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THE IMPACT OF THE INFODEMIC ON THE STOCK MARKET UNDER THE COVID-19: TAKING THE INVESTORS' INFORMATION INFECTION INDEX AS THE INTERMEDIARY VARIABLE

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Abstract. The outbreak of COVID-19 is synchronized with the outbreak of the infodemic, which directly affected the sentiment and behaviours of investors and thus affected the stock market. At the same time, the outbreak of the infodemic has led to the information infection of the public. With the information infection, panic, anxiety, and other emotions have spread among the public, affecting the behaviours of investors, and thus affecting the stock returns. This paper explores the impact of the infodemic on the stock market by selecting keywords related to the "epidemic situation", using the Baidu information index as an indicator to measure the infodemic, and the Baidu search index as an indicator to measure the degree of information infection. The empirical findings reveal that: First, the more serious the infodemic, the more severe the information infection; Second, the deeper the infodemic, the lower the stock returns of A-share listed companies; Third, there is a phenomenon that the infodemic affects the stock returns through the intermediary of information infection in the stock market.

Keywords: COVID-19, infodemic, information infection, emotional contagion, intermediary effect.

JEL Classification: G41.

Introduction

Like other major public health events, the outbreak of novel coronavirus pneumonia (hereinafter referred to as COVID-19) has had a significant impact on the economy of China and even the world. Existing literature has comprehensively analyzed the financial risk contagion effect of the epidemic and the cross-market contagion phenomenon of the global stock mar-

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ket from the macroeconomic perspective (Yang et al., 2020; He et al., 2020). He et al. (2020) proposed that the main path of the impact of the COVID-19 epidemic on China's economy is the supply and demand structure, import and export trade, purchasing manager index, and economic prosperity index, as well as the public psychology and behavior. They also believed that the epidemic had an impact on the financial market that cannot be ignored, with the emphasis on the impact on the stock market, bond market, and foreign exchange market. Many scholars have studied the impact of COVID-19 on the stock market. For example, Wang et al. (2020) studied the impact of the epidemic on the stock market from the perspective of daily new cases and found that the increase of the daily new confirmed cases would lead to changes in investor sentiment and make the stock price fall on the same day, and the more serious the epidemic, the faster the stock price fell. Chen and Qu (2020) also used the number of people infected with COVID-19 to measure the severity of epidemic, and found that there was an inverted U-shaped relationship between death cases and confirmed cases and stock returns, which was consistent with the conclusion that there was a U-shaped relationship between the epidemic and stock price fluctuations found by Wang et al. (2020). Lan and Zhuang (2021) constructed the COVID-19 development index by the number of new infections, and the cumulative number of confirmed and cured people, and studied the phased impact of the epidemic on the stock market. Tian et al. (2020) studied the impact of information diffusion of the COVID-19 epidemic on the yield and volatility of concept stocks such as "residential economy" from the perspectives of investors' attention, macro, meso, and micro. Wen and Li (2022) studied the impact of the COVID-19 on stock price fluctuations from the perspective of epidemic prevention and control in combination with investor sentiment. Lu and Xing (2022) also studied the relationship between the recovery phase of major public health events and stock price bias based on investor sentiment differentiation.

Most of the above literature uses the number of confirmed cases and deaths to describe the severity of the epidemic and to study the impact of the epidemic on the stock market. However, an outbreak of the epidemic brings not only a threat to people's physical health but also a threat to their mental health. In the all-media era, various reports on novel coronavirus and the epidemic have swept all corners of the network, and the infodemic has followed. Blendon et al. (2004) found that the loss caused by information uncertainty and panic is no less than the epidemic itself. Liu and Wang (2020) and Zhang et al. (2020) used the medical SEIR model to simulate the spread of rumors and emotions. They believed that the spread of rumors and emotions was like the spread of infectious diseases, and it is necessary to analyze the spread dynamics of epidemic infectious diseases and the impact of various behaviors on the epidemic situation. In behavioral finance, emotion is an important factor that affects people's investment behavior. Many kinds of literature have incorporated emotion into the factors that affect the prices of stocks and other financial instruments (Lu & Chen, 2020; Li & Wu, 2020). As a result, from the perspective of the infodemic of COVID-19, this paper links the infodemic with people's emotions, explores the relationship between the infodemic, investor behavior, and stock returns, to help people more fully understand the relationship between the outbreak of public health events and the stock market.

The contributions of this paper mainly include the following aspects: First, judging from the information at the time of the outbreak of major public health events, this paper uses the

Baidu information index to measure the severity of the infodemic, explores the relationship between the infodemic and the stock returns of A-share listed companies, and studies the relationship between the stock returns of 19 industries of A-share and the infodemic and the information infection according to the industry classification standard of China Securities Regulatory Commission. It finds that the more serious the infodemic, the lower the stock returns. Second, this paper refers to the information behavior theory (Wilson, 2020) and the SEIR model (Liu & Wang, 2020; Zhang et al., 2020), which defines information infection and information infectors, and finds that the deeper the degree of information infection of investors, the lower the return rate of shares. Third, through the summary of many relevant literatures, the mechanism of the impact of infodemic on the stock market is given, and the phenomenon of the intermediary role of information infection in the stock market is confirmed, too.

The structure of this paper is arranged as follows: Section 1 is literature review and hypothesis; Section 2 is the research design, introducing the sample source, variable definition, and empirical model; Section 3 reports and analyzes the empirical results of the impact of infodemic on the stock returns; Section 4 further studies the impact mechanism of the infodemic on the stock market; The final section is Conclusions and countermeasures.

