between high sentiment and low sentiment is 0.0228 in the high group in month 1. The positive differentials persist in month 2 and 3 at 0.0181 and 0.0155. In a nutshell, with respect to the positive impact on future stocks returns, stock-specific sentiment possesses incremental information that cannot be explained by short-term momentum effect caused by previous returns.

3.4.3 Fame-Macbeth regression

In this section, we further examine the marginal effect of textual sentiment on stock returns using Fama-MacBeth regressions (Fama and MacBeth, 1973) below:

$$\begin{aligned} Return_{i,t+s} = {} & \alpha + \beta_1 Sent_{i,t} + \beta_2 Read_{i,t} + \beta_3 Nc_{i,t} + \beta_4 52wh_{i,t} + \beta_5 His_{i,t} + \beta_6 Vol_{i,t} + \beta_7 Pr_{i,t} \\ & + \gamma_i Controls_{i,t} + +\varepsilon_{i,t+s} \end{aligned} \tag{3.2}$$

where $Return_{i,t+s}$ is the monthly stock return in month s (from 1 to 10), the independent variables of interest is textual sentiment in month t. We also include previous one-month volatility/return and several other sentiment/attention variables. The control variables are firm characteristics including market beta, market value, book-to-market ratio, earnings-price ratio, stock prices and institutional ownership, since firm-specific characteristics may influence the impact of sentiment on future stock returns (Baker and Wurgler, 2007). The results are reported in Table 3.10. From month 1 to month 10, the coefficients on textual sentiment are significantly positive which indicates the positive impact on future stock returns. For instance in Panel A, the slope coefficients of sentiment in month 1 and month 10 are 0.0325 and 0.008, respectively. We further include the prior month's return, volatility and variables measured sentiment and attention in Panel B. The coefficients on text-based sentiment are still significantly positive and a bit smaller in magnitude. To summarize, the textual sentiment has significantly positive effect on stock returns in subsequent ten months after controlling for other stock characteristics and existing sentiment and attention variables.

3.4.4 Economic value

The objective of this section is to investigate the potential profitability for investors who take long positions in stocks with high sentiment and short positions in stocks with low sentiment from two aspects. First, we control the short selling constraint that exists in the Chinese stock market. Prior to the implementation of policies on margin trading and short selling in March 2010, short selling was prohibited in China. Considering this constraint, we construct long-short portfolios exclusively from stocks that are available for short sale. The sample period for our analysis spans from March 2010 to December 2020.

Table 3.11 reports monthly returns and risk-adjusted ones for portfolios from month 1 to month 3. In month 1, we can find that low sentiment portfolios produce more negative returns than those in Table 3.2. Interestingly, despite this additional constraint, the net earnings for portfolios for the long-short strategy are still significantly positive at 0.0185 (t=3.17) in month 1 and 0.0159 (t=3.14) in month 2. This indicates that the strategy can produce a sizeable quarterly gain of 4.82% and significant risk-adjusted returns.

Active trading strategies often face higher turnover ratios and transaction costs compared to passive strategies. To address these challenges, we examine the profitability of the long-short portfolios in Table 3.12, taking into account the turnover ratio and break-even transaction costs by following previous studies (Barroso and Santa-Clara, 2015; Han et al., 2016). The turnover ratio for portfolios with long positions in high-sentiment stocks and short positions in low-sentiment stocks is 70.51% per month, which is close to the turnover rate observed in Barroso and Santa-Clara's (2015) price momentum strategy. In addition, we calculate two types of break-even transaction costs: the zero-return cost and the 5% insignificance cost. The results in Table 3.12 show that the strategy will become unprofitable if the monthly cost exceeds 1.97%, which is higher compared to the price momentum strategy (0.68%) and trend strategy (1.24%) reported in Han et al. (2016). Additionally, the monthly transaction costs required to make the return statistically insignificant at the 5% level are also higher than the common standard.

To summarize, the long-short strategy that involves taking a long position in high-sentiment stocks and a short position in low-sentiment stocks remains highly profitable after controlling short selling restrictions and transaction costs.

3.5 Conclusion

In this chapter, we use investor comments on stocks in a major online investor forum to construct textual sentiment in the Chinese stock market at a monthly frequency. We find that the sentiment measured by the difference between positive and negative comments can positively predict cross-sectional returns in the following ten months, the profitability remains for longer prediction horizons. The effect is still robust after excluding the bubble periods and controlling widely accepted risk factors and various stock characteristics, while the magnitude and duration of the impact are partially influenced by existing attention and sentiment variables. Besides, We further document the profitability of a trading strategy with long position in stocks with high sentiment and short position in stocks with low sentiment by controlling for restrictions on short selling and transaction costs.

Table 3.1: Descriptive statistics of Chapter 3

In Panel A, we report the summary statistics for the number of postive (Pos), negative (Neg) and neutral (Neu) comments, textual sentiment measure (Sent), the logarithmic value of comments read (Read), monthly return including dividends (Return), abnormal turnover (Aturn), Nearness to 52-week high (52wh), Nearness to the historical high (His), one-month volatility (Vol) and market value (Mv) on A-share stocks listed on Shanghai and Shenzhen stock exchanges. Panel B reports cross-correlation coefficients between textual sentiment and other sentiment and attention measures. *, ** and ***, indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from June 2008 to December 2020.

Panel A	N	Mean	Medium	Sd	Max	Min
Pos	367751	214	123	350	34356	0
Neg	367751	175	98	318	38013	0
Neu	367751	361	183	696	70181	0
Sent	367751	0.069	0.060	0.114	1.000	-1.000
Read	367751	0.756	0.743	0.314	1.189	0.001
Return	367751	0.013	-0.001	0.171	2.053	-0.864
ATurn	367751	0.578	0.353	0.702	3.067	0.000
52wh	367742	0.664	0.682	0.192	1.834	0.037
His	367751	0.375	0.330	0.220	3.489	0.001
Vol	367293	0.028	0.025	0.026	5.602	0.000
Mv	367751	0.637	0.582	0.049	0.891	0.000

Panel B	Sent	Read	Nc	Aturn	52wh	Hish
Sent	1					
Read	-0.0441^{***}	1				
Nc	-0.0832^{***}	0.1960^{***}	1			
Aturn	-0.0130^{***}	0.0275^{***}	0.1600^{***}	1		
52wh	0.1703^{***}	0.0005	0.0190^{***}	0.0035^{***}	1	
Hish	0.0978^{***}	0.0619^{***}	0.2813^{***}	0.0330^{***}	0.4012^{***}	1

Table 3.2: Textual sentiment and stock returns

In this table, Panel A summarizes portfolio returns sorted by textual sentiment from low-sentiment (1) to high-sentiment (5). Panel B and Panel C report the equal-weighted and valuer-weighted portfolio returns that taking long position in stocks with high-sentiment and short position in stocks with low-sentiment, respectively. The risk-adjusted returns based on the Carhart four-factor and Fama-French five-factor models are also reported. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from June 2008 to December 2020.

Panel A: Portfolio sorted by Sent	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
1 (low)	−0.0352***	−0.0047***	−0.0012***	0.0034***	0.0102***	0.0126***	0.0119***	0.0117***	0.0116***	0.0116***	0.0122***
2	−0.0121***	−0.0028***	−0.0005***	0.0056***	0.0091***	0.0128***	0.0126***	0.0118***	0.0123***	0.0121***	0.0116**
3	0.0205***	0.0059***	0.0082***	0.0102***	0.0132***	0.0138***	0.0135***	0.0139***	0.0126***	0.0123***	0.0117*
4	0.0351***	0.0131***	0.0132***	0.0141***	0.0146***	0.0162***	0.0154***	0.0148***	0.0141***	0.0137***	0.0120**
5 (high)	0.0485***	0.0175***	0.0156***	0.0175***	0.0175***	0.0179***	0.0163***	0.0168***	0.0162***	0.0156***	0.0140**

Panel B: Equal-weighted	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0837***	0.0222***	0.0168***	0.0141***	0.0073***	0.0054***	0.0044***	0.0049***	0.0045***	0.0039***	0.0018***
	(24.20)	(10.63)	(8.89)	(8.28)	(9.62)	(7.03)	(5.81)	(6.43)	(5.88)	(4.11)	(2.39)
Carhart α	0.0823***	0.0204***	0.0156***	0.0139***	0.0065***	0.0050***	0.0039***	0.0043***	0.0041***	0.0035***	0.0016***
	(22.71)	(3.99)	(4.17)	(4.49)	(4.85)	(3.50)	(2.81)	(3.45)	(3.47)	(2.84)	(1.78)
FF5F α	0.0797***	0.0208***	0.0157***	0.0133***	0.0056***	0.0050***	0.0034***	0.0039***	0.0042***	0.0031***	0.0019***
	(22.11)	(3.51)	(3.50)	(3.90)	(4.20)	(3.38)	(2.59)	(3.09)	(3.29)	(2.47)	(1.56)

Panel C: Value-weighted	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0893***	0.0202***	0.0164***	0.0140***	0.0059***	0.0040***	0.0039***	0.0047***	0.0043***	0.0036***	0.0014*
	(23.02)	(9.28)	(7.83)	(7.19)	(8.14)	(7.12)	(4.31)	(3.43)	(2.88)	(2.11)	(1.78)
Carhart α	0.0908***	0.0207***	0.0160***	0.0145***	0.0050***	0.0046**	0.0037**	0.0036**	0.0043**	0.0039*	0.0024
	(22.17)	(2.92)	(3.31)	(3.36)	(2.68)	(2.52)	(2.57)	(2.54)	(2.24)	(1.95)	(1.58)
FF5F α	0.0886***	0.0196***	0.0151***	0.0138**	0.0054**	0.0047**	0.0035**	0.0036**	0.0037*	0.0029	0.0021
	(21.20)	(2.68)	(2.59)	(2.54)	(2.16)	(2.31)	(2.28)	(2.16)	(1.87)	(1.62)	(1.65)

Table 3.3: Textual sentiment and stock returns over longer horizons

In this table, Panel A and Panel B report the equal-weighted and valuer-weighted portfolio returns that taking long position in stocks with high-sentiment and short position in stocks with low-sentiment over longer formation and holding horizons, respectively. The *t*-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from June 2008 to December 2020.

Panel A: Equal-weighted					
→ Formation periods	1 month	3 months	6 months	9 months	12 months
↓ Holding periods					
1 month	0.0222***	0.0209***	0.0195***	0.0179***	0.0164***
	(10.63)	(8.77)	(6.56)	(6.12)	(4.36)
3 months	0.0165***	0.0161***	0.0149***	0.0140***	0.0127***
	(5.82)	(4.33)	(4.01)	(4.31)	(3.21)
6 months	0.0052***	0.0047***	0.0041***	0.0042***	0.0023***
	(5.42)	(4.78)	(3.91)	(3.34)	(2.98)
9 months	0.0047***	0.0039***	0.0038***	0.0036***	0.0036**
	(4.37)	(4.37)	(4.37)	(4.21)	(2.24)
12 months	0.0031**	0.0037**	0.0035*	0.0023	0.0021
	(2.18)	(2.02)	(1.88)	(1.54)	(1.12)
Panel B: Value-weighted					
→ Formation periods	1 month	3 months	6 months	9 months	12 months
↓ Holding periods					
1 month	0.0202***	0.0199***	0.0189***	0.0173***	0.0158***
	(9.28)	(8.02)	(7.56)	(5.55)	(3.25)
3 months	0.0157***	0.0156***	0.0150***	0.0148***	0.0121***
	(5.23)	(4.12)	(3.87)	(3.23)	(2.87)
6 months	0.0043***	0.0047***	0.0043***	0.0042***	0.0019**
	(4.42)	(4.32)	(3.91)	(3.23)	(2.36)
9 months	0.0032***	0.0033***	0.0038***	0.0034**	0.0036**
	(4.33)	(3.96)	(3.10)	(2.78)	(2.24)
12 months	0.0029***	0.0028***	0.0023**	0.0023*	0.0021
	(2.76)	(2.65)	(2.23)	(1.82)	(1.25)

Table 3.4: The impact of textual sentiment on stock returns over subperiods

In this table, Panels A and B summarize portfolio returns of taking long position in stocks with high-sentiment and short position in stocks with low-sentiment over subperiods.The risk-adjusted returns based on the Carhart four-factor and Fama-French five-factor models are also reported. The *t*-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A: 2010.01- 2014.12	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0799***	0.0201***	0.0152***	0.0126***	0.0043***	0.0044**	0.0028*	0.0025	0.0021	0.0013	0.0012
	(23.23)	(4.73)	(3.44)	(3.29)	(2.76)	(2.06)	(1.81)	(1.53)	(1.52)	(1.12)	(0.99)
Carhart α	0.0772***	0.0188***	0.0143***	0.0115***	0.0038*	0.0036*	0.0018	0.0016	0.0008	0.006	0.0002
	(22.71)	(2.98)	(2.77)	(3.01)	(1.88)	(1.80)	(1.23)	(1.42)	(0.86)	(0.84)	(0.23)
FF5F α	0.0767***	0.0190***	0.0147***	0.0112***	0.0041*	0.0056	0.0024	0.0021	0.0012	0.0009	0.0005
	(23.54)	(2.80)	(2.60)	(2.69)	(1.86)	(1.60)	(1.39)	(1.09)	(0.69)	(0.98)	(0.58)

