

Review

Online public opinion and asset prices: a literature review

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Abstract: We review the research work undertaken to explore how online public opinion information through social media and news media affects asset prices. First, it summarizes the measurement of online public opinion from three aspects: data source of online public opinion, textual sentiment analysis, and measurement of online public opinion index. Second, it puts forward the related theoretical basis of the research on online public opinion and asset price such as the noise trading theory, arbitrage limitation demonstrations, limited attention assumption and divergence models, etc. Third, it summarizes the three transmission channels through which online public opinion affects asset prices: investor attention, investor perceptions, and investor sentiment. Last, it looks deeply into the area and classifies the empirical literature according to various sources of online public opinion chosen by the researcher. Therefore, this exploratory work contributes to the existing literature by introducing the first systematic review.

Keywords: online public opinion; asset prices; internet news media; internet social media

JEL Codes: G15, C81, G41

1. Introduction

With the rapid development of Internet information technology, the influence of online public opinion in finance and economics has grown consistently over the last decades. According to Hootsuite, the well-known social media management platform, the number of global Internet users has reached nearly 4.66 billion, accounting for more than half of the total population (Kemp & Simon, 2020). The Digital Global Overview Reports published by Hootsuite and We Are Social show that connected technology has become a more indispensable part of people's lives in the past few years. According to

their report in January 2021, although the COVID-19 has a significant impact on the number of Internet users, there are still as many as 4.20 billion online social media users worldwide, and in the past 12 months, this number has increased by 490 million, delivering year-on-year growth of more than 13%. Driven by big data technology, online public opinion has an increasingly significant impact on the cognitive sentiments and investment decisions of participants in the financial market, which in turn affects the financial market.

Active literature studies the relationship between online public opinion and asset price. According to the traditional “efficient market” hypothesis (Fama, 1970), the asset price should immediately and completely reflect changes in underlying fundamentals, while a large amount of theoretical and empirical evidence shows that asset prices and fundamentals are often continuously disconnected. Since the end of the 20th century, scholars have gradually discovered many “market anomalies” that contradict the efficient market hypothesis. For example, LeRoy & Porter (1981) and Shiller (1981) find that the actual volatility of asset prices is much greater than the volatility determined by fundamental factors such as interest rates, consumption, and dividends in the short-term period. Campbell (1999) calls this phenomenon “the mystery of asset price volatility”. Researchers have made numerous efforts to understand asset price, such as optimizing financial econometric models, gradually relaxing assumptions based on the efficient market theory, or introducing behavioral financial analysis methods. In recent years, relevant research has gradually explored online public opinion under the new media environment, in an attempt to interpret assets price from the perspective of market information and sentiment. For example, Mitchell & Mulherin (1994) find that the number of news announcements reported daily by Dow Jones & Company is directly related to securities market activity including trading volume and market returns. Compared with traditional public opinion, online public opinion involves larger samples, longer duration, and richer content, providing a broader perspective for asset price research.

The Internet has profoundly changed the way of life of human society, bringing great convenience to human interaction and the acquisition and dissemination of information, making the earth a true “global village”. It has gradually become the core platform for the generation, fermentation, and outbreak of public opinion. The rapid exchange of public opinion information on the Internet has changed the global capital market. Research shows that, under the strong influence of online public opinion, rather than relying on expert advice, individual investors are more inclined to actively follow other investors using social media or news media. Fisk et al. (2011) adopt the “grounded theory” approach to conducting an in-depth qualitative analysis of crowdfunding cases and found that project creators can share ideas, information, and opinions through online discussions to attract potential investors from various social media platforms. Luo & Zhang (2013) employ the vector autoregression with exogenous variables to examine the dynamic effects, interaction effects, and market competition effects. Their empirical results support the dynamic relationships of Web traffic and consumer buzz with firm value. Studies have shown that social media information, like microblogging metrics, can predict stock return comovement (Liu et al., 2015).