1. Literature review and hypothesis

1.1. Infodemic and information infection

During the outbreak of SARS in 2003, Rothkopf (2003) used the word "infodemic" for the first time, which is composed of information and pandemic/epidemic, and is interpreted as "some facts mixed with fear, speculation and rumors are rapidly amplified and spread worldwide by modern information technology, affecting national and international economy, politics and even security in a way completely inconsistent with the original reality". The World Health Organization (WHO) pointed out that there was an infodemic during the "COVID-19" epidemic. Eppler and Mengis (2004) found that information overload is one of the most common manifestations of the infodemic, and it is a state where an individual's information processing capacity is insufficient to meet the huge information processing demand. Wang et al. (2019b) proposed that information overload affects users' negative behaviors through user burnout and psychological resistance. In the context of the COVID-19 epidemic, rumors, gossip, and various reports spread rapidly through the Internet and other communication technologies. The information on the epidemic, which is mixed in good and bad, exceeds the information processing capacity of users, resulting in a cognitive burden, making it difficult for people to find trustworthy information sources and reliable guidance. Some literature summarized the propagation characteristics of "infodemic": exponential propagation speed, massive propagation objects, network decentralization, effect epidemic, overload of information, the universality of strategy, cross-domain of space, social media, difficulty in identifying authenticity, effect harmfulness, more channels of release, stronger interactive communication, lack of gatekeepers, etc. (Xu & Qian, 2020; Zhang & Huang, 2020; Wang, 2020).

The outbreak of the COVID-19 epidemic is accompanied by the spread of various relevant information. Many scholars proposed that the public's fear of epidemic infectious diseases is positively related to the amount of disease-related knowledge they have, that is, the more information they receive about the epidemic, the more people will feel fear (Latiff et al., 2012; Ahmad et al., 2016; Iliyasu et al., 2015). Therefore, the most intuitive consequence of the "infodemic" is to trigger public anxiety and irrational fear, even large-scale social panic, and ultimately have a destructive impact on social stability (Xu & Qian, 2020; G. M. Leung & K. Leung, 2020; Zhang & Huang, 2020; Chen et al., 2020b). Undoubtedly, during the outbreak of the infodemic, all kinds of reports related to the epidemic are the carriers of media emotions, which will affect the emotions of the information recipients. You and Wu (2012) found that when the media sentiment conveyed by news reports is too high or too low, the stock price will deviate from the basic value level. He et al. (2020) further studied and found that the fear and anxiety of investors caused by the epidemic may stimulate investors to sell stocks, leading to fluctuations in the stock market. Therefore, this paper proposes:

Hypothesis 1 (H1): The infodemic is negatively correlated with the stock returns of listed companies.

In fact, the spread of rumors and panic on social networks is very similar to that of epidemic infectious diseases. If not controlled, rumors will cause panic in the short term and lead to the peak of herding behavior. Wei used the medical infectious disease model (SEIR) to study the transmission mechanism of information and network public opinion (Wei et al., 2019). Liu and Wang (2020) further combined the SEIR model with rumors and panic emotions and divided the crowd into four categories to analyze the generation of herding behavior: The first category is susceptible group who are unaware of rumors; The second category is the latent group, that is, those who hear rumors but do not participate in herding; The third category is infected group, that is, people who are affected by panic and participate in herding; The fourth category is the convalescent group who have seen through rumors or have completed herding.

Based on the above literature, this paper uses the SEIR model to define "information infection" and "information infected person". According to the definition of Xinhua Dictionary, "infection" generally refers to viral infection, that is, pathological reaction and damage to the body caused by invasion and growth of pathogenic microorganisms and parasites. A pathogen invades another organism through a certain route from an infectious source, and it also refers to arousing the same thoughts and feelings of others through language or other forms. In this paper, "information infection" refers to the process of further continuous and excessive attention to relevant information, expressed as active search behavior on the Internet, caused by exposure to the environment of excessive information, which can lead to changes in the psychological state and behavior of information search subjects. The information search subject here is referred to as "information infected person" in this paper. Different from Liu and Wang's (2020) description of infected people, this paper refers to Wilson's (2000) viewpoint of information behavior and believes that information behavior refers to the sum of all information resources and information acquisition channels in human behavior, including not only positive and negative information-seeking behavior but also information utilization behavior. Therefore, the information infection defined in this paper is not only an infection rumor, but also includes the infection of a large amount of real information related to the epidemic situation, that is, the infection of all information related to the COVID-19 epidemic. Based on the above analysis of the literature related to the infodemic, this paper proposes:

Hypothesis 2 (H2): The infodemic situation is positively correlated with the degree of information infection.

1.2. Information infection and emotional infection

American psychologist McDougall (1923) first proposed emotional contagion. Since then, there are many definitions of emotional contagion. It can be roughly considered as an emotional experience caused by other people's emotions and matched with other people's emotions. It is a process of emotional transmission.

When the infodemic causes information infection, the information-infected people will be infected by the emotions carried by the information at the same time. Zuckerman (1984) showed in behavioral research that emotion is an important factor that affects people's decision-making. Wang et al. (2019a) found that during the epidemic period, factors such as death probability, news reports, and epidemic experience can affect investor sentiment, and then trigger unintentional herding behavior. Bikhchandani and Sharma (2001) divided herding behavior into intentional herding behavior and unintentional herding behavior. Unintentional herding is closely related to emotional contagion. It refers to the phenomenon that members of a group take similar behaviors when facing the same problems and information sets. It is mainly caused by emotional factors. After contacting the same public information, individuals are likely to have similar emotions and show highly consistent decision-making behavior. During the epidemic of COVID-19, people were exposed to the information related to the epidemic through various social media and were infected by the information. Under the effect of the same information, it is very easy to generate similar emotions and amplify the emotional experience of individuals in the process of communication through social media (Wang et al., 2017). The greater the intensity of group emotions, the more obvious the group emotion transmission behavior (Zhang et al., 2020), which further promoted the occurrence of herding behavior.