Panel B: 2017.01- 2020.12	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0756***	0.0173***	0.0132***	0.0092***	0.0074***	0.0048***	0.0038***	0.0043**	0.0040**	0.0032*	0.0015
	(18.05)	(6.43)	(4.36)	(4.12)	(4.47)	(3.25)	(2.71)	(2.59)	(2.21)	(1.78)	(1.34)
Carhart α	0.0733***	0.0171***	0.0136***	0.0106***	0.0063***	0.0042**	0.0042**	0.0035**	0.0033*	0.0023	0.0012
	(16.73)	(3.14)	(2.65)	(3.65)	(3.32)	(2.42)	(2.20)	(2.01)	(1.69)	(1.45)	(1.01)
FF5F α	0.0739***	0.0170***	0.0140***	0.0101***	0.0070***	0.0045**	0.0035**	0.0039**	0.0035*	0.0024	0.0019
	(16.21)	(3.27)	(2.61)	(3.19)	(3.52)	(2.55)	(2.40)	(2.16)	(1.67)	(1.39)	(1.24)

Table 3.5: Textual sentiment and stock returns: Control for abnormal turnover

In this table, stocks are first sorted into terciles based on abnormal turnover (Aturn). Within each group, portfolio returns of taking long position in stocks with high-sentiment and short position in stocks with low-sentiment are summarized respectively. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Low Aturn	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0581***	0.0215***	0.0141***	0.0138***	0.0038***	0.0034***	0.0032*	0.0017	0.0017	0.0015	0.0018
	(17.09)	(6.32)	(4.07)	(4.45)	(2.87)	(2.81)	(1.69)	(1.30)	(1.45)	(1.36)	(1.28)
Carhart α	0.0571***	0.0211***	0.0158***	0.0137***	0.0039**	0.0040**	0.0015*	0.0013	0.0019	0.0006	0.0007
	(16.37)	(4.38)	(2.74)	(3.59)	(2.53)	(2.56)	(1.87)	(1.46)	(1.50)	(1.27)	(0.99)
FF5F α	0.0549***	0.0211***	0.0149***	0.0131***	0.0039***	0.0036**	0.0019*	0.0012	0.0014	0.0011	0.0006
	(11.69)	(3.78)	(3.75)	(2.90)	(2.74)	(2.47)	(1.79)	(1.60)	(1.27)	(0.87)	(0.60)
Medium Aturn	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.0761***	0.0206***	0.0150***	0.0141***	0.0056***	0.0037***	0.0038***	0.0043***	0.0030**	0.0026*	0.0008
	(18.77)	(3.82)	(4.64)	(3.83)	(4.61)	(2.81)	(2.88)	(3.01)	(2.27)	(1.94)	(0.68)
Carhart α	0.0754***	0.0196***	0.0146***	0.0132***	0.0059***	0.0043***	0.0042***	0.0045**	0.0027**	0.0028*	0.0004
	(17.19)	(2.91)	(3.60)	(3.36)	(4.46)	(2.64)	(2.83)	(2.94)	(1.69)	(1.78)	(0.66)
FF5F α	0.0729***	0.0192***	0.0145***	0.0126***	0.0049***	0.0044***	0.0041***	0.0039**	0.0026*	0.0018	0.0003
	(17.33)	(3.39)	(2.97)	(2.86)	(3.09)	(2.69)	(2.63)	(2.47)	(1.59)	(1.03)	(0.87)
High Aturn	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.1243***	0.0247***	0.0176***	0.0155***	0.0081***	0.0061***	0.0054***	0.0054***	0.0057***	0.0043**	0.0021*
	(20.67)	(7.22)	(5.62)	(5.56)	(6.14)	(4.54)	(4.05)	(3.86)	(3.69)	(2.28)	(1.84)
Carhart α	0.1230***	0.0231***	0.0164***	0.0146***	0.0073***	0.0055***	0.0040***	0.0049***	0.0044***	0.0041**	0.0018
	(19.33)	(3.92)	(3.09)	(3.68)	(3.73)	(2.74)	(2.62)	(2.87)	(2.63)	(2.44)	(1.04)
FF5F α	0.1209***	0.0224***	0.0158***	0.0142***	0.0065***	0.0044***	0.0041**	0.0048***	0.0042**	0.0036*	0.0024
	(18.89)	(3.61)	(2.76)	(3.32)	(3.25)	(2.63)	(2.48)	(2.71)	(2.35)	(1.92)	(1.31)

Table 3.6: Textual sentiment and stock returns: Control for Read

In this table, stocks are first sorted into terciles based on the times of comments' read (Read). Within each group, portfolio returns of taking long position in stocks with high-sentiment and short position in stocks with low-sentiment are summarized respectively. The *t*-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Low Read	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0569***	0.0180***	0.0131***	0.0102***	0.0036***	0.0027**	0.0016*	0.0018	0.0012	0.0016	0.0008
	(14.20)	(2.89)	(2.75)	(2.62)	(2.79)	(2.03)	(1.78)	(1.35)	(0.95)	(1.19)	(0.88)
Carhart α	0.0561***	0.0173***	0.0129**	0.0118 **	0.0027**	0.0023**	0.0012*	0.0016	0.0008	0.0009	0.0004
	(14.83)	(2.78)	(2.40)	(2.29)	(2.45)	(2.18)	(1.82)	(1.61)	(1.41)	(1.23)	(0.64)
FF5F α	0.0547***	0.0179***	0.0128**	0.0099**	0.0028*	0.0026*	0.0013	0.0014	0.0009	0.0008	0.0003
	(14.38)	(2.99)	(2.30)	(2.18)	(1.87)	(1.74)	(1.58)	(1.44)	(1.22)	(1.01)	(0.74)
Medium Read	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.0823***	0.0201***	0.0161***	0.0137***	0.0065***	0.0045***	0.0034**	0.0022*	0.0024	0.0008	0.0005
	(15.89)	(4.40)	(5.61)	(5.36)	(5.27)	(3.46)	(2.56)	(1.69)	(1.61)	(0.89)	(0.65)
Carhart α	0.0804***	0.0192***	0.0157***	0.0131***	0.0046***	0.0036**	0.0022*	0.0021	0.0022	0.0009	0.0008
	(15.45)	(3.16)	(4.27)	(4.02)	(3.05)	(2.32)	(1.70)	(1.58)	(1.32)	(0.70)	(0.65)
FF5F α	0.0789***	0.0187***	0.0156***	0.0124***	0.0044***	0.0040**	0.0028*	0.0022	0.0019	0.0007	0.0006
	(15.85)	(3.18)	(3.24)	(3.03)	(2.70)	(2.20)	(1.85)	(1.47)	(1.36)	(0.87)	(0.62)
High Read	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.1339***	0.0255***	0.0189***	0.0153***	0.0086***	0.0078***	0.0065***	0.0068***	0.0075***	0.0052***	0.0032**
	(16.77)	(7.82)	(6.81)	(7.16)	(6.63)	(6.02)	(5.01)	(4.95)	(3.96)	(3.59)	(2.44)
Carhart α	0.1288***	0.0245***	0.0181***	0.0154***	0.0083***	0.0069***	0.0058***	0.0068***	0.0073***	0.0046**	0.0021
	(16.80)	(3.61)	(4.29)	(4.52)	(3.87)	(3.39)	(2.95)	(3.99)	(3.82)	(2.49)	(1.23)
FF5F α	0.1247***	0.0240***	0.0176***	0.0149***	0.0079***	0.0074***	0.0052***	0.0061***	0.0066***	0.0039**	0.0032
	(16.45)	(3.41)	(3.91)	(4.48)	(3.49)	(3.47)	(2.68)	(2.96)	(3.38)	(2.15)	(1.17)

Table 3.7: Textual sentiment and stock returns: Control for news coverage

In this table, stocks are first sorted into terciles based on news coverage (Nc). Within each group, portfolio returns of taking long position in stocks with high-sentiment and short position in stocks with low-sentiment are summarized respectively. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Low Nc	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0632***	0.0180***	0.0119***	0.0120***	0.0038***	0.0026**	0.0016	0.0011	0.0009	0.0011	0.0005
	(13.26)	(3.24)	(2.99)	(3.02)	(2.88)	(2.14)	(1.57)	(1.35)	(0.95)	(1.19)	(0.88)
Carhart α	0.0611***	0.0185***	0.0123***	0.0126**	0.0032**	0.0024*	0.0011	0.0011	0.0004	0.0008	0.0004
	(13.33)	(2.92)	(2.60)	(2.11)	(2.01)	(1.78)	(1.32)	(1.01)	(0.98)	(0.84)	(0.82)
FF5F α	0.0614***	0.0183***	0.0121**	0.0122**	0.0030*	0.0024*	0.0013	0.0013	0.0005	0.0008	0.0003
	(12.96)	(2.87)	(2.42)	(2.20)	(1.97)	(1.68)	(1.22)	(1.23)	(1.11)	(0.99)	(0.85)
Medium Nc	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.0903***	0.0201***	0.0140***	0.0141***	0.0058***	0.0047***	0.0042***	0.0021*	0.0019	0.0013	0.0004
	(15.35)	(5.21)	(4.88)	(5.48)	(4.56)	(3.44)	(2.98)	(1.95)	(1.45)	(0.98)	(0.77)
Carhart α	0.0884***	0.0199***	0.0130***	0.0138***	0.0056***	0.0046***	0.0029**	0.002	0.0017	0.0011	0.0006
	(15.11)	(3.78)	(3.21)	(4.16)	(3.15)	(2.67)	(2.39)	(1.64)	(1.22)	(1.34)	(1.29)
FF5F α	0.0859***	0.0198***	0.0137***	0.0132***	0.0054***	0.0042**	0.0029*	0.0024	0.0018	0.0013	0.0007
	(14.74)	(3.88)	(3.45)	(3.97)	(2.79)	(2.11)	(1.85)	(1.43)	(1.23)	(0.89)	(0.79)
High Nc	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.1214***	0.0241***	0.0187***	0.0192***	0.0087***	0.0068***	0.0064***	0.0063***	0.0059***	0.0054**	0.0025*
	(14.20)	(8.72)	(7.63)	(7.79)	(6.36)	(6.12)	(4.05)	(3.23)	(2.97)	(2.32)	(1.86)
Carhart α	0.1158***	0.0240***	0.0184***	0.0179***	0.0084***	0.0065***	0.0055***	0.0054***	0.0056**	0.0041**	0.0022
	(13.80)	(4.99)	(4.22)	(4.75)	(3.66)	(3.21)	(2.78)	(2.89)	(2.24)	(2.02)	(1.47)
FF5F α	0.1143***	0.0242***	0.0176***	0.0169***	0.0079***	0.0074***	0.0052***	0.0052***	0.0056***	0.0040*	0.0021
	(13.44)	(4.57)	(4.31)	(4.66)	(3.40)	(3.18)	(2.71)	(2.66)	(2.11)	(1.88)	(1.29)

Table 3.8: Textual sentiment and stock returns: Control for volatility

In this table, stocks are first sorted into terciles based on one-month volatility (Vol). Within each group, portfolio returns of taking long position in stocks with high-sentiment and short position in stocks with low-sentiment are summarized respectively. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Low Vol	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0505***	0.0182***	0.0139***	0.0096***	0.0040***	0.0036**	0.0023**	0.0027**	0.0027*	0.0019	0.0008
	(14.20)	(8.19)	(4.37)	(4.30)	(2.72)	(2.84)	(2.44)	(2.22)	(1.83)	(1.33)	(0.78)
Carhart α	0.0507***	0.0180***	0.0141***	0.0092***	0.0042***	0.0051**	0.0015*	0.0022	0.0024	0.0018	0.0011
	(12.52)	(5.45)	(3.48)	(3.44)	(2.96)	(3.18)	(1.67)	(1.38)	(1.50)	(1.13)	(0.70)
FF5F α	0.0475***	0.0175***	0.0139***	0.0092***	0.0041***	0.0047*	0.0019*	0.0023	0.0019	0.0014	0.0012
	(11.69)	(4.71)	(3.75)	(2.71)	(3.16)	(1.84)	(1.79)	(1.31)	(1.49)	(1.16)	(1.22)
Medium Vol	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.0776***	0.0193***	0.0158***	0.0103***	0.0061***	0.0051***	0.0056***	0.0058***	0.0052***	0.0036***	0.0016*
	(13.31)	(5.06)	(4.54)	(4.17)	(4.58)	(3.84)	(4.12)	(4.45)	(3.89)	(2.86)	(1.78)
Carhart α	0.0746***	0.0192***	0.0153***	0.0109***	0.0060***	0.0054***	0.0041***	0.0052**	0.0047**	0.0032*	0.0014
	(12.34)	(3.26)	(3.40)	(3.35)	(4.33)	(3.92)	(2.73)	(2.38)	(2.12)	(1.88)	(0.91)
FF5F α	0.0715***	0.0190***	0.0149***	0.0106***	0.0054***	0.0051***	0.0028***	0.0039**	0.0036*	0.0023	0.0008
	(12.62)	(3.35)	(2.60)	(2.63)	(3.45)	(3.18)	(2.85)	(2.27)	(1.83)	(1.53)	(0.49)
High Vol	**month 0**	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
High-low	0.1256***	0.0231***	0.0172***	0.00135***	0.0094***	0.0062***	0.0042***	0.0057***	0.0055***	0.0047***	0.0046**
	(16.32)	(6.26)	(5.72)	(6.66)	(6.64)	(4.31)	(2.89)	(3.61)	(3.28)	(3.01)	(2.32)
Carhart α	0.1206***	0.0227***	0.0164***	0.0126***	0.0069***	0.0043***	0.0036***	0.0045***	0.0047***	0.0043**	0.0035*
	(16.43)	(2.75)	(3.94)	(3.16)	(3.41)	(2.72)	(2.75)	(2.98)	(2.71)	(2.47)	(1.89)
FF5F α	0.1190***	0.0228***	0.0175***	0.0123***	0.0064***	0.0048***	0.0035**	0.0049***	0.0046**	0.0036*	0.0032*
	(16.89)	(2.68)	(2.61)	(3.42)	(3.04)	(2.65)	(2.26)	(2.61)	(2.35)	(1.91)	(1.85)