The Internet has also changed the relationship between individuals and news. In short, it is a shift from “I look for news” to “News find me”. From traditional paper-based news to current Internet news, the timeliness, authenticity, influence, and profitability of news are different from the past. In recent years, scholars have obtained sentiment indicators through text analysis of media content (such as newspaper columns, message boards, blogs, and Google search results), and fully proved that there is a close relationship between media sentiment and asset prices (Antweiler & Frank, 2004; Tetlock, 2007; Da et al., 2015). More importantly, the information from online news sources has high-frequency characteristics,

which has significant advantages for asset price returns and volatility forecasting (Joseph et al., 2011; Liew & Budavári, 2016; Shen et al., 2017, 2018; Li et al., 2018; Coqueret, 2020; Audrino et al., 2020). Scholars have introduced many large and novel data sets, including social media, news reports and search engine data, etc., and used the stock return or volatility calculated from high-frequency intraday data to investigate whether online public opinion contains predictive asset prices. Scholars have introduced many large and novel data sets, including social media, news reports and search engine data, etc., and used the income or volatility calculated from high-frequency intraday data to investigate whether online public opinion contains useful information for asset prices forecasting. For instance, Audrino et al. (2020) find that even after controlling a large number of economic and financial variables, the internet sentiment and attention variables obtained from financial news articles, social media, information consumption, and search engine data sources have predictive power for future stock volatility.

Plenty of work has been conducted to study the capital market reaction to the information dissemination and emotional contagion of online public opinion and to explore the underlying mechanism. However, the relationship between online public opinion and asset prices is still an emerging research field. This research aims to provide a more in-depth and comprehensive understanding of the research work, which focuses on the area of the capital market's response to online public opinion. This article focuses on the relationship between the capital market and online public opinion and attempts to systematically organize literature available in this field to evaluate the current situation of the research. The purpose of this study is to explore the theoretical mechanism of the influence of online public opinion on asset prices and to provide a comprehensive bibliography on the response of the capital market to online social media and online news media. Furthermore, it also suggests the prospects of future research on the topic of Internet public opinion and asset prices.

The rest of this article is structured as follows. Section 2 contains the relevant literature on the measurement method of online public opinion, Section 3 provides the theoretical framework, Section 4 discusses the empirical research on the impact of network public opinion on asset price, Section 5 consists of conclusions and future research directions.

2. Measurement of online public opinion

With the complexity, randomness, and variability of the network environment, the extensive coverage of network public opinion reflects the social sentiment and public opinion and deeply affects the attitude and consciousness of the public. How to effectively obtain key information from complex online public opinion has become a top priority. The effective measurement of online public opinion is the prerequisite and basis for studying the relationship between online public opinion and asset prices. Public opinion is usually regarded as the aggregate of feelings, wishes, attitudes, and opinions of individuals in a particular social group about public affairs with media as the carrier (Converse, 1987). In the new media environment, the process of informatization is getting faster and faster, and computers and mobile phones have become popular, which has greatly broadened the channels for people to express themselves. In addition, in the period of economic and social transformation, various social conflicts have emerged one after another, so online public opinion has never been so prosperous as it is today (Liu et al., 2017). This paper first summarizes the measurement of online public opinion from three aspects: data source of online public opinion, textual sentiment analysis, and measurement of online public opinion index.

2.1. The data source of online public opinion

Numerous studies have explored the influence of online public opinion information on asset price and the main sources of online public opinion data include search engine indexes and text data. Nowadays, search engines provide capital market participants with a simple and low-cost way to access information (Dastgir et al., 2018). Therefore, the search volume of keywords that can reflect online public opinion can be regarded as a potential indicator associated with asset prices (Hamid & Heiden, 2015; Andrei & Hasler, 2015; Meng et al., 2016). For instance, Bank et al. (2011) and Kim et al. (2019) conclude that the Google Search Volume Index is closely related to stock prices and can effectively predict stock price volatility in the short term. Mao et al. (2012) and Ackert et al. (2016) show that the keywords search volume data provides a more accurate prediction for asset price than the traditional survey-based market sentiment data. Fang et al. (2020) use the search volume of relevant keywords from Baidu, China's leading search engine, for investor sentiment. They conclude that similar to the findings from existing literature based on Google Trends data, the Baidu index can also help predict stock price volatility especially during periods of economic fluctuations.