Sun and Xiao (2018) elaborated on emotional contagion among investors, indicating that online emotional contagion is strong. The Internet makes social interaction between investors more convenient and accelerates the contagion of investors' emotions. Luo et al. (2018) pointed out that investors in the capital market are not independent individuals, they will communicate and learn from each other, and investor sentiment contagion will further affect the capital price in the financial market. Based on the review of the infodemic, information infection, and emotional infection-related literature, this paper believes that the infodemic makes people suffer from information infection, and information infection is one of the sources of people's emotions in this epidemic. This paper will start from the information infection which is the source of public emotion, to explore the relationship between information infection and the stock market and put forward hypothesis:

Hypothesis 3 (H3): The degree of information infection is negatively correlated with the stock returns of listed companies.

2. Study design

2.1. Data source and sample selection

On January 20, 2020, the National Health Commission announced that COVID-19 would be included in the Class B infectious disease stipulated in the Infectious Disease Prevention and Control Law, and that Class A infectious disease prevention and control measures would be taken. As a result, COVID-19 began to attract widespread attention. Therefore, the starting time of this study is January 20, 2020. Through the observation of the "epidemic situation" information index and search index data from Figure 1, it is found that the information epidemic phenomenon mainly exists before July 31, 2020. Finally, the sample time frame of this paper is from 20 January 2020 to 31 July 2020. After excluding the data of non-trading days, 128 daily sample observations are finally obtained. The data of this paper includes three parts: The first part is the data of infodemic and the data of information infection, which are respectively from the information index and the search index of the keywords related to "epidemic situation" on Baidu Index; The second part is the data of the stock returns of A-share listed companies, which come from CSMAR database; The third part is the data of the number of newly confirmed cases in Chinese Mainland, Hong Kong, Macao, and Taiwan, which is from the Wind database.

2.2. Variable definition

2.2.1. Explained variable

In the analysis of different industries, this paper takes the stock returns rate of A-share listed companies as the research object and excludes: (1) ST and * ST listed companies; (2) Financial industry companies; (3) In the absence of data samples, 405121 effective samples are finally obtained, and the above-mentioned companies are studied according to the industry classification standards of the China Securities Regulatory Commission. As shown in Table 1, CSRC divides all companies into 19 industry categories and numbers them with the letters A to S.

2.2.2. Explanatory variables

2.2.2.1. Infodemic

This paper uses the Baidu information index (IZX) of the keyword related to the word "epidemic situation" as the proxy variable of the infodemic. According to the official website of the Baidu Index, the information index reflects the attention and continuous change of news information on specific keywords on the Internet. Based on Baidu's intelligent distribution and recommended content data, the information index is obtained by weighted summation of the number of Internet users' reading, comments, forwarding, likes, dislikes, and other behaviors. That is, from the concept of information index, it can be concluded that the higher the information index, the higher the attention of news information to specific keywords on the Internet, and the more reports.

Table 1. Industry classification of CSRC

Industry Code	Industry Name
A	Agriculture, forestry, animal husbandry and fishery
B	Mining
C	Manufacturing
D	Power, heat, gas and water production and supply industry
E	Construction
F	Wholesale and retail
G	Transportation, storage, and postal services
H	Accommodation and catering
I	Information transmission, software, and information technology
J	Finance
K	Real estate
L	Leasing and business services
M	Scientific research and technology services
N	Water conservancy, environment, and public facilities management
O	Resident service, repair, and other services
P	Education
Q	Health and social work
R	Culture, sports, and entertainment
S	Comprehensive

The accurate selection of specific keywords is an important link. In the existing papers, most of them choose "COVID-19, novel coronavirus, public health emergencies, epidemic dynamics, body temperature, isolation, nucleic acid detection, etc." to measure investors' attention to the epidemic (Lu & Chen, 2020; Tian et al., 2020). However, this paper finds that in the relevant search keywords, information related to the word "epidemic situation" occupied the dominant position of relevant information. Taking 10 February 10 2020 to 16 February 2020 as an example, the number of keyword searches related to the word "epidemic situation" reached 89064400, while the frequency of search terms related to "COVID-19" is only 7617. It is obviously that inaccurate keyword selection will cause deviation in the measurement of attention. Therefore, this paper believes that the more serious the infodemic caused by COVID-19, the higher the information index of the keywords related to "epidemic situation".

At present, few papers use the Baidu information index to study the impact of information release on people's behavior. As one of the products of the COVID-19 outbreak, the infodemic is an important factor that causes public anxiety and panic and affects investors' behavior. Therefore, this paper attempts to use the Baidu information index of the keyword – "epidemic situation" as the proxy variable of the infodemic to explore the impact of the COVID-19 outbreak on the stock returns from the perspective of the infodemic.

2.2.2.2. Information infection

The Baidu search index is the degree of Internet users' attention to keyword search and its continuous change. Many kinds of literature used Baidu index data as an indicator to measure investors' attention to a certain industry, a certain plate, or a certain stock (Tian et al., 2020). However, as a non-investment application software, the Baidu search index is more suitable for measuring people's attention to a hot social event, that is, more people use the Baidu app as a search tool for popular science and social hot issues rather than a search tool of investment. Because of the unknown of COVID-19, the public is more inclined to capture relevant information through online real-time coverings and active searches. Therefore, it is more reasonable to use Baidu Index to measure people's attention to the public event of COVID-19. According to the definition of "information infection" in the previous paper, the process of further continuous and excessive attention to relevant information (expressed as active search behavior on the Internet) caused by exposure to the environment with excessive information, which leads to changes in the psychological state and behavior of information search subjects, corresponding to the information index keywords. In this paper, the search index (ISS) of the keyword "epidemic situation" is used as the proxy variable of "information infection" intensity. Because the absolute quantity of information index and search index is large, this paper makes a natural logarithm of them.