Table 3.9: Textual sentiment and stock returns: Control for returns in the previous month

In this table, stocks are first sorted into terciles based on stock returns in the previous month (Pr). Within each group, portfolio returns of taking long position in stocks with high-sentiment and short position in stocks with low-sentiment are summarized respectively. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Low Pr	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0737***	0.0208***	0.0163***	0.0138***	0.0067***	0.0055***	0.0049***	0.0037***	0.0037***	0.0028**	0.0015
	(15.72)	(4.92)	(4.70)	(4.44)	(4.97)	(3.93)	(2.97)	(3.01)	(2.66)	(2.28)	(1.2)
Carhart α	0.0716***	0.0206***	0.0162***	0.0129***	0.0065***	0.0052***	0.0046**	0.0033*	0.0031	0.002	0.0012
	(14.23)	(3.32)	(3.29)	(3.44)	(2.99)	(2.78)	(2.01)	(1.78)	(1.49)	(1.31)	(1.04)
FF5F α	0.0693***	0.0205***	0.0159***	0.0125***	0.0058***	0.0048***	0.0041**	0.0031*	0.0025	0.0018	0.0009
	(14.11)	(3.01)	(3.25)	(2.89)	(3.05)	(2.88)	(1.99)	(1.66)	(1.34)	(1.17)	(0.95)
Medium Pr	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.0642***	0.0211***	0.0168***	0.0131***	0.0046***	0.0044***	0.0041***	0.0032***	0.0052**	0.0029**	0.0006
	(16.59)	(5.71)	(4.27)	(3.35)	(4.51)	(3.24)	(3.12)	(2.72)	(2.24)	(1.83)	(0.64)
Carhart α	0.0640***	0.0210***	0.0164***	0.0132***	0.0045***	0.0043***	0.0039***	0.0027**	0.0047*	0.0022*	0.0009
	(15.34)	(4.11)	(3.67)	(3.31)	(3.78)	(2.99)	(2.81)	(2.21)	(1.85)	(1.70)	(1.19)
FF5F α	0.0623***	0.0209***	0.0161***	0.0130***	0.0054***	0.0051***	0.0028***	0.0039**	0.0036	0.0022	0.0008
	(14.82)	(4.35)	(3.43)	(3.04)	(3.28)	(3.02)	(2.99)	(2.43)	(1.56)	(1.33)	(0.82)
High Pr	month 0	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
High-low	0.1008***	0.0228***	0.0181***	0.0155***	0.0083***	0.0056***	0.0045***	0.0042***	0.0044***	0.0027***	0.0028*
	(17.74)	(5.96)	(6.13)	(5.48)	(5.74)	(4.34)	(3.36)	(3.21)	(2.97)	(2.06)	(1.76)
Carhart α	0.0993***	0.0224***	0.0177***	0.0153***	0.0079***	0.0043***	0.0039***	0.0032**	0.0033*	0.0021	0.0019
	(16.11)	(4.66)	(4.09)	(3.78)	(3.89)	(2.82)	(2.68)	(2.34)	(1.89)	(1.60)	(1.21)
FF5F α	0.0987***	0.0223***	0.0172***	0.0157***	0.0070***	0.0044***	0.0037***	0.0031**	0.0032*	0.0019	0.002
	(16.35)	(4.31)	(3.91)	(4.11)	(2.89)	(2.69)	(2.88)	(2.11)	(1.77)	(1.44)	(0.78)

Table 3.10: Fama-Macbeth regression: Textual sentiment and stock returns

This table reports the Fama-Macbeth regression results of monthly stock returns on textual sentiment, volatility, past stock returns, and other sentiment/attention measures. The control variables are firm characteristics including market beta, market value, book-to-market ratio, earnings-price ratio, stock prices and institutional ownership. See also notes to Table 3.1 for other variables' definition. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. We also present average R^2 from series of cross-sectional regressions.

Panel A	month 1	month 2	month 3	month 4	month 5	month 6	month 7	month 8	month 9	month 10
Sent	0.0325***	0.0296***	0.0217***	0.0213***	0.0231***	0.0197***	0.0156***	0.0139***	0.0126***	0.0080**
	[5.60]	[4.73]	[4.99]	[5.16]	[4.32]	[3.59]	[4.19]	[3.60]	[3.24]	[1.83]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	333497	327714	322795	318437	314438	310732	307222	303782	300353	296960
Avg. R^2	0.045	0.043	0.041	0.039	0.038	0.036	0.035	0.035	0.035	0.035
Panel B	**month 1**	**month 2**	**month 3**	**month 4**	**month 5**	**month 6**	**month 7**	**month 8**	**month 9**	**month 10**
Sent	0.0295***	0.0189***	0.0181***	0.0163***	0.0153***	0.0097***	0.0109***	0.0092***	0.0090**	0.0075**
	[7.42]	[5.84]	[5.60]	[4.50]	[3.79]	[2.63]	[3.23]	[2.74]	[2.51]	[2.15]
Read	-0.0036***	-0.0020**	-0.0014*	-0.0016*	-0.0023***	-0.0025***	-0.0020***	-0.0019**	-0.0020***	-0.0017**
	[-4.19]	[-2.41]	[-1.70]	[-1.98]	[-2.89]	[-3.31]	[-2.68]	[-2.59]	[-2.65]	[-2.51]
Aturn	-0.0002***	-0.0001***	-0.0001**	-0.0000*	-0.0000**	-0.0001**	-0.0000	-0.0000	-0.0000	-0.0000
	[-4.97]	[-3.01]	[-2.05]	[-1.66]	[-2.17]	[-2.31]	[-1.61]	[-0.70]	[-0.13]	[-1.21]
52wh	-0.0034	0.0041	0.0066	0.0087	0.0059	0.0070	0.0049	0.0022	-0.0003	0.0030
	[-0.45]	[0.63]	[1.12]	[1.46]	[1.04]	[1.19]	[0.87]	[0.41]	[-0.06]	[0.56]
His	-0.0107**	-0.0086**	-0.0080*	-0.0112**	-0.0099**	-0.0096 *	-0.0086*	-0.0075	-0.0056	-0.0045
	[-2.55]	[-2.09]	[-1.92]	[-2.39]	[-2.07]	[-1.92]	[-1.71]	[-1.61]	[-1.22]	[-0.98]
Vol	-0.0478	0.0526	0.0462	0.0067	0.0538	-0.0154	0.0143	-0.0170	-0.0835	-0.0381
	[-0.43]	[0.54]	[0.50]	[0.08]	[0.57]	[-0.16]	[0.15]	[-0.18]	[-1.00]	[-0.41]
Pr	-0.0292***	-0.0110	-0.0034	0.0003	0.0004	0.0002	0.0018	0.0046	0.0064	-0.0069
	[-3.75]	[-1.65]	[-0.53]	[0.04]	[0.06]	[0.03]	[0.31]	[0.84]	[1.05]	[-1.25]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	332904	327100	322143	317772	313756	310038	306529	303091	299667	296275
Avg. R^2	0.095	0.080	0.074	0.069	0.066	0.062	0.060	0.059	0.056	0.056

Table 3.11: Economic value: short selling restriction

In this table, we report equal-weighted portfolio returns of taking long position in stocks with high sentiment, and short position in stocks with low sentiment. The portfolio is constructed from the stocks that are permitted for short selling. The sample period is from March 2010 to Dec 2020. See also notes to Table 3.2.

Portfolios that long high-sentiment stocks and short low-sentiment stocks:					
	High	Low	High-Low	Carhart α	FF5F α
month 1	0.0113*	-0.0072**	0.0185***	0.0181***	0.0184***
	(1.79)	(2.01)	(3.17)	(2.71)	(2.64)
month 2	0.0102*	-0.0057**	0.0159***	0.0157**	0.0152**
	(1.69)	(2.07)	(3.14)	(2.28)	(2.34)
month 3	0.0095*	-0.0043*	0.0138***	0.0135**	0.0134**
	(1.77)	(1.85)	(3.04)	(2.33)	(2.49)

Table 3.12: Economic value: transaction cost

This table reports the turnover ratio of the strategy that longing stocks with high sentiment and shorting stocks with low sentiment and the monthly break-even transaction costs. The long and short legs are equal weighted. Zero return refers to the transaction costs that make the sentiment-based strategy to yield a zero-return, and 5% insignificance refers to the transaction costs that deliver a return statistically insignificant at the 5% level. The sample period is from June 2008 to Dec 2020.

Portfolios that long high-sentiment stocks and short low-sentiment stocks:			
	Turnover(%)	Break-even costs(%)	
	Mean	Zero Return	5% Insignifificance
Return	70.51	1.97	1.54
Carhart α	70.51	2.32	2.09
FF5F α	70.51	2.25	2.04

Chapter 4

Disaster-induced sentiment and stock returns: Evidence from Google Trends and Baidu Index

4.1 Introduction

Negative sentiment and anxiety affect investor trading decisions, anxious people can be more pessimistic regarding future returns. (Kaplanski and Levy, 2010). Research related disasters has attracted renewed interest since the probability of disasters might produce a non-negligible impact on stock markets through sentiment channels. Disaster can induce negative sentiment among investors. Evidence in the psychology literature documents that disaster events increase depression, anxiety, and helplessness (Evans et al., 1987). Jha et al. (2021) find that popular sentiment relying on financial-related text analysis becomes lower after epidemics and earthquakes but turns higher following severe droughts, floods, and landslides.

Disasters can be regarded as non-finance, exogenous shocks to stock markets (Ramcharan, 2007; Mahajan and Yang, 2020). Sentiment induced by disasters is able to predict stock returns, since the shifts of sentiment have a significant impact specifically on economic decision-making (Lerner et al., 2004). For examples, Choi et al. (2020) document that retail investors revise their sentiment and change the trading strategy about carbon-intensive firms when experiencing extremely warm temperatures in their area. Kaplanski and Levy (2010) show that disasters, such as airline crashes, have a negative impact on stock prices as they result in negative mood such as fear and anxiety. As Nordhaus (2019) documents, disaster events have important implications for stock markets since having the experience of a disaster affects risk perceptions and preferences of households as well as the risk-taking behaviors of corporate managers. Furthermore, due to the relative efficiency of stock markets, the impact of disaster events should be reflected in the short term. Individual investors' abnormal trading behaviors lead to variations in future returns which might arise from the outbreak of the disasters (Chen et al., 2022).

Against this background, in this chapter we use search data to construct disaster-induced sentiment and aim to examine the effect of sentiment caused by disasters on stock returns at monthly frequency in the US and the Chinese stock markets during the sample period between 2007 and 2021. Search data provide new ways for disaster research, because it evaluates the public sentiment to attention-grabbing events and presents prompt feedback on investment dynamics (Nofsinger, 2005). For most of individuals, their online behaviors reveal their sentiment, and the level of sentiment can forecast returns in the short term.

However, stock return prediction analysis on the basis of tracking online behavior is mainly studied based on the finance-related search data. For example, Mao et al. (2011) examine the relations between financial sentiment measures derived from Google search volumes and the volatility of the Dow Jones Industrial Average. Da et al. (2015) develop a novel sentiment measure based on search terms from financial and economic attitudes. These terms have been identified with "positive" and "negative" sentiment in financial dictionary beforehand (Tetlock, 2007), although there are no terms with a positive relation with market returns, the measures composed by terms with negative financial attitudes are considered as (negative) sentiment. As yet, the studies of disaster events based on search data have received little attention. Gao et al. (2020) use search terms unrelated to economics and finance from six categories (including disaster) to construct sentiment measure, and discover that the sentiment negatively correlates to subsequent market returns across 36 countries.

Search data have several advantages in studying the relation between the effect of disaster events and stock market. First, traditional studies on this topic mainly indirectly investigate the impacts of such events through the methods of event study and intervention analysis (Kowalewski and Śpiewanowski, 2020; Lanfear et al., 2017). Both approaches use dummy variables to evaluate the subsequent impacts, which are not able to measure investors' sentiment and reaction to disasters directly. On the one hand, a real disaster can exact huge economic losses leading to a slump in the financial market; on the other hand, people's concern about unforeseen disasters is more likely to influence their trading behaviors, thereby affecting the stock market (Manela and Moreira, 2017). Search data provide direct evidence to show the mechanism by influencing investors' mood, disasters have correlation with stock returns predictions. Second, since disaster events occur intermittently, it is difficult to construct continuous time series to predict stock returns (Chen et al., 2022). Search engines collect online searching information which can capture disaster-induced sentiment of investors from different regions even if there is no disaster in the short term.

The reasons that we conduct the exercise in China and the US arise from two aspects. First, the Chinese market is well known for its speculative feature with a huge amount of inexperienced retail investors and is characterized by heavy regulation (Han and Li, 2017). Sentiment-induced mispricing is difficult to arbitrage away due to the stringent constraints on short selling. Sentiment is more likely to be pervasive in this kind of market in comparison with the more efficient market in the US. Second, Baidu is the third largest search engine in world market share, over 90% users of Baidu are located in China. However, most of papers studied search-based sentiment take Google Trends as data source to measure Chinese investor sentiment (Choi et al., 2020; Gao et al., 2020). As Chinese individual investors, search records from Baidu reveal their thoughts to a much greater extent instead of Google.