Analyzing asset prices using text data by Information and Communication Technology methods has become more popular in recent years. Researchers have explored various sources of online public opinion information such as Internet financial news articles, Internet stock forums, microblogging websites, etc. The data mining and text processing technology opened the door to the quantitative analysis of online public opinion and promoted the research of online public opinion and asset prices to a new level. It involves discovering the emotions hidden in the online public opinion text information through specialized semantic analysis. Researchers use various machine learning algorithms to obtain sentiment data from Internet news, discussion forums, Twitter, Facebook, etc., to study the impact of online public opinion on financial markets (Rao & Srivastava, 2013; Leitch & Sherif, 2017; Wang & Wang, 2017; Nasseri et al., 2018; Chen et al., 2018; Meng et al., 2019). Text data not only allows us to understand the popularity of online public opinion but also can in-depth reflect the information of dimensions such as sentiment and disagreements. For example, Li et al. (2019) find that textual sentiment and disagreement indexes for China's stock market can predict future market returns, volatility, and trading volume. Due to its diverse sources, huge volume, and high data frequency, text data has become the key data source for online public opinion research.

2.2. Textual sentiment analysis

Stone et al. (1966) describe that words and sentences are the essence of human beings, the products, and experiences of social construction, and they provide the necessary evidence for financial activities and behaviors. By analyzing the raw data of words and sentences, scholars have become more and more proficient in discovering emotions in online public opinion texts. The most common content analysis methods in text sentiment literature are dictionary-based methods and machine learning (Yu, 2013; Wang & Wu, 2015; Bandhakavi et al., 2016; Xu & Gao, 2017). Li (2010) defines Dictionary-based methods as a mapping algorithm in which a computer program reads text and classifies words, phrases, or sentences according to predefined dictionary categories. The dictionary-based method has two important issues: the word lists containing keywords for each emotion category and the weighting method of each word in the word list. The word lists commonly used in the existing literature include the General Inquirer (GI) word lists (Stone et al., 1966), Harvard word lists,

DICTION 5.0 (Hart, 2001), and the Loughran-McDonald(L&M) lists. More importantly, the dedicated financial word list has also been developed. For example, Loughran & McDonald (2011) develop an alternative negative word list that can better reflect the tone of the financial text. They linked the textual sentiment variable with other financial variables such as asset returns, trading volume, return volatility, and so on. Most literature uses proportional weighting, which means that every word in the list is considered equally important. However, some scholars have argued about it. For example, Jegadeesh & Wu (2013) propose a weighting scheme that is particularly suitable for finance applications.

Text sentiment analysis based on machine learning is the pioneer of mathematicians and computer scientists. This method relies on statistical techniques to infer the content of documents and classify them based on statistical inference. Researchers have used various machine learning algorithms for the research of online public opinion. Antweiler & Frank (2004) adopt the Naive Bayesian algorithm within the Rainbow package to classify more than 1.5 million internet stock messages. They proved that the information content of Internet stock message boards is statistically significant for asset price prediction. Mittermayer (2004) uses the NewsCATS (News Categorization and Trading System), which automatically analyzes and categorizes press releases to “Good News” and “Bad News” by the “Support Vector Machines” (SVM) algorithm, for intraday stock price trends forecasting. Mukwazvur & Spreethi (2015) employ the Support Vector Machine and K-Nearest Neighbour (kNN) algorithms for sentiment analysis of news comments. Their experimental results show that SVM performs better. In addition, there is a body of research there is a large amount of research focused on using ready-made software for “sentiment analysis” or “idea mining” of online public opinion (Tetlock, 2007; Tetlock et al., 2008; Schumaker et al., 2012). But these sentiment analysis systems are designed based on machine learning technology.