Referring to the research of Wang et al. (2020), this paper takes the number of newly confirmed cases in the Chinese Mainland with one-period lagged and two-period lagged, and the sum of the number of newly confirmed cases in Hong Kong, Macao, and Taiwan lagging with one-period lagged and two-period lagged as the control variables. Because the development trend of the macro-economy has a certain effect on the behavior of investors, to exclude the impact of the macrocycle, according to the research of Xiong et al. (2018), this paper selects SHIBOR as the empirical model of the control variable. In addition, this paper also refers to Tian et al. (2020) to take the logarithm of stock trading volume as the control variable. The symbols and meanings of all variables are listed in Table 2.

2.3. Empirical model

2.3.1. Infodemic (*IZX*) and information infection (*ISS*)

In order to test the relationship between infodemic (*IZX*)and information infection (*ISS*) in Hypothesis 3, this paper constructs a regression model (1), where ISS_t represents the search index measuring the degree of information infection in the period t. IZX_t is the information index representing the severity of infodemic in the period. ε_0 is the disturbance term. According to hypothesis 2, we expected β_0 to be significant positive, that is, excessive information causes excessive attention from investors.

$$\ln ISS_t = \alpha_0 + \beta_0 \ln IZX_t + \gamma_t DLXZ_{t-1} + \gamma_2 DLXZ_{t-2} + \gamma_3 GXZ_{t-1} + \gamma_4 GXZ_{t-2} + \varepsilon_0. \quad (1)$$

2.3.2. Infodemic (*IZX*) and stock returns (*R*)

In order to test the relationship between the infodemic and the stock returns of A-share listed companies in Hypothesis 1, this paper constructs a regression model (2), where $R_{i,t}$ is

Table 2. Variable definitions

	Variable	Variable meaning	Time Frame	Frequency
Explained variable	$R_{i,t}$	$R_{i,t} = \left(\begin{array}{c}\text{today's closing price } - \\ \text{yesterday's closing price}\end{array}\right) /$ yesterday's closing price × 100%, which reflects the stock returns of the ith listed companies.	20 January 2020 to 31 July 2021	Daily
Explanatory variables	*ISS*	*ISS* is the information search index, which is used to measure the degree of information infection. The search index in this paper is the result of taking the logarithm of the original value of Baidu search index.		
	IZX	*IZX* is the information index used to measure the severity of infodemic. The search index in this paper is the result of taking the original value of Baidu information index as a logarithm.		
Control variables	$DLXZ_{t-1}$	The number of newly confirmed cases in Chinese Mainland with one period lag.		
	$DLXZ_{t-2}$	The number of newly confirmed cases in Chinese Mainland with two period lags.		
	GXZ_{t-1}	The number of newly confirmed cases in Hong Kong, Macao, and Taiwan with one period lag.		
	GXZ_{t-2}	The number of newly confirmed cases in Hong Kong, Macao, and Taiwan with two periods lag.		
	SHIBOR	*SHIBOR* is the inter-bank overnight lending rate, usually overnight or within 1 to 7 days. It is the most basic and core interest rate in the developed money market.		
	CJL	It refers to the stock trading volume in a day. In this paper, the trading volume of the stock are logarithmically processed.		

the stock returns of the company in period t. It is easy to see that β_1 in the model measures the impact of the severity of the infodemic on the stock returns of A-share listed companies. Model (2) adopts the bidirectional fixed effect model of individual and time of panel data for estimation. μ_i represents the individual effect. λ_t represents the time effect. $\varepsilon_{i,t}$ represents the disturbance term.

$$R_{i,t} = \alpha_1 + \beta_1 IZXS + \gamma'_1 DLXZS + \gamma'_2 DLXZ_{t-2} + \gamma'_3 GXZ_{t-1} + \gamma'_4 GXZ_{t-2} + \gamma'_5 SHIBOR_t + \gamma'_6 \ln CJL_t + \mu_i + \lambda_t + \varepsilon_{i,t}. \quad (2)$$

2.3.3. Information infection (*ISS*) and stock returns (*R*)

In order to test the relationship between the information infection and the stock returns of A-share listed companies in Hypothesis 3, this paper constructs a regression model (3). It is easy to see that β_2 in the model measures the impact of information infection on the stock returns of A-share listed companies, and model (3) adopts the bidirectional fixed effect model of individual and time of panel data for estimation.

$$R_{i,t} = \alpha_2 + \beta_2 ISS_t + \gamma_1'' DLXZ_{t-1} + \gamma_2'' DLXZ_{t-2} + \gamma_3'' GXZ_{t-1} + \\ \gamma_4'' GXZ_{t-2} + \gamma_5'' SHIBOR_t + \gamma_6'' \ln CJL_t + \mu_i' + \lambda_t' + \varepsilon_{i,t}'. \quad (3)$$

3. Empirical analysis of the impact of infodemic on stock returns

3.1. Descriptive statistical analysis

According to the Baidu Index, on 19 January 2020, the information index of "epidemic situation" is 1.8883 million times. On the next day, after COVID-19 is confirmed to have the phenomenon of human-to-human transmission, the information index increased to 1992.3050 million times. After that, the maximum value of the information index is 943 million, and the average value is 231 million times, indicating that the amount of information about the "epidemic situation" is huge and the infodemic situation is serious. Before 20 January 2020, the search index for "epidemic situation" is only several thousand times a day, while after 20 January 2020, the maximum value is 1204900 times, and the average value is 407800 times. It shows that people have frequent active searches for "epidemic situation" and high attention to "epidemic situation", that is, the degree of information infection is serious.

Table 3 shows that from the end of January to the beginning of February 2020, the information index of the "epidemic situation" reaches the highest point. Similarly, the search index also reaches the highest point. Similarly, at the end of June 2020, the information index and the search index reach a peak at the same time. These phenomena indicate that there may be a relationship between information epidemic and information infection.