We collect the search volume related to disaster terms around the world from Google Trends. Google, as the most popular search engine worldwide, offers a perfect platform for studies that evaluate investor sentiment and examine its price effects (Da et al., 2011; Gao et al., 2020). However, because Google is censored in China from 2010, Baidu becomes the first choice for most of Chinese investors as their search engine, and a frequently-used big data analysis service is provided by Baidu Index in China like Google Trends in the world. Although Google is the most widely used search engine in the world which covers 219 countries, its share of desktop search traffic is only 2.93% in China which is much less than 85.48% for Baidu in 2021.[1] Within this framework, Chinese disaster sentiment index (DSI_C) is

[1]See https://99firms.com/blog/search-engine-statistics/

formed by the same search terms in China from Baidu Index. Besides, we construct global disaster sentiment index (DSI_G) and US disaster sentiment index (DSI_U) based on disaster-related search terms in the world and in the US from Google Trends, respectively.

Motivated by the Googling sentiment index of Gao et al. (2020), we develop DSI_G, DSI_U and DSI_C by aggregating the volume of search queries related to disaster events in Google and Baidu search engines, respectively.[2] For example, we use "rainstorm" as a search query for Google, " 暴风雨" for Baidu. We rely on the University of South Florida Free Association Norms to collect the associated words of disaster events, which is "the largest database of free association ever collected in the U.S. available to researchers" (Steyvers and Tenenbaum, 2005). There are 41 associated words related to disasters, and we also collect 41 Chinese keywords according to Google translation. We define our measures as disaster-induced sentiment since all of 41 search terms related to disaster events are identified with negative sentiment (Hu and Liu, 2004).

We aim to address three research questions in this article: i) to examine whether the DSI_U and DSI_C have predictive power for the US and the Chinese stock market returns, respectively, and whether DSI_C is more reliable in China compared with DSI_G.[3] ii) to examine whether the DSI_U and DSI_C have effect on different industries in the US and Chinese markets, as Choi et al. (2020) document that firms in different industries react to global warming in various ways, and iii) to investigate whether disaster sentiment exerts different impacts on diverse regions in China, the degree to which disaster events affect stock returns might vary with the geographical locations (Jha et al., 2021).

Our first set of results shows that both DSI_U and DSI_C can independently negatively predict market returns. DSI_C derived from Baidu index displays stronger ability than DSI_G in predicting the Chinese market. The results of baseline are

[2]In Table 4.A6, we also examine the sentiment effect from other finance-unrelated categories in Gao et al. (2020), we find that sentiment derived from the categories of "holiday" and "sport" does not have predictive power for future returns.

[3]Taking into consideration of the interconnection of companies and financial systems on a global scale, Gao et al. (2020) suggest that sentiment derived from search data based on Google might reverberate across stock markets of various countries.

robust to other developed countries and after excluding periods of crisis.[4] Furthermore, following the suggestions proposed by Sibley et al. (2016), this chapter controls a number of widely used economic variables to conduct the analysis as well. The findings remain, which alleviates concerns that the return prediction of sentiment indexes is dominated by risk factors and business cycles. We further demonstrate that the predictive power of our disaster sentiment for returns is pervasive across industries. There are nine of ten industries' returns significantly decline in the following month caused by DEI_U in the US, and eight of 16 industries are influenced in China based on DEI_C. It is consistent with the evidence in Han and Li (2017) which shows that the effect of sentiment varies in different industries.

Since Baidu index provides unique search volume data for different provinces in China, we are able to test whether Chinese investors in different regions show the similar response to disaster events. We weigh the returns of all companies in each province by market capitalization to obtain the index returns for each province in China. The results show that 17 of 31 provinces are influenced by sentiment caused by disaster events. Furthermore, in these 17 provinces, there are 12 of them belonging to the coast. We further find that the sentiment stemming from investors in coastal provinces has a greater effect on stock returns than that in inland provinces. This might be explained by the geographical distribution of the disaster, since coastal areas are more threatened by natural disasters than inland (Kron, 2013). Storm and tsunamis expend their destructive energy when they reach the coastline, while most of sea-related disasters have little impact on inland provinces. This suggests that investors in coastal regions are more susceptible to the impact of disaster-induced sentiment.

This research contributes to the literature from two perspectives. First, this chapter presents a novel view that the internet search is useful in quantifying the sentiment induced by disaster events. Search data provides continuous time series, thus improving statistical approaches of using dummy variables to represent the disaster events. The vast amount of data produced by the internet reflect the shifts of sentiment with the particular sectors people pay attention to. In this chapter,

[4]Table 4.3 shows that eight additional developed countries are Netherlands, Austria, France, England, Germany, Canada, Korea and Japan.

we further divide the effect of unrelated-finance sentiment in Gao et al. (2020) into several sectors and show that sentiment derived from disaster sectors is a powerful predictor for stock returns. Second, our findings shed some light on the market prevalence of negative sentiment emerging with disaster events by using two search engines in China and the US. It is more appropriate to use Baidu index to explore search-based sentiment in China. In comparison with the US market, the Chinese market is less efficient, indicating that stock prices may deviate from their fundamental level in the long term.

The rest of this chapter is structured as follows. Section 4.2 provides a literature review on the related studies and methodologies. In Section 4.3, the data and methodology used to develop the sentiment index for this chapter are detailed. Section 4.4 presents and discusses the empirical results. Section 4.5 concludes.

4.2 Literature review

The impact of disasters on asset prices has long been studied in financial research field. For instance, Shelor et al. (1992) explore the relationship between market volatility with earthquakes in 1991 and 1992; and Angbazo and Narayanan (1996) evaluate the influences of hurricanes. In recent years, there are also many studies on related topics. Robinson and Bangwayo-Skeete (2016) investigate the effects of tropical storms and hurricanes on economics of developing countries with small island topography. In the study of Lanfear et al. (2017), the authors examine landfalling hurricanes' impact on stock returns. The results show that compared to growth stocks, value stocks are more vulnerable to disasters. Based on the study of Lee et al. (2018), disaster events have a spill-over effect. They find that the 2008 Sichuan Earthquake in China affects the stock markets of nearby Asian nations with the significant contagious effect.

The majority of traditional studies in this area employ intervention analysis and event study for indirectly examining the impact of disasters and extreme weather. According to Box and Tiao (1975), intervention analysis is concerned with rigorous statistical modeling in order to determine whether a particular event has an impact on a time series factor, as well as the direction and magnitude of that impact. With this approach, a hypothetical incident is frequently expressed as a dummy variable. Event study is a standard analytical approach for determining the impacts of unanticipated events (MacKinlay, 1997). This approach is used to estimate cumulative abnormal returns and assess their significance using normal return models that have been established during a given time excluding the event. Researchers mainly apply the event study approach to assess the impact of information disclosure, as well as the abnormal reaction of stock prices caused by specific events. These approaches are both indirect in nature as they use dummy variables to analyze the impacts generated. In addition, they are unable to directly quantify the effect of disasters based on investors' behaviors.

In comparison with the methods mentioned above, search data provides a novel way to study the impact of disaster events, since online behaviors of the majority of people encompass information related to their sentiment, and the people's concern about unforeseen disasters influences their financial decisions (Chen et al., 2022). Google Trends is a tool that analyzes the terms searched for by Google users. It provides the keywords that have been the focus of users and media in the previous period, respectively. In previous literature, financial market analysis on the basis of online behavior tracking has been extensively considered using Google search data. For example, Gao et al. (2020) develop a weekly sentiment indicator for 38 nations over the period of 2004 to 2014 and demonstrate that the sentiment indicator is a contrarian predictor of market returns at a country level based on households' Google search behavior. In general, tracking human behavior on the internet might help us better understand the price movement in the stock markets.

4.2.1 Effect of disasters on stock returns

With the increasing number of disaster events occurring throughout the world, researchers pay more attention to the influence of these events on the worldwide stock markets. These disasters often occur suddenly and unpredictably, and will increasingly affect a huge proportion of the population in the decades following their occurrence. Fernandez-Perez et al. (2021) discover that countries with lower individualism and higher uncertainty avoidance show larger declines and greater volatilities in the stock markets for three weeks since their first COVID-19 case announcement. Worthington and Valadkhani (2004) investigate Australian capital markets, and discover that earthquakes, cyclones and bushfires significantly impact market returns, and the majority of net effect manifests on the day of the outbreak of disasters. While severe storms and floods have no such impact.

In the cross section, Bai et al. (2019) incorporate the disaster into a standard investment-based asset-pricing model for the purpose of determining whether the inclusion of infrequent disasters may help explain the subject of value premiums. In their model, the disaster is considered as substantial declines in consumption, production, and total factor productivity. Their results indicate that the value premium is produced by the greater exposures of value stocks to the disaster compared to growth stocks. In addition, Lanfear et al. (2017) document that the impact of hurricanes on future stock returns varies across stocks sorted by market equity and book-to-market ratio.

At the firm level, Addoum et al. (2020) demonstrate that corporate earnings can be negatively impacted by extreme temperatures. For individuals, Alok et al. (2020) discover that managers in regions suffering major disasters place much less importance on stocks in the disaster area than those far from the disaster area, and that this aversion to stocks in the disaster area is associated with a salience bias that diminishes with time and distance from the disaster. Besides, Bernile et al. (2017) demonstrate that a company's risk-taking capacity is related to the degree of its CEO's exposure to weather-related disasters in the early years of his or her life. CEOs who survived from deadly disasters without suffering extreme negative consequences tend to manage their companies with a more aggressive attitude, while those who witnessed the highly negative effects of disasters have a more conservative investment style.

4.2.2 Research based on disaster-related measure

Previous research has demonstrated that disaster-related measures contain unique forecasting power for stock returns in international markets. For instance, Manela and Moreira (2017) derive rare disaster concerns from the comovement between the front-page news coverage of the Wall Street Journal and option-implied volatility and Chen et al. (2022) suggest that this index predicts market returns across countries both in- and out-of-sample. Besides, Gao et al. (2020) present an approach of measuring finance-unrelated sentiment to stocks through Google Trends, which is the first time that search data has been applied to predict stock returns in the disaster sector.

In recent years, online transactions basically dominate the stock trading, and most of investors use internet services. According to Bollen et al. (2011), searching information in Twitter contains a number of metrics that can be used to predict stock prices. The internet can rapidly disseminate information about events associated with stock prices and swiftly reflects popular sentiment. For example, using search data as a measure for investor sentiment, Joseph et al. (2011) are able to predict abnormal stock returns with a high degree of accuracy. Liu et al. (2019b) show that the outbreak of disasters can increase volatility temporarily, and negatively influence stock returns in certain periods based on people's sentiment from the internet. Therefore, we construct disaster-induced sentiment measures using search data to analyze the impact of disasters on stock returns. Our method of integrating online search data allows us to measure public sentiment directly compared to the event study that indirectly employs dummy variables that take a value of 0 or 1 depending on the time of the event. It provides a more accurate measure of the disasters' effect on stock markets. Besides, we use two search engines, Google and Baidu, to avoid that our results ensue from sample bias.

4.3 Data description

In this study, we use the volume of queries of internet search engines as indicators of investor sentiment caused by disaster events. The disaster-induced sentiment is constructed based on search data from Google Trends and the Baidu Index. Google Trends is able to capture regional variations in internet searches worldwide by enumerating keyword-based queries. Baidu Index, the principal search engine in China, provides data services related to Baidu's wide range of users. It is able to generate demand maps and data trends. In contrast to Google Trends' open-source data and search volumes, users cannot directly download the search volumes from the Baidu Index. Therefore, a Python-based spider program is required to acquire the search data from the Baidu Index.

To determine the disaster-induced sentiment towards economic conditions, this study first follows Gao et al. (2020) in obtaining the monthly search volumes for terms associated with disaster events in Google Trends and Baidu Index. Utilizing words from the University of South Florida Free Association Norms, which contains 5019 stimulus words and 72,000 related terms in total, a dataset of disaster-related search terms is generated. "Disaster" is considered as a stimulus word to obtain 41 associated terms.[5]

Following Hu and Liu (2004), the Opinion Lexicon is used to identify the sentiment of 41 terms. Moreover, only terms considered having positive or negative sentiment are retained, and terms with neutral sentiment are removed. The results show that all of these 41 associated terms are identified with negative sentiment, since disaster events are always accompanied by personnel casualties and associated with people's negative emotions. The 41 English terms are then translated into Chinese via Google Translate, then we download the monthly search volume index (SVI) of 41 search terms from January 2007 to December 2021 in Google Trends and Baidu Index, respectively. Since several terms are not recorded by search engine due to a small number of search frequency, we finally obtain 39 monthly time series of search volume index in Google Trends and 37 monthly time series of search volume index in Baidu Index.

Next, with the aim of identifying the relationship between the search terms and market returns, we let the market data speak for itself. To be specific, this study sets 48 months from January 2007 to December 2010 as our initial sample, and then runs expanding backward rolling regressions of each time series of search volume on the contemporaneous market returns. The top five search terms with the largest negative t-statistics are selected to construct disaster sentiment index (DSI) for the following 12 months from January 2011 to December 2011. Following the above step, we expand the initial sample to the most recent December after 2011 once a

[5]Panel A of Table 4.A1 tabulates search terms used to construct the sentiment measures in Google Trends and Baidu Index.

year to form the DSI for the next year until December 2021:

$$DSI_t = \sum_{i=1}^{5} D_i/5 \tag{4.1}$$

where $\sum_{i=1}^{5} D_i$ is the sum of the search volume from top five negative disaster-related search terms. Moreover, we winsorize extreme observations, eliminate seasonality and standardize each sentiment index to have a mean of zero and unit variance.