2.3. Measurement of online public opinion index

The online public opinion index refers to a reasonable measurement of various dimensional variables in the index system based on the sentiment analysis of online public opinion texts through comprehensive evaluation technology. Antweiler & Frank (2004) study whether the information content of internet stock message boards can contribute to the prediction of market volatility, and comprehensively considered the information of different dimensions of the message, including the quantity, emotional tendency, and degree of disagreement. Gao et al. (2011) construct the public opinion monitoring index-system through Analytic Hierarchy Process (AHP) based on information broadcasting mechanisms in micro-blogging. Zhang et al. (2011) propose an index system method to estimate the heat degree of online public opinion for an unexpected emergency. Liu & McConnell (2013) reconstructed the media attention and media tone indicators in their empirical studies and found that when deciding whether to abandon an impaired acquisition attempt, the sensitivity of the manager’s response to the company’s stock price in the announcement is affected by media attention and media tone of the proposed transaction. Chen et al. (2017) present a novel method of trend prediction and evaluation of online public opinion by the fuzzy comprehensive evaluation model. Lee & Kim (2021) introduce an SDG Social Index to measure and evaluate the outspoken feelings and opinions of the public toward the Sustainable Development Goals. However, when analyzing the relationship between online public opinion and asset prices, most researchers only consider one or a few aspects of online public opinion. Few studies can compile a scientific online public opinion index based on quantitative and qualitative information and analyze its impact on the financial market.

3. Theoretical research on online public opinion and asset prices

3.1. The related theoretical basis

As the basic framework of traditional finance, the efficient market hypothesis proposed by Fama (1970) holds that if the market is strictly effective, there will be no market friction and no information asymmetry, and then asset price will respond to new information on time. The efficient market theory has been supported by extensive empirical research evidence. However, in recent years, scholars have discovered more and more empirical research evidence that contradicts the theory of efficient markets, called “market anomalies” (Merton, 1973; Kim and Mei, 2001; Schneider & Troeger, 2006). Merton (1987) put forward the hypothesis of investor cognition based on the equilibrium model of the capital market, that is, investors have different understandings of different stock information, and only willing to buy stocks that they understand, so investors’ cognition will affect stock prices. In other words, as investors increase new information disseminated by Internet media, it will lead to an increase in current and forward returns on stocks. Some scholars have found that the price of small stocks is highly responsive to good news and low to bad news, and empirical studies in the US and Asian markets have reached a consensus (McQueen et al., 1996; Chang et al., 1999; Barberis et al., 2005).

In recent years, scholars have begun to pay attention to the relationship between public opinion and the special market anomaly of excessive volatility in financial asset prices. Investors’ behavioral decisions are not rational. Investors’ cognition, emotions, personality variables, social interaction, interpersonal communication, and many other factors can affect their investment decisions (Feng & Seasholes, 2004; Kumar & Lee, 2006; Ivković & Weisbenner, 2007; Kaustia & Knüpfer, 2012; Tauni et al., 2017; Kudryavtsev, 2017; Su & Liao, 2019; Uddin, 2020; Awan, 2021). Meanwhile, the noise trading theory and arbitrage limitation demonstrations, as well as limited attention and divergence models have provided theoretical support for the influence of online public opinion on asset prices (De Long et al., 1989; Hubalek & Schachermayer, 2001; Corwin & Coughenour, 2008; Chatterjee et al., 2012; Li et al., 2019). Existing research has explored the quantitative and qualitative information of online public opinion, and has reached a consensus on the importance of online public opinion to the price of financial assets.