Table 3. Descriptive statistics of variables

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Information index	405121	222828800	203124300	19923050	943037600
Search index	405121	407846	244648	5531	1204940
$DLXZ_t$	405121	426	1496.6080	0	14109
GXZ_t	405121	21	33.8825	0	149

3.2. Information index and search index

From Figure 1, we can observe that the trend of the search index and the information index are highly similar. Further, from the regression results of the information index and the search index in column (1) of Table 4, the infodemic (*IZX*) coefficient is positive and significant at the level of 1%. It shows that the infodemic is positively related to information infection. The more serious the infodemic situation is, the stronger the information infection

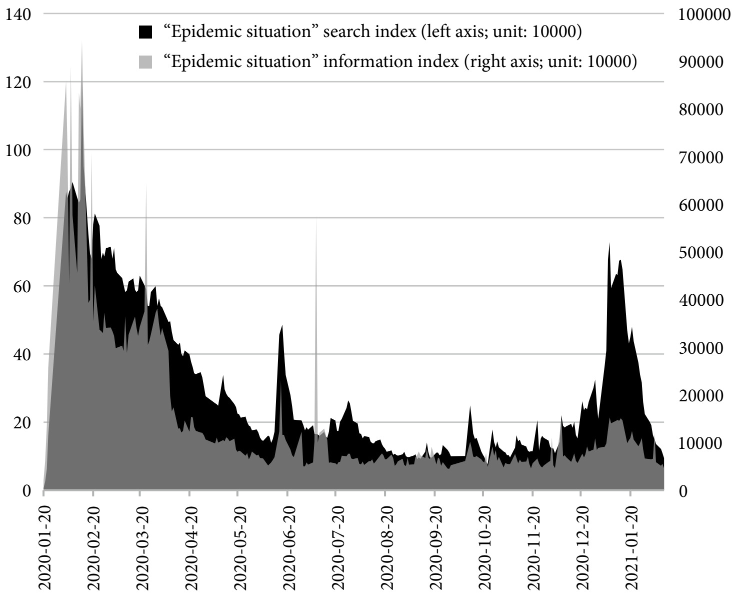

Figure 1. "Epidemic Situation" search index and information index

degree is. Hypothesis 3 is verified. This result is inconsistent with the research conclusion put forward by Chen et al. (2020a) that "information overload will cause users to have negative emotions and exaggerate the possibility of COVID-19 infection, thus causing users to have defensive psychology towards relevant information and reduce their contact behavior with information". Overall, the more frequently people search for relevant information when excessive "epidemic situation" related information appears, which does not show obvious evasion behavior.

3.3. Infodemic and stock returns

In this paper, we first conduct overall panel regression on 3265 A-share listed companies. The p-value of the Hausman test is 0.0000. We reject the random effect model and use the time individual two-way fixed effect model to estimate. Column (2) of Table 4 reports the regression results between the stock returns of all eligible A-share listed companies and the "epidemic situation" information index. The coefficient of *IZX* is significantly negative, indicating that the more serious the infodemic, the lower the return of A-share listed companies. Hypothesis 1 is verified. To deeply study the impact of the infodemic on various industries, this paper classifies these companies according to the 19 industry categories classified by the CSRC, and estimates each industry separately. According to the regression results in columns (3)~(5) of Table 4 and Table 5~Table 7, except for the residents' service, repair, and other service industries (O) which cannot estimate the results due to the insufficient number of data samples, the other 17 industry categories show that the more serious the infodemic is, the lower the stock returns rate, which again verifies hypothesis 1.

Table 4. Impact of infodemic on stock market 1

	(1)	(2)	(3)	(4)	(5)
Explained variable	*ISS*	$R_{i,t}$			
Industry Code		Whole	A	B	C
IZX	0.7530***	−0.5011***	−0.2952***	−0.3065***	−0.5220***
	(11.8620)	(−61.9474)	(−3.8454)	(−4.9100)	(−49.8983)
$DLXZ_{t-1}$	−0.0047	0.0028***	0.0012***	0.0018***	0.0029***
	(−0.1394)	(82.1410)	(3.3799)	(8.9823)	(67.4452)
$DLXZ_{t-2}$	−0.0095	−0.0056***	−0.0029***	−0.0036***	−0.0058***
	(−0.2780)	(−68.8957)	(−3.6403)	(−6.3214)	(−56.0185)
GXZ_{t-1}	1.2120	0.0056***	0.0037***	0.0037***	0.0059***
	(0.9717)	(59.2781)	(4.5015)	(5.3083)	(47.8333)
GXZ_{t-2}	−1.4250	0.0437***	0.0354***	0.0360***	0.0461***
	(−0.1898)	(55.4513)	(6.5517)	(6.9254)	(45.5237)
SHIBOR	–	0.0168***	0.0963**	0.0992***	0.0224***
	–	(4.9821)	(2.5009)	(3.9867)	(5.1292)
ln *CJL*	–	0.0070***	0.0084***	0.0084***	0.0070***
	–	(32.6230)	(7.8572)	(9.6642)	(24.4076)
Constant	−1.5150	8.2850***	4.6115***	4.7962***	8.6269***
	(−1.2795)	(61.0535)	(3.4262)	(4.4624)	(49.1315)
Individual effect	–	control	control	control	control
Time effect	–	control	control	control	control
R-square	0.6770	0.3290	0.5020	0.5060	0.3220
Observations	128	402307	4534	8132	263956
Number of Companies		3265	36	65	2136

Notes: Robust t-statistics in parentheses: *** $p < 0.01$, ** $p < 0.05$,* $p < 0.1$, similarly hereinafter.