In Panel A of Table 4.1, the global disaster sentiment index (DSI_G) and the US disaster sentiment index (DSI_U) are obtained based on disaster-related search volume index in the global and in the US from Google Trends. The Chinese disaster sentiment index (DSI_C) is obtained based on disaster-related search volume index in China from Baidu Index. [6] The sentiment measures span 11 years from January 2011 to December 2021.[7] The positive values of skewness indicate that disaster-related search volume is relatively large in a few months.

The market index returns from ten countries in Panel B are collected from China Stock Market & Accounting Research (CSMAR) database. We use two of the most well-known market indexes to measure the performance of the US (Dow-Jones index (DJI) and Nasdaq Composite Index (IXIC)) and the Chinese (Shanghai and Shenzhen 300 index (CSI300) and Shanghai Stock Exchange Composite index (SSE)) markets. Besides, industries index returns of Chinese and the US market are obtained from the Refinitiv database.

Panel C presents the correlation coefficients of three disaster sentiment indexes. The average correlation between DSI_C and DSI_U across our sample is only 0.116, which is not significant. Since China and the United States suffer different major natural disasters, the low correlation implies that two measures capture disaster-induced sentiment in different dimensions. For example, in the whole sample period, "crisis" and "hurricane" cause the greatest negative sentiment in the US and Chinese market, respectively. DSI_G and DSI_U are positive correlated indicating that the

[6] In Table 4.A7, two different methods of unit root and stationarity tests, Augmented Dickey Fuller (ADF) test and Phillip-Perron (PP) test, are employed to ensure that disaster-inducecd sentiment are unit root stationary.

[7] One may concern that some words, like "crisis", may capture other information related to financial crisis, we thus use an alternative sentiment measure based on specific disaster events in Panel B of Table 4.A1, and apply it to our main prediction test in Section 4. The results are significant, although the magnitude is smaller. Please refer to Table 4.A2 in the Appendix.

US market is a barometer for global markets, a catastrophic event in the United States can affect financial markets around the world.

4.4 Empirical results

4.4.1 Disaster-induced sentiment and market returns

In this section, we examine the relationship between disaster-induced sentiment measures and market returns in the US and Chinese stock markets. We first regress the US and Chinese market returns on the DSI_G based on Google Trends, and then run the same regressions based on DSI_U and DSI_C derived from search volumes based on Google Trends and Baidu Index, respectively. Two of representative market indexes are applied for the Chinese (SSE and CSI300) and the US stock markets (DJI and IXIC) to validate that our results are robust:

$$Return_{i,t} = \alpha + \beta_{1i} DSI_{i,t-1} + \beta_{2i} DSI_{i,t-2} + \gamma_{1i} Return_{i,t-1} + \gamma_{2i} Return_{i,t-2} + \varepsilon_i \tag{4.2}$$

where $Return_{i,t-1}$ and $Return_{i,t-2}$ are lagged market returns in month $t-1$ and month $t-2$. In Table 4.2, the results from column (1) to column (4) show that DSI_G can negatively predict market returns in the following month. Moreover, we find that the global disaster-induced sentiment provides a stronger prediction for future returns in the US stock market with higher t-value (-2.36) in column (4) than Chinese stock market with lower t-value (-1.77) in column (2). While it may be not appropriate to use search volume in Google as Chinese sentiment measure since Google is censored in China from 2010. In column (5) and (6), we use disaster-induced sentiment measure based on Baidu Index to predict market returns in China. Compared column (5) with column (1), the larger coefficients and t-values in magnitude indicate that DSI_C has greater impact on future stock returns in China, and R^2 (7.6%) in column (5) is also larger than R^2 (5%) in column (1). In the US market, DSI_U in column (7) and (8) show a similar predictive power for future returns compared with DSI_G in column (3) and (4).[8] In addition, it

[8]In Table 4.A6, we also examine the effect of other kinds of finance-unrelated sentiment in Gao et al. (2020) based on search terms of pollution, weather, holiday and sport, respectively. The results show that search terms from sport and holiday do not exhibit predictive power for stock returns in the US and Chinese market, people's concern about disaster, pollution and weather

is interesting to note that there is a clear reversal pattern in the second month for the US market return prediction, while the Chinese market does not show this pattern. The reason can be attributed to that the Chinese market is less efficient than the US market, stock prices may deviate from their fundamental level in the long term. Han and Li (2017) document that Chinese investor sentiment displays the reversal pattern after two years. In addition, the Chinese sample in Gao et al. (2020) shows their Googling sentiment has little explanatory power with R^2 values of only 2.8%. By contrast, we find that approximately 7.6% of the return variations can be explained by disaster sentiment based on the Baidu Index, implying that Baidu is more appropriately used to measure Chinese investor sentiment than Google.

Besides, in Table 4.3, we construct a dataset for the 10-country sample from January 2011 to December 2021. In this panel, we run Regression 4.2 for market returns around the world based on DSI_G. The results show that all of countries exhibit a negative correlation between disaster-induced sentiment and market returns. This kind of pattern is significant at the 10% level in eight of the ten countries, which is consistent with Gao et al. (2020) findings, sentiment is contagious across the markets, not just in the US where it has been most extensively studied. Among these countries, disaster sentiment shows the strongest forecasting power in Korea, where a 1-standard-deviation increase in sentiment predicts a decrease in monthly returns of 1.9%. In addition, market returns in seven countries show the reversal pattern in the second month, which indicates the negative predictive power of disaster sentiment only exists in one month, since most of disaster events do not aggravate people's negative emotions in the long term (Yang et al., 2021). Relying on the financial data, Baker et al. (2012) prove that global sentiment can only exist in one month.

Business-cycle and risk factors mentioned by Sibley et al. (2016) may explain sentiment predictive power of stock returns in the time series. We further confirm that the return prediction of disaster-induced sentiment is not driven by economic fundamentals. In Table 4.4, we perform our return prediction tests again with six economic fundamentals which are treasury bill rate, unemployment rate, consumer price index, term spread, consumption and industrial production. The results show

creating negative sentiment mainly drives the market returns.

that most of sentiment measures consistently lead to mispricing and predict future returns in the following month. However, the results in column (1) show that the disaster sentiment is no longer significant in predicting stock market when SSE is used to represent the market returns in China. The reason can be attributed that disaster-induced sentiment may not exert impact on stock returns in all industries and provinces, it will be explained in detail in the following sections. By contrast, we find that Chinese disaster sentiment based on Baidu Index can predict future returns in column (5). Instead of using Google Trends, Fang et al. (2020) also apply Baidu index as sentiment measure to predict volatility in China. Besides, column (3) and (4) reveal that the reversal pattern in the US market after sentiment retreating in the first month based on DSI_G, market prices revert to fundamentals. By using the disaster search volume in the US, the similar effects of the sentiment exist when augmented by economic predictors in column (7) and (8).

Since both financial investor sentiment and disaster sentiment have forecasting power for the stock market, it is important to examine whether the effect of disaster sentiment measure is driven by existing investor sentiment. In Table 4.5, we take financial sentiment measures constructed by Han and Li (2017) and Baker and Wurgler (2006) as control variables. Han and Li (2017)'s aligned investor sentiment, S_{HL}, is an alternative investor sentiment measure which aggregates three stock market-based sentiment measures in the Chinese stock market based on the principal component approach. In column (2), the coefficient of $DSI_{C,t-1}$ remains significant at the 5% level after controlling S_{HL}, which suggests that disaster sentiment contains incremental information in predicting the Chinese market. In column (3) and (4), we include Baker and Wurgler (2006)'s investor sentiment (S_{BW}), the most famous sentiment measure which aggregates six market-based sentiment proxies in the US market. Our results demonstrate that DSI_U and S_{BW} contain little overlapping information and capture different sides of sentiment in the US market. In summary, sentiment associated with disasters provides supplementary information that goes beyond existing sentiment measures and enhances the predictive power on stock returns.[9]

[9]One may concern that the return predictability of disaster sentiment might ensue from the outbreak of real disasters. In Table 4.A3, we control the effect of real disasters by using measures of the frequency of disasters from January 2015 to December 2021 and find the results remain.

We further conduct the analysis while excluding the global COVID-19 epidemic period from January 2020 to December 2021, as Chen et al. (2022) concern that the effect of disaster can be caused by the outbreak of the COVID-19 pandemic leading to unprecedented panic worldwide. For the Chinese market, we further exclude stock market disaster period from January 2015 to December 2015, considering that the huge changes of sentiment caused by market crash may drive our results (Chen et al., 2010). Table 4.6 shows that the effects remain significant in the non-crisis period on the basis of Table 4.4. In column (5) and (6), Chinese disaster-induced sentiment perform better in predicting market returns after excluding the crisis period. Overall, we conclude that our disaster sentiment measures contain unique information in forecasting the stock market.[10]

4.4.2 Disaster-induced sentiment and industries' returns

As shown in the baseline results, our disaster-induced sentiment exerts the negative impact on stock returns in the following month. Given that the market returns cover a large amount of stock returns from different industries, notable discrepancies might occur caused by our sentiment measures across these industries. Previous research mainly focuses on market return predictions (Da et al., 2015; Gao et al., 2020). We divide market returns into industries to check whether our disaster-induced sentiment measures lead to decreasing of all industries' returns in the short term.

According to China Securities Regulatory Commission industry classification in 2012, there are 16 industry categories in the Chinese market. In Panel A of Table 4.7, 8 of 16 industries display a pattern that negative coefficients are significant at the 10% level. Interestingly, outdoor work is required extensively in the most of eight industries, such as mining and agriculture. Natural disaster events are more likely to cause greater economic losses to these industries, and the t-value of agriculture (-2.42) in column (9) has the largest magnitude among the industries. In contrast, the service and IT sectors are barely affected by the disaster-induced sentiment, since severe natural disasters tend to cause less deficiency to the supply and demand

[10]In Table 4.A8, we also compare the disaster sentiment measures with existing disaster concern measures from Chen et al. (2022) and find both types of measures affect stock returns.

sides of these industries. Besides, the insignificant effect on SSE market index in Table 4.4 might attribute that half of industries are not affected by disaster-induced sentiment.

Panel B reports the results for 10 industries in the US markets. Compared with the Chinese market, all regression slopes on indusries' returns except utilities remain statistically significant. Similar with the findings in Choi et al. (2020), they find that firms in the US are more likely to be affected by global warming in comparison with firms in other countries. Jha et al. (2021) use the financial sentiment to show that firms from various industries react differently to natural disasters. We find that disaster-induced sentiment in the US provides a weaker prediction for future returns in some industries. For instance, A 1-standard-deviation increase in sentiment leads to a decrease in the US technology industries' return of 2.1% in the following month. The magnitude is smaller than the 2.8% decrease in the Chinese technology industries. In a nutshell, the results indicate that sentiment induced by disasters exerts a non-negligible impact on diverse industries across countries.

4.4.3 Disaster-induced sentiment and stock returns in different regions

Due to the characteristics of Baidu index data, we can obtain the search volume data of disaster event keywords in various provinces in China. This provides a way to study whether the effects of disaster-induced sentiment are consistent across regions. Based on the Handbook of disaster research (Rodríguez et al., 2007), local bias will lead that people pay more attention to the disaster when they are in this disaster-covered region. Thus, we conjecture that search results are mainly related to the disaster happened in the province where searchers are located. Besides, Huang et al. (2016) find that individual investors are more likely to hold stocks of local companies than to those of non-local companies. We tend to explore whether the geographic location matters for the predictability of disaster sentiment.

To estimate the number of firms in different provinces, we utilize the location of the headquarters of each firm as reference since the majority of firm operations take place there.[11] We then aggregate stock returns weighted by market capitalization

[11] In Table 4.A4, we report the number of companies for each province.

in each province of China to obtain the province-index returns:

$$Return_{p,t} = \sum_{i=1}^{N} Return_{pi,t} * mv_{pi,t} / \sum_{i=1}^{N} mv_{pi,t} \tag{4.3}$$

where $Return_{pi,t}$ is the return of company i in province p in month t, $mv_{pi,t}$ is the circulation market value of company i in province p in month t. We consider whether geographic characteristics are relevant to stock return predictions in disaster-induced sentiment. Based on the disaster-related search volume data in each province, we regress search volume index on the contemporaneous province-index returns and keep the top 5 search terms with the largest negative t-statistics. By applying Equation 4.1 to calculate the average, we construct disaster sentiment for each province (DSI_P) based on search volume of disaster-related terms in each province. In Table 4.A5, we list the most negatively significant search term in each province estimated in the whole sample period. The results show that these search terms represent the disasters frequently happened in certain provinces, such as "earthquake" in Sichuan and "hurricane" in Zhejiang, indicating that there is significant relation between stock returns and people's concern about the disaster in this disaster-affected area.