3.2. Transmission channels between online public opinion and asset price

Under the incomparable communication power of modern Internet media, public opinion information is rapidly and widely diffused, which greatly affects investors’ attention, emotional bias, and psychological cognition, which affects investors’ subjective judgments and investment decisions, and ultimately causes fluctuations in asset prices. This article combines classic finance and behavioral finance theories, and sort out the relevant literature in this area from three aspects: investor attention, investor perceptions, and investor sentiment.

3.2.1. Investor attention channel

Investor attention is the primary transmission channel through which online public opinion affects asset prices. The current online media platform promotes the integration of netizens and retail investors. Online public opinion can not only quickly reflect the interest and concern of market entities, but also

occupy most of the attention resources. Internet public opinion information subtly affects the value concept of investors, investor decision-making, and transaction methods, and ultimately affects asset prices. Based on the limited attention theory, scholars have found that the “secondary dissemination” of market information through online media has attracted more investors’ attention and affected their investment behavior. This is the direct channel through which online public opinion affects asset prices (Hong & Stein, 1999; Liu, 2014; Li et al., 2018). Existing empirical evidence also shows that online public opinion can attract the attention of investors. The “framework dependence deviation” formed by investors on online public opinion information has a significant impact on investors’ behavioral decisions, which in turn will affect asset prices (Savor & Wilson, 2013). Andrei & Hasler (2015) investigate the joint role of investors’ attention to news and learning uncertainty in determining asset prices by a theoretical approach. They showed theoretically that the increasing relationship between investor attention and asset price is quadratic.

3.2.2. Investor sentiment channel

The information and tendentious opinions conveyed by online public opinion spread widely in the online community, which will affect investors’ psychological cognition and investment decision-making. Investor perceptions refer to return expectations, risk tolerance, and risk perception of individual investors. Recent studies have shown that investor psychology has a continuing impact on trading and risk-taking behavior (Barber & Odean, 2001). Hoffmann et al. (2013) find that during the financial crisis from 2008 to 2009, investors’ perceptions fluctuated greatly, leading to changes in trading and risk-taking behavior. Hoffmann et al. (2015) show that investors with higher levels of risk perception are more likely to trade, have higher turnover, larger amounts per transaction, and use derivatives. Martin (2019) concludes that information format one of the main factors affecting investor perception. The rapid dissemination and development of online public opinion have changed the way investors obtain information, which has a subtle impact on investor perception. Although some studies hold that investor perception is an important channel for online public opinion to affect asset prices, related theoretical studies are still relatively scarce.

3.2.3. Investor sentiment channel

Another transmission channel through which online public opinion affects asset prices is investor sentiment. Some scholars measured investor sentiment by mining online public opinion information, and then conclude that there is a close correlation between investor sentiment and asset prices (Rao & Srivastava, 2013; Nofer & Hinz, 2015). Yang & Zhang (2013) propose an asset pricing model that includes investor sentiment and information and found that investor sentiment has a systematic and significant impact on the asset price. This theoretical model can partially explain some financial anomalies: price bubbles, high volatility, momentum effects, and reversal effects of asset prices. By forming a financial community within the Twitter universe, Yang et al. (2015) find that influential Twitter users provide a proxy for the relationship between social sentiment and financial market movement. Füss et al. (2020) introduce a new sentiment-augmented asset pricing model and found that news and social media search-based indicators are significantly related to excess returns of the asset price. Adding the emotional factor of online public opinion to the classic pricing model and the latest pricing model will result in a significant improvement in model performance. Jiao et al. (2020)

proposed a theoretical model of asset pricing where social media acts as an “echo chamber”. Their theoretical and empirical analysis showed that online public opinion of social media and news media predicted increases in volatility and turnover.

4. Empirical research on online public opinion and asset prices

Theoretical literature reviews related to online public opinion and asset prices focus on conceptual definitions, theoretical frameworks, grounded theory, etc., while empirical literature reviews focus on previous research findings that we want to study, compare and cite, such as the reliability and validity of the impact of online public opinion on asset prices, the correlation between the two and the strength of the relationship. Theoretical and empirical literature are related because when we study, compare, and cite theoretical content, we may need to do the same for empirical content. Therefore, this paper will integrate both theoretical and empirical studies to provide an in-depth analysis of the literature related to online public opinion and asset prices.