Table 5. Impact of infodemic on stock market 2

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	D	E	F	G	H
IZX	−0.3441***	−0.5002***	−0.4856***	−0.3874***	−0.5911***
	(−12.4841)	(−12.8165)	(−12.7093)	(−11.7584)	(−4.2983)
$DLXZ_{t-1}$	0.0016***	0.0026***	0.0027***	0.0020***	0.0029***
	(11.3537)	(16.3380)	(17.5752)	(13.2087)	(4.2988)
$DLXZ_{t-2}$	−0.0034***	−0.0054***	−0.0054***	−0.0042***	−0.0063***
	(−11.2289)	(−13.3792)	(−14.5810)	(−11.7404)	(−4.4979)
GXZ_{t-1}	0.0039***	0.0056***	0.0054***	0.0044***	0.0067***
	(11.9884)	(11.7983)	(12.2842)	(11.5556)	(4.0565)
GXZ_{t-2}	0.0335***	0.0405***	0.0430***	0.0368***	0.0494***
	(11.8437)	(9.8961)	(11.8625)	(12.7153)	(3.5705)

End of Table 5

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	D	E	F	G	H
SHIBOR	0.0305**	–0.0077	0.0169	0.0354**	–0.0142
	(2.3832)	(–0.4925)	(1.0683)	(2.5335)	(–0.2175)
ln *CJL*	0.0053***	0.0066***	0.0068***	0.0063***	0.0014
	(4.9265)	(8.4011)	(7.3440)	(7.8901)	(0.5355)
Constant	5.6345***	8.3267***	8.0263***	6.3395***	9.9329***
	(12.1851)	(12.7557)	(12.4129)	(11.3304)	(4.3911)
Individual effect	control	control	control	control	control
Time effect	control	control	control	control	control
R–square	0.4410	0.4420	0.2900	0.4180	0.5240
Observations	12209	10909	17551	11513	779
Number of Companies	102	87	148	94	8

Table 6. Impact of infodemic on stock market 3

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	I	K	L	M	N
IZX	–0.5489***	–0.3477***	–0.4937***	–0.5270***	–0.5674***
	(–18.8911)	(–9.1503)	(–10.6005)	(–9.0107)	(–10.0719)
$DLXZ_{t-1}$	0.0035***	0.0021***	0.0029***	0.0027***	0.0027***
	(27.5413)	(12.3957)	(12.9815)	(10.2635)	(13.1311)
$DLXZ_{t-2}$	–0.0066***	–0.0040***	–0.0054***	–0.0056***	–0.0060***
	(–21.6006)	(–10.2822)	(–10.9536)	(–9.4697)	(–11.0904)
GXZ_{t-1}	0.0060***	0.0036***	0.0053***	0.0059***	0.0064***
	(17.1053)	(7.9070)	(9.7111)	(8.8348)	(10.0363)
GXZ_{t-2}	0.0423***	0.0240***	0.0340***	0.0493***	0.0477***
	(13.5513)	(5.6342)	(7.3813)	(8.3174)	(10.3210)
SHIBOR	–0.0151	–0.0531***	–0.0531**	0.0385	–0.0048
	(–1.3365)	(–3.1228)	(–2.4002)	(1.6223)	(–0.2311)
ln *CJL*	0.0059***	0.0063***	0.0057***	0.0079***	0.0070***
	(7.8323)	(8.3248)	(4.0290)	(4.5747)	(6.1673)
Constant	9.1743***	5.8679***	8.3261***	8.6660***	9.4428***
	(19.2757)	(9.3985)	(10.5548)	(8.8909)	(9.8149)
Individual effect	control	control	control	control	control
Time effect	control	control	control	control	control
R-square	0.4710	0.4290	0.3570	0.3770	0.4180
Observations	31440	12427	6639	5709	6797
Number of Companies	253	105	55	45	55

Table 7. Impact of infodemic on stock market 4

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	O	P	Q	R	S
IZX	−0.1694	−0.5375***	−0.6721***	−0.4624***	−0.2630*
	(.)	(−6.9628)	(−6.5324)	(−9.7771)	(−2.1963)
$DLXZ_{t-1}$	0.0011	0.0031***	0.0033***	0.0027***	0.0019**
	(.)	(6.3821)	(12.1567)	(13.9146)	(2.9616)
$DLXZ_{t-2}$	−0.0016	−0.0063***	−0.0069***	−0.0053***	−0.0030*
	(.)	(−6.7655)	(−8.0258)	(−11.4606)	(−2.1291)
GXZ_{t-1}	0.0016	0.0061***	0.0078***	0.0053***	0.0020
	(.)	(6.9668)	(6.1868)	(9.7377)	(1.1636)
GXZ_{t-2}	0.0166	0.0468***	0.0679***	0.0377***	0.0027
	(.)	(5.2190)	(5.0528)	(8.2458)	(0.1318)
SHIBOR	0.0120	0.0060	0.1175*	−0.0177	−0.1594
	(.)	(0.1631)	(2.3029)	(−0.9870)	(−1.4914)
ln *CJL*	0.0016	0.0083***	0.0107***	0.0048***	0.0073***
	(.)	(5.7099)	(8.0947)	(3.1769)	(3.4187)
Constant	2.8095	8.8936***	10.8657***	7.7174***	4.6765**
	(.)	(7.0103)	(6.3551)	(9.6915)	(2.5554)
Individual effect	control	control	control	control	control
Time effect	control	control	control	control	control
R-square	1.000	0.4920	0.4210	0.4190	0.4260
Observations	128	896	1151	6395	1142
Number of Companies	1	7	9	50	9

3.4. Information infection and stock returns

To completely explore the effect of information infection on the securities exchange, this paper also conducts A-share listed companies overall and by industry. Column (1) of Table 8 reports the regression results between the stock returns of all eligible A-share listed companies and the "epidemic situation" search index. The results show that the coefficient of ISS is significantly negative, indicating that information infection will affect people's investment behavior, thus affecting the overall stock returns of the A-share market, and this impact is adverse and will cause the stock returns to drop.

From the perspective of industries, according to the regression results in columns (2)~(5) of Table 8 and Table 9~Table 11 the regression results show that the impact of the infodemic on the stock returns is the same as that of the infodemic. The residents' service, repair, and other service industries (O) cannot be estimated due to the insufficient number of sample observations. In addition, other industries show that the deeper people's information awareness, the lower the stock returns. Hypothesis 2 is verified.