Table 4.8 reports that disaster-induced sentiment has negative significant predictive power at the 10% level in 17 of 31 provinces. Among these provinces, Shaanxi has the strongest pattern with -0.023 coefficient in column (22). Besides, there is greater effect of sentiment in company-intensive provinces like Zhejiang, Jiangsu and Guangzhou. We note that sentiment effect is particularly strong in coastal and developed regions, which is inconsistent with the findings of Huang et al. (2016). They document that the pattern of local bias in attention is strong in underdeveloped regions. The potential reason is that our search data in province may not capture the local sentiment precisely. There are some special situations that the disaster searching actions are recorded in certain provinces, while the searchers may come from other provinces. We take their disaster searching reactions as measuring the disaster sentiment in the searcher-located province. It is reasonable that the searchers pay attention to the disaster-related information in the province where they are truly located.

To further support our findings, in Table 4.9, we aggregate weighted stock returns in all of coastal provinces and inland provinces to construct coastal-index returns and inland-index returns, respectively.[12] Following the method that we construct DSI_P, disaster sentiment measures in coastal provinces (DSI_{Co}) and in inland provinces (DSI_I) are derived based on search volume of disaster-related terms in corresponding regions. The results in column (1) and (2) show that disaster-induced sentiment effect is mainly concentrated in the coastal provinces with 0.01 larger in magnitude than inland provinces. There are two potential reasons. First, people in coastal provinces suffer more natural disasters and are more sensitive to disaster events than inland provinces. For example, there are 7 hurricanes hitting the coastal provinces in China in 2021 and causing over \$10 billion in economic losses, while hurricanes and all sea-related natural disasters have little impact on inland provinces. Second, over 70% firms' headquarters are located in the coastal provinces in China, local investors who hold stocks of these companies in coastal provinces incline to feel relatively more pessimistic than investors in inland provinces due to the local bias. Besides, we aggregate weighted stock returns in provinces with top five highest GDP and provinces with top five lowest GDP of China to obtain high-GDP index and low-GDP index returns in column (3) and column (4).[13] Disaster sentiment in high-gdp provinces (DSI_H) and in low-gdp provinces (DSI_L) are developed based on the same method of DSI_P construction. The results show that provinces with higher GDP are more prone to be affected by disaster-induced sentiment than provinces with lower GDP. As documented by Chen et al. (2020), companies in provinces with GDP lower than the national level are more inclined to engage in earnings and risk management than companies in other provinces. These preparations support them to deal with the risk of disasters better. Overall, the negative effect of disaster-induced sentiment is stronger in more disaster-hit provinces and provinces with less disaster risk management.

[12] Liaoning, Heibei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi and Hainan are the coastal provinces in China, the rest are the inland provinces in China.

[13] Guangdong, Jiangsu, Shandong, Zhejiang and Henan are provinces with top five highest GDP in China; Gansu, Hainan, Ningxia, Qinghai and Xizang are provinces with top five lowest GDP in China

4.5 Conclusion

In this chapter, we use search volume on associated words of disaster events in Google Trends and Baidu Index to construct disaster-induced sentiment in the US and Chinese stock markets at monthly frequency, respectively. We find that disaster sentiment measured by search volume can negatively predict country-level market returns in the following month. The sentiment based on Baidu Index shows a better performance in predicting the Chinese stock market. Compared with the Chinese stock market, the effect of disaster sentiment in the US market displays a reversal pattern in the second month. The effect is still robust after excluding the crisis periods and controlling widely accepted economic fundamental factors. Moreover, the sentiment measures also exhibit negative predictive power in the large proportion of industries. In the Chinese market, the disaster sentiment effect varies substantially in different provinces. It is particularly strong in the coastal provinces and provinces with high GDP. This chapter expounds the role of Internet search data in financial applications. Exploring searching contents is an objective way to reflect and quantify investor sentiment. We expect that the exploration of search data will continue to generate innovative insights into the trading behavior of investors in the future.

Table 4.1: Descriptive statistics of Chapter 4

In Panel A, we show the summary statistics for the Chinese disaster sentiment index (DSI_C), the US disaster sentiment index (DSI_U), the global disaster sentiment index (DSI_G). Panel B reports the descriptive statistics of market returns in 11 countries. Shanghai Stock Exchange Composite index (SSE) and Shanghai and Shenzhen Composite index (CSI300) measure the market returns in China. Dow-Jones index (DJI) and Nasdaq Composite Index (IXIC) measure the market returns in the US. Panel C reports cross-correlation coefficients between three disaster sentiment indexes. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2011 to December 2021.

	N	Mean	St. dev.	Min	Median	Max	Skewness
Panel A: Sentiment measures							
DSI_C	132	0	1	-1.594	-0.023	2.423	0.235
DSI_U	132	0	1	-1.844	-0.014	2.409	0.112
DSI_G	132	0	1	-1.982	-0.085	2.662	0.146
Panel B: Market returns							
Austria	132	0.004	0.058	-0.282	0.011	0.243	-0.643
Canada	132	0.004	0.033	-0.177	0.006	0.105	-1.099
CSI300 (China)	132	0.005	0.064	-0.210	0.004	0.258	0.349
DJI (US)	132	0.009	0.039	-0.137	0.011	0.118	-0.438
England	132	0.002	0.035	-0.138	0.008	0.124	-0.435
France	132	0.006	0.047	-0.172	0.009	0.201	-0.096
Germany	132	0.008	0.051	-0.192	0.008	0.150	-0.532
IXIC (US)	132	0.014	0.044	-0.101	0.015	0.154	-0.101
Japan	132	0.009	0.049	-0.105	0.013	0.150	-0.279
Korea	132	0.004	0.042	-0.134	0.007	0.143	-0.124
Netherlands	132	0.007	0.040	-0.110	0.012	0.135	-0.211
SSE (China)	132	0.004	0.059	-0.226	0.004	0.206	0.102

Panel C	DSI_C	DSI_U	DSI_G
DSI_C	1		
DSI_U	0.116	1	
DSI_G	0.114	0.891***	1

Table 4.2: Disaster-induced sentiment and market returns

In this table, we regress Chinese and the US market returns on the corresponding disaster sentiment measures. Shanghai Stock Exchange Composite index (SSE) and Shanghai and Shenzhen Composite index (CSI300) represent the market returns in China. Dow-Jones index (DJI) and Nasdaq Composite Index (IXIC) represent the market returns in the US. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2011 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SSE	CSI300	DJI	IXIC	SSE	CSI300	DJI	IXIC
$DSI_{G,t-1}$	-0.012*	-0.013*	-0.014**	-0.016**				
	[-1.84]	[-1.77]	[-2.34]	[-2.36]				
$DSI_{G,t-2}$	0.008	0.007	0.011**	0.012*				
	[1.16]	[1.02]	[2.03]	[1.81]				
$DSI_{C,t-1}$					-0.015**	-0.018**		
					[-2.22]	[-2.10]		
$DSI_{C,t-2}$					-0.001	-0.001		
					[-0.05]	[-0.08]		
$DSI_{U,t-1}$							-0.014*	-0.022**
							[-1.83]	[-2.18]
$DSI_{U,t-2}$							0.007*	0.011**
							[1.78]	[2.11]
$Return_{t-1}$	0.151*	0.254*	0.055	0.080	0.154*	0.093	-0.002	0.012
	[1.73]	[1.91]	[0.66]	[0.92]	[1.75]	[0.99]	[-0.02]	[0.14]
$Return_{t-2}$	-0.073	0.060	-0.098	-0.064	-0.124	-0.093	-0.153*	-0.098
	[-0.87]	[0.71]	[-1.21]	[-0.76]	[-1.33]	[-1.01]	[-1.96]	[-1.20]
Constant	0.002	-0.002	0.007**	0.009**	0.003	0.006	0.015**	0.014**
	[0.55]	[-0.35]	[2.04]	[2.06]	[0.60]	[1.05]	[2.12]	[2.26]
N	132	132	132	132	132	132	132	132
R^2	0.050	0.049	0.065	0.071	0.076	0.067	0.052	0.061

Table 4.3: Disaster-induced sentiment and market returns around the world

In this table, we regress market returns from 10 countries on the global disaster-induced sentiment measures. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2011 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SSE	CSI300	DJI	IXIC	Netherlands	Austria	France	England	Germany	Canada	Korea	Japan
$DSI_{G,t-1}$	-0.012*	-0.013*	-0.014**	-0.016**	-0.018***	-0.014**	-0.011**	-0.018***	-0.010	-0.017**	-0.019***	-0.011
	[-1.84]	[-1.77]	[-2.34]	[-2.36]	[-3.28]	[-2.01]	[-2.10]	[-2.64]	[-1.31]	[-2.48]	[-2.71]	[-1.59]
$DSI_{G,t-2}$	0.008	0.007	0.011**	0.012*	0.014***	0.009	0.010**	0.007**	0.013	0.012*	0.014**	0.011
	[1.16]	[1.02]	[2.03]	[1.81]	[2.70]	[1.31]	[2.34]	[2.15]	[1.63]	[1.74]	[2.27]	[1.49]
$Return_{t-1}$	0.151*	0.254*	0.055	0.080	0.010	0.106	0.232***	0.044	0.087	0.081	0.118	0.182**
	[1.73]	[1.91]	[0.66]	[0.92]	[0.11]	[1.22]	[2.68]	[0.50]	[0.96]	[0.93]	[1.38]	[2.14]
$Return_{t-2}$	-0.073	0.060	-0.098	-0.064	-0.093	-0.193**	0.114	-0.004	-0.006	-0.050	-0.043	0.122
	[-0.87]	[0.71]	[-1.21]	[-0.76]	[-1.12]	[-2.42]	[1.34]	[-0.05]	[-0.06]	[-0.60]	[-0.53]	[1.43]
Constant	0.002	-0.002	0.007**	0.009**	0.002	0.007	0.000	0.004	0.005	0.011**	0.003	0.002
	[0.55]	[-0.35]	[2.04]	[2.06]	[0.63]	[1.57]	[0.01]	[0.86]	[1.01]	[2.32]	[0.91]	[0.36]
N	132	132	132	132	132	132	132	132	132	132	132	132
R^2	0.050	0.049	0.065	0.71	0.056	0.048	0.070	0.053	0.028	0.056	0.073	0.008

Table 4.4: Disaster-induced sentiment and market returns with control variables

In this table, we regress Chinese and the US market returns on the corresponding disaster sentiment measures with a set of fundamental control variables used in Sibley et al. (2016) and Ruan et al. (2020). The control variables include three-month Treasury bill rate (TBR), monthly unemployment rate (UR), monthly consumer price index (CPI), monthly term spread (TS), monthly consumption (MS), monthly industrial production (IP), Exchange rate (ER) and Central bank reserve ratio (CRR) into control variables. for China and the US.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SSE	CSI300	DJI	IXIC	SSE	CSI300	DJI	IXIC
$DSI_{G,t-1}$	-0.008	-0.010*	-0.009*	-0.015*				
	[-1.14]	[-1.77]	[-1.83]	[-1.90]				
$DSI_{G,t-2}$	0.003	0.003	0.014*	0.011*				
	[0.32]	[0.35]	[1.78]	[1.82]				
$DSI_{C,t-1}$					-0.012*	-0.015*		
					[-1.70]	[-1.87]		
$DSI_{C,t-2}$					0.003	0.003		
					[0.32]	[0.35]		
$DSI_{U,t-1}$							-0.010**	-0.014**
							[-2.05]	[-2.08]
$DSI_{U,t-2}$							0.010*	0.013**
							[1.84]	[2.01]
$Return_{t-1}$	0.073	0.032	0.033	0.091	0.054	0.014	0.044	0.071
	[0.52]	[0.33]	[0.14]	[0.93]	[0.38]	[0.11]	[0.56]	[0.87]
$Return_{t-2}$	-0.201	-0.212	-0.138*	-0.082	-0.197	-0.179	-0.135*	-0.078
	[-1.52]	[-1.38]	[-1.81]	[-1.23]	[-1.51]	[-1.40]	[-1.76]	[-0.97]
TBR_{t-1}	0.021	0.018	0.017**	0.016**	0.017	0.020	0.012**	0.014**
	[0.79]	[0.91]	[2.21]	[2.37]	[0.79]	[0.91]	[2.02]	[2.01]
UR_{t-1}	0.021	0.005	-0.009	-0.027	-0.013	-0.015	-0.019	-0.017
	[0.23]	[0.34]	[-1.31]	[-1.43]	[-0.62]	[-0.74]	[-1.41]	[-1.03]
TS_{t-1}	-0.002	-0.006	-0.008	-0.017	-0.004	-0.005	-0.012	-0.016
	[-0.89]	[-0.72]	[-1.32]	[-1.21]	[-0.70]	[-0.92]	[-1.17]	[-1.27]
MS_{t-1}	0.002	0.041	-0.004	-0.003	0.009	0.011	-0.002	-0.001
	[1.11]	[1.39]	[-0.56]	[-0.47]	[1.05]	[1.22]	[-0.16]	[-0.23]
IP_{t-1}	-0.038	-0.029	-0.013*	-0.012*	-0.027	-0.028	-0.015*	-0.017*
	[-1.25]	[-1.07]	[-1.81]	[-1.82]	[-1.45]	[-1.46]	[-1.76]	[-1.82]
CPI_{t-1}	0.027**	0.022**	0.008	0.011	0.023**	0.024**	0.007	0.009
	[2.22]	[2.41]	[1.11]	[1.13]	[2.28]	[2.27]	[1.11]	[1.13]
ER_{t-1}	0.013	0.004	0.018	0.023	0.014	0.012	0.009	0.016
	[1.52]	[1.32]	[1.02]	[1.35]	[1.48]	[1.26]	[1.41]	[1.19]
CRR_{t-1}	0.018*	0.014	0.019*	0.021*	0.014*	0.016*	0.012*	0.011
	[1.77]	[1.52]	[1.82]	[1.71]	[1.90]	[1.76]	[1.89]	[1.32]
Constant	0.005	-0.001	0.008**	0.011**	0.007	0.002	0.009**	0.013**
	[0.73]	[-0.45]	[2.34]	[2.16]	[0.41]	[1.34]	[2.42]	[2.16]
N	132	132	132	132	132	132	132	132
R^2	0.146	0.149	0.163	0.167	0.168	0.165	0.162	0.166

Table 4.5: Disaster-induced sentiment and market returns: Control for investor sentiment

In this table, we regress Chinese and the US market returns on the corresponding disaster sentiment measures with investor sentiment control variables. Chinese investor sentiment measure (S_{HL}) constructed by Han and Li (2017). The US investor sentiment measure (S_{BW}) constructed by Baker and Wurgler (2006). The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2011 to December 2021.