Many studies have provided considerable empirical evidence that online public opinion does affect asset price worldwide (Tetlock, 2007; Fang & Peress, 2009; Loungrian & McDonald, 2011; Chen et al., 2018; Kruse, 2020). Researchers have explored the relationship between various sources of online public opinion such as Internet search volume, Internet financial news articles, Internet stock forums, microblogging websites, and asset prices. This section looks deeply into the area and classifies the literature according to various sources of online public opinion chosen by the researcher.

4.1. *Public opinion from Internet news media and asset price*

Most of the literature in this area can be grouped into two broad categories concerning the technique used by the researchers to explore the relationship between public opinion from Internet news media and asset price: 1) quantitative techniques (i.e. number of Internet news articles; 2) text processing techniques. It is a traditional approach to explore the relationship between the number of Internet news articles and asset prices through quantitative techniques. Many studies use the number of online news as a direct indicator to predict financial market activity such as asset return and trading volume. Mitchell & Mulherin (1994) is the first to study the relation between the number of news announcements and security market activity such as trading volume and market returns. They found that the number of news announcements reported daily by Dow Jones & Company is directly related to market activity, but their observed relation is not particularly strong. Chan (2003) uses a comprehensive sample of headlines for large companies to test the impact of public news on stock returns. The result confirms that investors appear to underreact to public signals but overreact to perceived private signals. Fang & Peress (2009) find that mass media can alleviate informational frictions and affect stock pricing even if it does not supply genuine news by collecting data from the number of media coverage. Alanyali et al. (2013) find that movements in the daily number of financial news and movements in the daily transaction volume are intrinsically interlinked. Since they have provided quantitative support for Internet financial news and financial markets, a large number of scholars have researched this area, and the relevant empirical evidence is abundant.

Although most researchers pay attention to the public opinion from Internet news media of the overall market and its relationship with asset returns and trading volume, the impact of Internet news on asset volatility has also attracted the attention of scholars. Berry & Howe (1994) adopt the number

of news releases by Reuter's New Service to measure public information. They found a positive relationship between public opinion information and trading volume and an insignificant relationship with asset price volatility. But some scholars have found the opposite conclusion. For example, Aman & Moriyasu (2017) find that media coverage can reduce stock volatility but the firm-released disclosure information tends to increase total stock volatility. After decomposing the stock volatility into the different components by the generalized dynamic factor model, Qiao & Su (2020) find that the impact of online media coverage on the market-driven volatility component appears to be U-shaped, but the influence on the idiosyncratic volatility component is negative. This shows that for the Chinese capital market, the main role played by the public opinion from Internet news media depends on different market trends. Zhang et al. (2021) employ the number of news articles on the Baidu News platform to measure information arrival and found a positive impact of public opinion from Internet news media on the conditional volatility of stock returns.

Due to the continuous progress of text processing techniques, the research of public opinion from Internet news media and asset price has been greatly developed. This method can reveal the hidden emotions in Internet news through specialized semantic analysis, making relevant research no longer limited to the quantitative level. Under this approach, empiricists have constructed measures for a public opinion from Internet news media using a variety of textual data, including general news (Wuthrich et al., 1998; Jin et al., 2013), financial news (Peramunetilleke & Wong, 2002; Mittermayer, 2004; Soni et al., 2007; Tetlock et al., 2008; Schumaker et al., 2012), company news (Fung et al., 2003), market-sector news (Zhai et al., 2007), macroeconomic news (Chatrath et al., 2014), broker newsletters (Lugmayr & Gossen, 2012), etc. The burgeoning literature on public opinion from Internet news media and asset price is fueled by the increasing availability of computational tools for data collection and natural language processing. Compared with survey-based or market-based approaches, public opinion measures for Internet news media through text processing techniques are more primitive and often available at a higher frequency. However, constructing public opinion measures by text processing techniques is not easy. Because the textual online public opinion datasets are not readily available from the standard financial databases. Gathering the massive online public opinion datasets is costly and technically difficult, which means that applied economists in this area need to master and improve the current computational tools.