Table 8. Influence of information infection on stock market 1

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	Whole	A	B	C	D
ISS	–0.1452***	–0.0856***	–0.0888***	–0.1513***	–0.0997***
	(–61.9474)	(–3.8454)	(–4.9100)	(–49.8983)	(–12.4841)
$DLXZ_{t-1}$	0.0019***	0.0007***	0.0013***	0.0020***	0.0010***
	(85.1810)	(2.8793)	(10.8155)	(70.7915)	(9.7264)
$DLXZ_{t-2}$	–0.0035***	–0.0017***	–0.0023***	–0.0037***	–0.0020***
	(–71.7663)	(–3.4250)	(–7.2964)	(–58.7639)	(–10.1387)
GXZ_{t-1}	0.0049***	0.0033***	0.0033***	0.0051***	0.0034***
	(58.8230)	(4.5937)	(5.3630)	(47.4779)	(11.8979)
GXZ_{t-2}	0.0508***	0.0396***	0.0404***	0.0535***	0.0384***
	(57.0941)	(6.3626)	(6.7108)	(46.7736)	(12.1421)
SHIBOR	0.1622***	0.1819***	0.1881***	0.1738***	0.1303***
	(39.5865)	(5.8833)	(7.6476)	(32.9629)	(8.4992)
ln *CJL*	0.0070***	0.0084***	0.0084***	0.0070***	0.0053***
	(32.6230)	(7.8572)	(9.6642)	(24.4076)	(4.9265)
Constant	0.7876***	0.1951	0.2098	0.8168***	0.4866***
	(46.9414)	(0.9316)	(1.3900)	(37.4934)	(8.0102)
Individual effect	control	control	control	control	control
Time effect	control	control	control	control	control
R-square	0.3290	0.5020	0.5060	0.3220	0.4410
Observations	402307	4534	8132	263956	12209
Number of Companies	3265	36	65	2136	102

Table 9. Influence of information infection on stock market 2

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	E	F	G	H	I
ISS	–0.1450***	–0.1407***	–0.1123***	–0.1713***	–0.1591***
	(–12.8165)	(–12.7093)	(–11.7584)	(–4.2983)	(–18.8911)
$DLXZ_{t-1}$	0.0017***	0.0019***	0.0014***	0.0018***	0.0025***
	(16.4120)	(18.1693)	(12.5499)	(3.6725)	(30.8677)
$DLXZ_{t-2}$	–0.0034***	–0.0034***	–0.0026***	–0.0039***	–0.0043***
	(–13.4299)	(–15.5119)	(–11.4454)	(–4.4792)	(–22.9623)
GXZ_{t-1}	0.0049***	0.0047***	0.0038***	0.0059***	0.0052***
	(11.6505)	(12.2088)	(11.5166)	(4.0187)	(16.8474)
GXZ_{t-2}	0.0476***	0.0499***	0.0423***	0.0578***	0.0501***
	(10.3429)	(12.1447)	(12.7717)	(3.6980)	(14.2903)

End of Table 9

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	E	F	G	H	I
SHIBOR	0.1374***	0.1578***	0.1477***	0.1573	0.1442***
	(6.8448)	(8.6241)	(9.6721)	(1.8636)	(8.9283)
ln *CJL*	0.0066***	0.0068***	0.0063***	0.0014	0.0059***
	(8.4011)	(7.3440)	(7.8901)	(0.5355)	(7.8323)
Constant	0.8436***	0.7612***	0.5438***	1.0896***	0.9612***
	(10.9257)	(9.1108)	(7.3631)	(4.1139)	(19.7036)
Individual effect	control	control	control	control	control
Time effect	control	control	control	control	control
R-square	0.4420	0.2900	0.4180	0.5240	0.4710
Observations	10909	17551	11513	779	31440
Number of Companies	87	148	94	8	253

Table 10. Influence of information infection on stock market 3

	(1)	(2)	(3)	(4)	(5)
Explained variable	$R_{i,t}$				
Industry Code	K	L	M	N	O
ISS	–0.1008***	–0.1431***	–0.1528***	–0.1645***	–0.1411
	(–9.1503)	(–10.6004)	(–9.0107)	(–10.0719)	(.)
$DLXZ_{t-1}$	0.0015***	0.0020***	0.0018***	0.0017***	0.0019
	(13.2194)	(12.2703)	(9.4000)	(14.0755)	(.)
$DLXZ_{t-2}$	–0.0025***	–0.0034***	–0.0035***	–0.0037***	–0.0038
	(–10.7935)	(–10.6815)	(–9.2767)	(–11.5620)	(.)
GXZ_{t-1}	0.0031***	0.0045***	0.0052***	0.0056***	0.0048
	(7.7309)	(9.5613)	(8.7996)	(10.0237)	(.)
GXZ_{t-2}	0.0289***	0.0410***	0.0567***	0.0557***	0.0504
	(6.0856)	(7.9536)	(8.5023)	(10.4376)	(.)
SHIBOR	0.0477**	0.0902***	0.1914***	0.1599***	0.1460
	(2.0569)	(3.7176)	(6.4459)	(7.1149)	(.)
ln *CJL*	0.0063***	0.0057***	0.0079***	0.0070***	0.0379
	(8.3248)	(4.0290)	(4.5747)	(6.1673)	(.)
Constant	0.6659***	0.9393***	0.7806***	0.9529***	0.3537
	(10.0866)	(8.7384)	(6.7144)	(7.3924)	(.)
Individual effect	control	control	control	control	control
Time effect	control	control	control	control	control
R-square	0.4290	0.3570	0.3770	0.4180	1.0000
Observations	12427	6639	5709	6797	128
Number of Companies	105	55	45	55	1