	(1)	(2)	(3)	(4)
	SSE	CSI300	DJI	IXIC
$DSI_{C,t-1}$	-0.014*	-0.017**		
	[-1.83]	[-2.03]		
$DSI_{C,t-2}$	0.008	0.004		
	[1.19]	[0.73]		
$DSI_{U,t-1}$			-0.010*	-0.014**
			[-1.94]	[-2.08]
$DSI_{U,t-2}$			0.010*	0.013**
			[1.84]	[2.01]
$S_{HL,t-1}$	0.011	0.012*		
	[1.54]	[1.70]		
$S_{HL,t-2}$	0.004	0.007		
	[0.85]	[0.57]		
$S_{BW,t-1}$			-0.024*	-0.018*
			[-1.76]	[-1.88]
$S_{BW,t-2}$			0.044	0.031
			[1.46]	[1.51]
Control	Yes	Yes	Yes	Yes
N	132	132	132	132
R^2	0.150	0.162	0.201	0.189

Table 4.6: Disaster-induced sentiment and market returns with subsample

In this table, we regress Chinese and the US market returns on the corresponding disaster sentiment measures excluding the crisis periods. For the Chinese market, we exclude the periods which are from January 2015 to December 2015 (Chinese stock market disaster) and January 2020 to December 2021 (COVID-19 epidemic) in column (1), (2), (5) and (6). For the US market, we exclude the period from January 2020 to December 2021 (COVID-19 epidemic) in column (3), (4), (7) and (8). The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SSE	CSI300	DJI	IXIC	SSE	CSI300	DJI	IXIC
$DSI_{G,t-1}$	-0.010	-0.013*	-0.011*	-0.012**				
	[-1.34]	[-1.90]	[-1.91]	[-2.03]				
$DSI_{G,t-2}$	0.001	0.005	0.014**	0.009*				
	[0.41]	[0.79]	[1.99]	[1.72]				
$DSI_{C,t-1}$					-0.014**	-0.017*		
					[-2.11]	[-2.34]		
$DSI_{C,t-2}$					0.002	0.004		
					[0.32]	[0.35]		
$DSI_{U,t-1}$							-0.012**	-0.016**
							[-2.34]	[-2.36]
$DSI_{U,t-2}$							0.011**	0.012*
							[2.03]	[1.81]
$Return_{t-1}$	0.101	0.073	0.123	0.098	0.067	-0.043	0.055	0.08
	[1.52]	[1.33]	[0.89]	[0.87]	[0.32]	[-0.14]	[0.66]	[0.92]
$Return_{t-2}$	-0.003	-0.092	-0.038	-0.034	-0.047	-0.056	-0.098	-0.064
	[-0.23]	[-0.89]	[-0.31]	[-1.01]	[-1.81]	[-1.14]	[-1.21]	[-0.76]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	96	96	108	108	96	96	108	108
R^2	0.140	0.137	0.152	0.147	0.155	0.160	0.159	0.153

Table 4.7: Disaster-induced sentiment and industries' returns

In this table, we regress industries' returns in the Chinese and the US stock market on the corresponding disaster sentiment measures. In Panel A, there are 16 industries in China according to China Securities Regulatory Commission industry classification in 2012. In Panel B, we obtain 10 industries' index returns in the US market from Refinitiv database. The *t*-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A: Chinese industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mining	Utility	Realestate	Construction	Transportation	Education	Finance	Technology
$DSI_{C,t-1}$	-0.022**	-0.018*	0.003	-0.024**	-0.018**	-0.004	-0.002	-0.028**
	[-2.26]	[-1.88]	[0.19]	[-2.32]	[-2.11]	[-1.11]	[-1.04]	[-2.24]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	132	132	132	132	132	132	132	132
R^2	0.161	0.153	0.070	0.148	0.155	0.065	0.048	0.164
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Agriculture	Environment	Sanitation	Entertainment	IT	Manufacturing	Foodservice	Service
$DSI_{C,t-1}$	-0.039**	-0.010*	-0.001	-0.002	-0.004	-0.014*	-0.007	-0.004
	[-2.42]	[-1.83]	[-0.29]	[-0.38]	[-0.49]	[-1.85]	[-0.42]	[-0.75]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	132	132	132	132	132	132	132	132
R^2	0.143	0.132	0.061	0.048	0.053	0.128	0.072	0.078

Panel B: US industry

	(1)	(2)	(3)	(4)	(5)
	BasicMaterials	Cyclicals	Energy	Financials	Healthcare
$DSI_{U,t-1}$	-0.021***	-0.033***	-0.024***	-0.022**	-0.029***
	[-3.02]	[-2.87]	[-2.84]	[-2.17]	[-3.01]
Control	Yes	Yes	Yes	Yes	Yes
N	132	132	132	132	132
R^2	0.177	0.181	0.179	0.169	0.165
	(6)	(7)	(8)	(9)	(10)
	Industrials	NonCyclical	Technology	Telecomm	Utilities
$DSI_{U,t-1}$	-0.031**	-0.017**	-0.021**	-0.033**	-0.005
	[-2.33]	[-2.25]	[-2.10]	[-2.29]	[-0.56]
Control	Yes	Yes	Yes	Yes	Yes
N	132	132	132	132	132
R^2	0.143	0.147	0.149	0.157	0.122

Table 4.8: Disaster-induced sentiment and stock returns in different provinces

In this table, we aggregate stock returns weighted by market capitalization in each province of China to obtain 31 time series of province-index returns. We construct $DSI_{P,t-1}$ based on search volume of disaster-related terms and province-index returns in each province. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Anhui	Beijing	Chongqing	Fujian	Gansu	Guangdong	Guangxi	Guizhou	Hainan	Henan	Heilongjiang
$DSI_{P,t-1}$	-0.006	-0.014*	-0.006	-0.012*	0.006	-0.013*	-0.016**	-0.014**	-0.016*	-0.005	-0.007
	[-0.61]	[-1.84]	[-0.72]	[-1.85]	[0.07]	[-1.69]	[-2.21]	[-2.29]	[-1.79]	[-0.45]	[-1.32]
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	132	132	132	132	132	132	132	132	132	132	132
R^2	0.043	0.125	0.045	0.131	0.052	0.134	0.135	0.155	0.127	0.042	0.027
	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	
	Hebei	Hubei	Hunan	Jilin	Jiangsu	Jiangxi	Liaoning	Neimenggu	Ningxia	Qinghai	
$DSI_{P,t-1}$	-0.015*	-0.011*	-0.009	-0.007	-0.017*	-0.016*	-0.020*	-0.001	0.009	-0.002	
	[-1.86]	[-1.84]	[-0.80]	[-0.40]	[-1.95]	[-1.72]	[-1.84]	[-0.11]	[1.62]	[-0.27]	
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
N	132	132	132	132	132	132	132	132	132	132	
R^2	0.031	0.148	0.045	0.051	0.138	0.135	0.139	0.036	0.078	0.020	
	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	
	Shaanxi	Shandong	Shanxi	Shanghai	Sichuan	Tianjin	Xizang	Xinjiang	Yunnan	Zhejiang	
$DSI_{P,t-1}$	-0.023**	-0.015**	-0.004	-0.021**	-0.011	-0.017*	-0.011	-0.005	-0.016**	-0.018**	
	[-2.17]	[-2.06]	[-0.52]	[2.32]	[-1.42]	[-1.75]	[-1.01]	[-1.18]	[-2.12]	[-2.17]	
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
N	132	132	132	132	132	132	132	132	132	132	
R^2	0.172	0.175	0.019	0.166	0.041	0.146	0.032	0.011	0.155	0.181	

Table 4.9: Disaster-induced sentiment and stock returns in regions with unique features

In this table, we aggregate stock returns weighted by market capitalization in coastal and inland provinces of China to obtain coastal-index and inland-index returns. Liaoning, Heibei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi and Hainan are the coastal provinces, the rest are the inland provinces. We aggregate stock returns weighted by market capitalization in provinces with five highest GDP (Guangdong, Jiangsu, Shandong, Zhejiang and Henan) and provinces with five lowest GDP (Gansu, Hainan, Ningxia, Qinghai and Xizang) of China to obtain High-GDP index and Low-GDP index returns. We construct DEI_{Co}, DEI_I, DEI_H, DEI_L based on search volume of disaster-related terms in corresponding regions. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)
	Coastal	Inland	High GDP	Low GDP
$DSI_{Co,t-1}$	-0.018*			
	[-1.85]			
$DSI_{I,t-1}$		-0.008		
		[-0.97]		
$DSI_{H,t-1}$			-0.015**	
			[-2.01]	
$DSI_{L,t-1}$				-0.002
				[-0.54]
Control	Yes	Yes	Yes	Yes
N	132	132	132	132
R^2	0.182	0.042	0.188	0.039

Appendix

Table 4.A1: Search Terms Used for Google Trends and Baidu Index

Highlighted several terms are not recorded by search engine due to a small number (less than 10) of search frequency.

Panel A: Disaster-related terms		Panel B: Disaster-event terms	
Google	Baidu	Google	Baidu
DISASTER	灾难	DISASTER	灾难
EARTHQUAKE	地震	EARTHQUAKE	地震
CYCLONE	飓风	CYCLONE	飓风
TRAUMA	挫折	HURRICANE	台风
CRISIS	危机	TORNADO	龙卷风
HURRICANE	台风	TWISTER	旋风
MESS	肮脏	FLOOD	洪水
CHAOS	混乱	**WRECK**	**沉船**
DESTRUCTION	破坏	EPIDEMIC	传染病
RUIN	毁灭	FIRE	火灾
TORNADO	龙卷风	STORM	风暴
TRAGEDY	悲剧	RAINSTORM	暴雨
TWISTER	旋风	DROUGHT	干旱
FLOOD	洪水	HEAT	高温
WRECK	**沉船**	FROST	霜冻
DANGER	危险	**SLEET**	**冻雨**
PROBLEM	问题	FREEZE	**结冰**
ACCIDENT	意外	SNOWSTORM	暴风雪
EPIDEMIC	传染病	HAIL	冰雹
AWFUL	**糟糕**	THUNDER	雷电
CRASH	坠毁	FOG	雾
FIRE	火灾	SMOG	烟雾
HORRIBLE	可怕	ACID RAIN	酸雨
STORM	风暴	AIR CRASH	空难
TROUBLE	麻烦	AVALANCHE	雪崩
RAINSTORM	暴雨	MUDSLIDE	泥石流
DROUGHT	干旱	TSUNAMI	海啸
HEAT	高温		
FROST	霜冻		
SLEET	**冻雨**		
FREEZE	**结冰**		
SNOWSTORM	暴风雪		
HAIL	冰雹		
THUNDER	雷电		
FOG	雾		
SMOG	烟雾		
ACID RAIN	酸雨		
AIR CRASH	空难		
AVALANCHE	雪崩		
MUDSLIDE	泥石流		
TSUNAMI	海啸		

Table 4.A2: Disaster-event sentiment and market returns around the world

In this table, we regress market returns from 10 countries on the global disaster-event sentiment measures which are constructed by disaster-event terms in Panel B of Table A1. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2011 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SSE	CSI300	DJI	IXIC	Netherlands	Austria	France	England	Germany	Canada	Korea	Japan
$DSI_{G,t-1}$	-0.011*	-0.014*	-0.010*	-0.013**	-0.015***	-0.010*	-0.014**	-0.015**	-0.007	-0.015**	-0.015**	-0.010
	[-1.87]	[-1.80]	[-1.94]	[-2.04]	[-2.80]	[-1.88]	[-2.08]	[-2.26]	[-0.93]	[-2.25]	[-2.58]	[-1.40]
$DSI_{G,t-2}$	0.004	0.007	0.010*	0.011*	0.012**	0.008	0.013**	0.011	0.009	0.014**	0.014**	0.010
	[1.14]	[0.86]	[1.84]	[1.75]	[2.20]	[1.55]	[2.01]	[1.62]	[1.31]	[2.03]	[2.34]	[1.51]
$Return_{t-1}$	0.141*	0.219**	0.044	0.085	0.039	0.178**	0.070	0.091	0.102	0.075	0.131	0.138*
	[1.73]	[2.44]	[0.56]	[1.05]	[0.47]	[2.20]	[0.87]	[1.10]	[1.23]	[0.92]	[1.63]	[1.73]
$Return_{t-2}$	-0.066	0.043	-0.135*	-0.137*	-0.101	0.048	-0.078	-0.001	-0.059	-0.069	-0.084	0.158*
	[-0.82]	[0.51]	[-1.76]	[-1.69]	[-1.27]	[0.59]	[-0.97]	[-0.01]	[-0.70]	[-0.86]	[-1.06]	[1.95]
Constant	0.005	0.001	0.009**	0.003	0.003	0.002	0.013***	0.006	0.006	0.015***	0.005	0.004
	[1.15]	[0.15]	[2.43]	[0.78]	[0.90]	[0.63]	[2.89]	[1.51]	[1.26]	[3.24]	[1.43]	[0.88]
N	132	132	132	132	132	132	132	132	132	132	132	132
R^2	0.035	0.037	0.052	0.044	0.031	0.048	0.052	0.046	0.030	0.036	0.059	0.014

Table 4.A3: Disaster-induced sentiment and market returns: Control for the frequency of disaster events

In this table, we regress Chinese and the US market returns on the corresponding disaster sentiment measures with the control variable of the monthly frequency of disaster outbreak. The seven types of disasters are recorded in Global Natural Disaster Information Database, which are geological disaster, meteorological disaster, marince disaster, flood disaster, crops disasters, forest disasters and astronomical disasters. The monthly frequency of disaster outbreak in the US (FD_U) and China (FD_C) are collected by summing the number of seven types of disasters in each month. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2015 to December 2021.