4.2. *Public opinion from Internet social media and asset price*

The rapid development of Internet social media has promoted the integration of the two main bodies of netizens and investors. Behavioral finance has been committed to studying the relationship between investor sentiment and asset price movements. Measuring investor sentiment through Internet social media data and quantifying the impact of public opinion from Internet social media on asset price has become a new challenge in this field. Social media (including Internet message boards, stock forums, Twitter, Facebook, and other online platforms) are playing an increasingly important role.

4.2.1. Internet search volume

Numerous studies have employed internet search volume of various platforms such as Google search, Baidu search, America Online (AOL) as a proxy for the online public opinion from social media. Mondria et al. (2010) are the first to adopt internet search volume from AOL to measure

investors' attention. They found empirical evidence of a causality relationship between home bias and investors' attention. Da et al. (2011) adopt the Google Search Volume Index (GSVI) to measure investor attention. They compared this new measure with the traditional measures of investor attention (turnover, extreme returns, news, advertising expense, etc.) and found that SVI captures the attention of investors better and more directly. They also observed that the increase of search volume index indicates that the stock price index will rise in the next two weeks. Since then, GSVI and SVI of other Internet search platforms have become more and more popular. Studies have provided abundant empirical evidence that Internet search volume is closely related to asset price (Ap et al., 2014; Ruan & Zhang, 2016; Klemola et al., 2017; Zhang et al., 2021).

4.2.2. Internet stock message boards

Many capital market participants devoting a considerable amount of time and effort to create, read or spread public opinion information on internet stock message boards. Recent studies such as Antweiler & Frank (2004) and Leung & Ton (2015) show that Internet stock message boards can move markets. The effect of public opinion information from internet stock message boards on asset returns and volatility is statistically significant. The amount of information on online message boards is large, the information dissemination speed is fast, and the number of participants is large. At present, it has become an important place for retail investors to share investment experiences and obtain useful information. Wysocki (1998) studies the 50 companies with the largest number of forum posts from January to August in 1998 and found that the number of forum posts had a significant predictive effect on the trading volume and excess return of the next day. Jones (2006) use stock message data of 87 listed companies of S&P 100 from the website of yahoo.com to find that the daily trading volume of each stock has increased significantly since the establishment of the online message board, which indicates that either new investors are attracted, or the present investors trade more frequently. Delort et al. (2009) use the post data of a famous forum in Australia and found that there was a significant positive correlation between hype and earnings, volatility and trading volume, and there was information manipulation on the message board. Sabherwal et al. (2011) test the relationship between the company's stock without fundamental information release and the online message board and found that online investors have stock manipulation mode, which indicates that the stock message board is a herding mechanism driving the price up temporarily. Jones (2006) use the firms' message boards on Yahoo! Finance and found that daily trading volume increased significantly after a firm's internet message board was established. More importantly, daily stock returns were significantly lower in the post-message boards era. Li et al. (2018) use the data from the Chinese stock market and found that idiosyncratic volatility significantly increased after Internet stock message boards were established. The result indicated that internet stock message boards can convey firm-specific information. Using Growth Enterprise Market firms in China's Shenzhen Stock Exchange as a research sample, Yang et al. (2020) find that internet individual investors' sentiments expressed in the internet stock forum may lead to abnormal trading and even impose significant effects on asset price crash.