	(1) SSE	(2) CSI300	(3) DJI	(4) IXIC
$DSI_{C,t-1}$	-0.014*	-0.017**		
	[-1.83]	[-2.03]		
$DSI_{C,t-2}$	0.008	0.004		
	[1.19]	[0.73]		
$DSI_{U,t-1}$			-0.010*	-0.014**
			[-1.94]	[-2.08]
$DSI_{U,t-2}$			0.010*	0.013**
			[1.84]	[2.01]
$FD_{C,t-1}$	-0.008	-0.006		
	[-1.37]	[-1.25]		
$FD_{C,t-2}$	0.002	0.004		
	[0.15]	[0.74]		
$FD_{U,t-1}$			-0.007	-0.005
			[-1.03]	[-1.11]
$FD_{U,t-2}$			0.006	0.005
			[1.38]	[1.21]
Control	Yes	Yes	Yes	Yes
N	83	83	83	83
R^2	0.121	0.118	0.129	0.127

Table 4.A4: The number of companies in province

This table reports the number of companies whose corporate headquarters are located in certain province. The ST (special treatment) and PT (particular transfer) stocks are excluded in our sample.

Province	No. of companies	Province	No. of companies
Anhui	123	Jiangxi	72
Beijing	328	Jinlin	45
Chongqin	52	Liaoning	63
Fujian	103	Neimenggu	30
Gansu	35	Ningxia	16
Guangdong	589	Qinghai	11
Guangxi	38	Shandong	195
Guizhou	35	Shaanxi	64
Hainan	32	Shanxi	42
Heilongjiang	30	Shanghai	423
Heibei	61	Sichuan	156
Henan	103	Tianjin	55
Hubei	90	Xinjiang	57
Hunan	137	Xizang	20
Jiangsu	489	Yunnan	39
		Zhejiang	422
		Sum	3955

Table 4.A5: Disaster-related search term in province

In this table, we list the most negatively significant search term in each province by regressing returns of province on all time series of search volume in the whole sample period.

Province	Search term	Province	Search term
Anhui	rainstorm (暴雨)	Jinlin	hail (冰雹)
Beijing	disaster (灾难)	Liaoning	crisis (危机)
Chongqin	heat (高温)	Neimenggu	heat (高温)
Fujian	tornado (龙卷风)	Ningxia	rainstorm (暴雨)
Gansu	disaster (灾难)	Qinghai	disaster (灾难)
Guangdong	tornado (龙卷风)	Shandong	crisis (危机)
Guangxi	crisis (危机)	Shaanxi	drought (干旱)
Guizhou	twister (旋风)	Shanxi	heat (高温)
Hainan	cyclone (飓风)	Shanghai	hurricane (台风)
Heilongjiang	snowstorm (暴风雪)	Sichuan	earthquake (地震)
Heibei	hurricane (台风)	Tianjin	twister (旋风)
Henan	flood (洪水)	Xinjiang	drought (干旱)
Hubei	crisis (危机)	Xizang	snowstorm (暴风雪)
Hunan	rainstorm (暴雨)	Yunnan	drought (干旱)
Jiangsu	hurricane (台风)	Zhejiang	hurricane (台风)
Jiangxi	crisis (危机)		

Table 4.A6: Finance-unrelated sentiment and stock returns

Based on another four kinds of search terms (pollution, weather, holiday and sport) in constructing finance-unrelated sentiment in Gao et al. (2020), we collect search data from Google Trends separately and construct the global pollution-related sentiment ($Pollution_G$), the global weather-related sentiment ($Weather_G$), the global holiday-related sentiment ($Holiday_G$) and the global sport-related sentiment ($Sport_G$) by using the method that we measure our diasaster sentiment. The "terror" part is excluded since its associated words are less than ten. We then regress Chinese and the US market returns on the corresponding sentiment measures, respectively. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2011 to December 2021.

Panel A	(1)	(2)	(3)	(4)	Panel B	(1)	(2)	(3)	(4)
	SSE	CSI300	DJI	IXIC		SSE	CSI300	DJI	IXIC
$Pollution_{G,t-1}$	-0.015*	-0.012*	-0.011*	-0.013*	$Weather_{G,t-1}$	-0.009*	-0.011**	-0.023**	-0.015**
	[-1.79]	[-1.90]	[-1.74]	[-1.88]		[-1.88]	[-2.03]	[-2.29]	[-2.16]
$Pollution_{G,t-2}$	0.005	0.006	0.029*	0.023*	$Weather_{G,t-2}$	0.010	0.022	0.021*	0.019*
	[0.34]	[0.86]	[1.84]	[1.75]		[1.40]	[1.65]	[1.91]	[1.85]
$Return_{t-1}$	0.141*	0.219**	0.052	0.073	$Return_{t-1}$	-0.046	0.026	-0.009	-0.093
	[1.73]	[2.64]	[0.56]	[1.05]		[-0.57]	[0.31]	[-0.11]	[-1.17]
$Return_{t-2}$	-0.046	0.034	-0.127*	-0.188*	$Return_{t-2}$	-0.085	-0.087	-0.146*	-0.105
	[-0.82]	[0.56]	[-1.86]	[-1.79]		[-1.07]	[-1.09]	[-1.79]	[-1.35]
Constant	0.004	0.002	0.011***	0.001	Constant	0.003	0.026***	0.012*	0.004
	[1.24]	[0.28]	[2.68]	[0.91]		[0.44]	[2.67]	[1.92]	[0.58]
R^2	0.039	0.044	0.047	0.053	R^2	0.034	0.048	0.055	0.051

Panel C	(1)	(2)	(3)	(4)	Panel D	(1)	(2)	(3)	(4)
	SSE	CSI300	DJI	IXIC		SSE	CSI300	DJI	IXIC
$Holiday_{G,t-1}$	0.007	0.008*	-0.009	-0.013	$Sport_{G,t-1}$	-0.013*	-0.021	-0.006	-0.003
	[1.37]	[1.75]	[-1.39]	[-1.39]		[-1.78]	[-1.47]	[-1.02]	[-0.27]
$Holiday_{G,t-2}$	0.009	0.020**	0.010	0.009	$Sport_{G,t-2}$	0.009	0.014	0.017	0.001
	[0.70]	[2.20]	[1.59]	[1.05]		[1.22]	[1.00]	[1.07]	[0.07]
$Return_{t-1}$	-0.030	0.144*	-0.052	0.041	$Return_{t-1}$	-0.020	0.060	-0.011	-0.061
	[-0.37]	[1.84]	[-0.65]	[0.52]		[-0.24]	[0.68]	[-0.13]	[-0.71]
$Return_{t-2}$	-0.021	-0.150*	-0.045	-0.069	$Return_{t-2}$	-0.032	-0.052	-0.125	-0.040
	[-0.25]	[-1.92]	[-0.55]	[-0.87]		[-0.39]	[-0.61]	[-1.46]	[-0.47]
Constant	0.003	0.006	0.011***	0.009*	Constant	0.003	0.020*	0.009	0.005
	[0.49]	[1.31]	[3.22]	[1.96]		[0.49]	[1.71]	[1.20]	[0.88]
R^2	0.021	0.031	0.023	0.020	R^2	0.021	0.025	0.023	0.020

Table 4.A7: Stationary tests

This table presents the results of time-series unit root tests for the monthly disaster-induced sentiment measures. Two different methods of unit root and stationarity tests, Augmented Dickey Fuller (ADF) test and Phillip-Perron (PP) test, are employed to examine whether the DSI_C, DSI_U and DSI_G are unit root stationary. The Schwarz information criterion (SIC) is chosen in determining the lag length and individual intercepts are included in the test.

Unit root and stationarity tests	DSI_C		DSI_U		DSI_G	
	Test statistic	p-value	Test statistic	p-value	Test statistic	p-value
ADF test	-9.05	0.00	-7.36	0.00	-7.72	0.00
PP test	-5.25	0.00	-5.92	0.00	-6.11	0.00

Table 4.A8: Disaster-induced sentiment and market returns: Control for disaster risk

In this table, we regress Chinese and the US market returns on the corresponding disaster sentiment measures with the control variable of disaster risk. The natural disaster risk measures (D_{Natu}) is constructed by Chen et al. (2022) based on the co-movement between the front-page news coverage of the natural disasters in Wall Street Journal and options implied volatility. The t-statistics are based on Newey-West (1987) standard errors adjusted for autocorrelation. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 2011 to March 2016.

	(1)	(2)	(3)	(4)
	SSE	CSI300	DJI	IXIC
$DSI_{C,t-1}$	-0.014*	-0.017**		
	[-1.83]	[-2.03]		
$DSI_{C,t-2}$	0.008	0.004		
	[1.19]	[0.73]		
$DSI_{U,t-1}$			-0.010*	-0.014**
			[-1.94]	[-2.08]
$DSI_{U,t-2}$			0.010*	0.013**
			[1.84]	[2.01]
$D_{Natu,t-1}$	0.008	0.003	0.013*	0.015**
	[1.37]	[1.25]	[1.82]	[2.11]
$D_{Natu,t-2}$	0.002	0.004	0.013	0.015
	[0.15]	[0.74]	[0.28]	[0.69]
Control	Yes	Yes	Yes	Yes
N	63	63	63	63
R^2	0.121	0.118	0.129	0.127

Chapter 5
Conclusion

Investor sentiment is closely tied to the asset pricing area. Understanding investor sentiment is crucial for both theoretical asset pricing and practical investment. By understanding sentiment, investors can make more informed decisions, achieve better returns and manage risk more effectively. This thesis constructs various investor sentiment measures and examines their applications in asset pricing based on the whole market, specific stocks and disaster events.

The second chapter documents the collective predictability of investor sentiment for the aggregate stock market in China. To obtain the accurate estimate of the unobservable sentiment, it is necessary to aggregate data from various sources. We measure the aggregate investor sentiment by using four types of data: market-, survey-, text- and search-based data from 2008 to 2019. We find that the aggregate investor sentiment measures can significantly and positively predict the monthly market excess returns, both in-sample and out-of-sample. By contrast, individual sentiment proxies have limited predictability. The predictive power of aggregate sentiment is still present after considering economic variables and other existing sentiment measures. Besides, the sizable economic profits for mean-variance utility investors can be derived from the strong predictability of aggregate sentiment.

Our study highlights the important role of investor sentiment in the Chinese stock market. The positive predictive power indicates that the effect of investor sentiment tends to persist in the short term, which is inconsistent with the findings in the developed market that investor sentiment are considered as a contrarian predictor with the short-term reversal. More research is needed to show whether this is the case in other emerging markets.

The third chapter builds stock-specific sentiment measures by aggregating disagreement based on the number of positive and negative comments in each stock. The comments are demonstrated to affect investor trading decisions and have an impact on subsequent stock returns in the cross-sectional analysis. The study investigates the asset pricing implications of the sentiment measure for stock returns in the Chinese market from 2008 to 2020. We reveal that stocks with high sentiment significantly outperform those with low sentiment in the formation month, and the better performance persists in following months. The results are robust after controlling for popular firm characteristics and return predictors. We also provide evidence of the profitability of a trading strategy that involves long positions in high-sentiment stocks and short positions in low-sentiment stocks, while taking into account short selling restrictions and transaction costs.

The fourth chapter constructs novel disaster-induced sentiment measures based on disaster-related search data in Google and Baidu search engines and examines their predictive power on stock returns. Interestingly, we find our disaster-induced sentiment measures negatively and significantly predict the market excess returns in the next month. However, the forecasting power is relatively short-lived for up to one month. After taking consideration of economic and disaster-related variables, the negative predictability is not subsumed which suggests our sentiment measures contain incremental predictive information. Moreover, negative predictive power of disaster-induced sentiment also exhibits in the large part of industries. In China, the impact of this sentiment varies widely across regions. It is particularly strong in the coastal and developed areas.

As shown in this thesis, we find the sentiment proxies that are well studied in developed stock markets have differential or negligible effect on the Chinese stock market. The underlying explanations may be that this emerging market has different trading environment and unsophisticated investors proportion. Besides, there is a lack of studies that build Chinese-featured sentiment proxies at higher frequency. Therefore, future studies can construct daily sentiment measures by exploring high frequency data in China. In addition, understanding the stochastic process of sentiment is crucial for maximizing its potential use in solving the utility maximization problem in China, which can significantly increase the economic value of sentiment-based trading.

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