4.2.3. Facebook and twitter

Facebook, Twitter, and other social media have become so pervasive that they have become the public square to share opinions on investment decisions. Many studies have been conducted to

investigate the impact of online public opinion, as explained by social activities on Facebook and Twitter, over the asset markets. Smailović et al. (2014) show that public sentiment expressed in stock-related Twitter feeds can indicate stock price movements by adapting the Support Vector Machine sentiment classifier and the Granger causality test. Danbolt et al. (2015) proxy daily sentiment based on Facebook status updates across international markets and found that the relationship between investor sentiment and firm-specific bidder announcement abnormal returns is significantly positive. Siganos et al. (2017) measure the divergence of sentiment daily by using data from status updates on Facebook and found a significantly positive relation between sentiment divergence and stock price volatility. By adopting event study methodology and Python specifications, Leitch et al. (2017) show that Twitter sentiment on the announcement of CEO succession in the UK and USA has a negative contemporaneous relationship with stock returns. Behrendt & Schmidt (2018) discover statistically significant co-movements of individual-level stock return volatility and Twitter sentiment from the high-frequency perspective. But the high-frequency stock-related Tweets information is not particularly useful for stock return forecasting. Understanding human emotions through written messages can be very complicated, and further research is needed to discover newer methods to comprehensively explore online public opinions expressed on Facebook and Twitter to predict asset price trends.

4.3. Online public opinion from various sources and asset price

Many studies have combined online public opinion from various sources and investigated their combined effect on the asset price. Yu et al. (2013) investigate the effect of social media (blogs, forums, and Twitter) and conventional media (major newspapers, television broadcasting companies, and business magazines) on companies' short-term stock market performances. They found the impact of public opinion from different types of media varies significantly. Their study is among the first to examine the heterogeneous influence of various sources of conventional and social media on asset price. Liu & Ye (2014) find that self-initiated or news-driven Internet search volume collected from Baidu Index is more likely to generate buy or sell pressure. Audrino et al. (2020) find the impact of sentiment and attention measures from social media, news articles, information consumption, and Google search volume contains additional predictive power for realized volatility of asset price. When unexpected announcements or breaking news occurs, online public opinion from various sources such as micro-blogging, search engines, and financial news articles, etc. can significantly improve stock volatility forecasting. According to observations, many researchers emphasize that online public opinion information has greatly changed the behavior of investors. With the current increasing popularity of smartphones in the arena, further research can be conducted to explore the impact of online public opinion information from mobile applications on asset prices.

5. Conclusions

This article reviews the research work undertaken to explore how online public opinion information through social media and news media affects asset prices. This section discusses some of the observations from this survey and outlines the characteristics of existing literature in this field. Some technical challenges and research gaps have also been raised, requiring further contributions from researchers.

With the rapid development of Internet information technology, the influence of online public opinion in finance and economics has grown consistently over the last decades. This article focuses on the relationship between online public opinion and asset prices. After reviewing the papers, it can be found that the number of studies exploring the impact of online public opinion information on asset price trends has grown tremendously. The decline in technology costs and the penetration of online public opinion in human life can be proved by the increase in the number of Internet users and the popularity of social media, which may be the reason for the increase in interest of researchers in this field. First, this paper summarizes the measurement of online public opinion from three aspects: data source of online public opinion, textual sentiment analysis, and measurement of online public opinion index. Second, it puts forward the related theoretical basis of the research on online public opinion and asset price such as the noise trading theory, arbitrage limitation demonstrations, limited attention assumption and divergence models, etc. Third, this article combines classic finance and behavioral finance theories, summarizes the three transmission channels through which online public opinion affects asset prices: investor attention, investor perceptions, and investor sentiment. Last, it looks deeply into the area and classifies the empirical literature according to various sources of online public opinion chosen by the researcher.

So far, the main part of the research work has focused on online public opinion to improve the predictability of asset prices and decrease the volatility of asset returns. Further research can discover the potential nonlinearity of online public opinion variables on asset prices, and investigate in more detail the heterogeneity of the impact of online public opinion data of different companies, periods, or time frequencies on asset prices.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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