Table 11. Influence of information infection on stock market 4

	(1)	(2)	(3)	(4)
Explained variable	$R_{i,t}$			
Industry Code	P	Q	R	S
ISS	–0.1558***	–0.1948***	–0.1340***	–0.0762*
	(–6.9628)	(–6.5324)	(–9.7770)	(–2.1963)
$DLXZ_{t-1}$	0.0022***	0.0022***	0.0019***	0.0015**
	(5.7881)	(10.0331)	(14.5529)	(3.0584)
$DLXZ_{t-2}$	–0.0041***	–0.0042***	–0.0034***	–0.0019*
	(–6.3003)	(–8.4837)	(–12.2830)	(–2.0527)
GXZ_{t-1}	0.0053***	0.0069***	0.0046***	0.0016
	(6.9590)	(6.1253)	(9.7160)	(1.0465)
GXZ_{t-2}	0.0544***	0.0774***	0.0442***	0.0065
	(5.4448)	(5.2745)	(8.5573)	(0.2902)
SHIBOR	0.1619**	0.3125***	0.1164***	–0.0831
	(3.2987)	(4.9383)	(5.2890)	(–0.6165)
ln *CJL*	0.0083***	0.0107***	0.0048***	0.0073***
	(5.7099)	(8.0947)	(3.1769)	(3.4187)
Constant	0.8510***	0.8107***	0.7991***	0.7422***
	(6.1532)	(3.9643)	(8.1404)	(4.6346)
Individual effect	control	control	control	control
Time effect	control	control	control	control
R-square	0.4920	0.4210	0.4190	0.4260
Observations	896	1151	6395	1142
Number of Companies	7	9	50	9

4. Further study

4.1. The mechanism of infodemic on the stock market: the intermediary role of information infection

This paper depicts the impact mechanism of the infodemic on the stock returns by alluding to the development law of netizens' emotions studied by Yi and Li (2021). As shown in Figure 2, The emergence of the COVID-19 epidemic has brought an infodemic. The impact of the infodemic on the stock market can be divided into two paths. The first path is that the infodemic directly affects people's emotions, leading to changes in investors' behavior, and ultimately changing the stock returns under the combined effect of other factors. The second path is that the information epidemic causes information infection, that is, it causes people to continuously search and pay attention to relevant information, leading to the spread of various emotions among the crowd. When the emotional infection among investors produces highly consistent decision-making behavior, under the joint influence of other factors, the

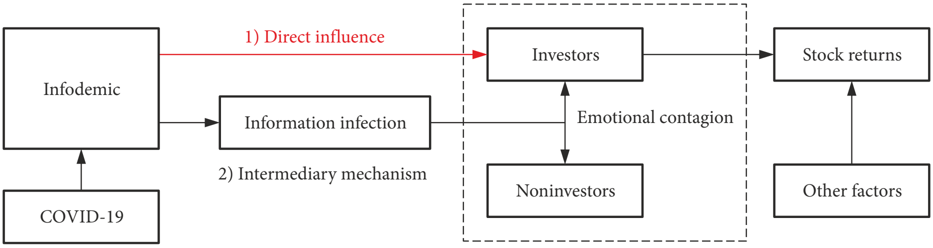

Figure 2. Influence mechanism of information epidemic on stock market

stock returns will change accordingly. Therefore, we expect that the infodemic will affect the stock returns through the intermediary of information infection. Based on this, a regression model is established as follows:

$$R_{i,t} = \alpha_3 + \beta_3 \ln IZX_t + \beta_3' \ln ISS_t + \gamma_1^* DLXZ_{t-1} + \gamma_2^* DLXZ_{t-2} + \gamma_3^* GXZ_{t-1} + \gamma_4^* GXZ_{t-2} + \gamma_5^* SHIBOR_t + \gamma_6^* \ln CJL + \mu_i^* + \lambda_t^* + \varepsilon'_{i,t}. \quad (4)$$

4.2. Intermediary effect test steps

For the test of intermediary effect, Wen and Ye (2014) proposed the new test steps as follows:

Step 1: Test the coefficient c of Eq. (5). If it is significant, it is based on the intermediary effect; Otherwise, it is based on the masking effect.

Step 2: Test the coefficient a of Eq. (5) and the coefficient b of Eq. (6) in turn. If both are significant, the indirect effect is significant, and go to the fourth step; If at least one is not significant, go to step 3.

Step 3: Test H_0: $ab = 0$ by the bootstrap method. If significant, the indirect effect is significant, and then go to step 4; Otherwise, the indirect effect is not significant, and the analysis is stopped.

Step 4: Test the coefficient c' of Eq. (7). If it is not significant, it indicates that there is only an intermediary effect. If it is significant, the direct effect is significant, go to step 5.

Step 5: Compare the symbols of ab with c'. The same sign is part of the mediating effect, and the amount of mediating effect is ab/c; Different signs are masking effects.

Refer to (5) ~ (7) for specific formula:

$$Y = cX + e_1; \quad (5)$$

$$M = aX + e_2; \quad (6)$$

$$Y = c'X + bM + e_3. \quad (7)$$

4.3. Analysis of empirical results

For the three steps of the intermediary test: First, test the main effect, that is, the impact of the infodemic agent index IZX on the stock returns. According to the previous conclusion, only when the main effect is significant can it be reported according to the intermediary effect. Table 12 (1) reports the test results of the main effect *c*. The coefficient (*c*) shown in the results is –0.5011 and is significant at the level of 1%. The second step is to test the coefficient *a* of Eq. (6) and the coefficient *b* of Eq. (7) in turn. The coefficient *a* (the coefficient of *IZX*) reflects the impact of the infodemic on the information infection. The conclusion is reported in column (2) of Table 12, and the coefficient a is 3.4502, which is significantly positive. The coefficient *b* reflects the influence of the intermediate variable ISS on the dependent variable $R_{i,t}$ after controlling the influence of the independent variable *IZX*. Column (3) of Table 12 shows that the regression coefficient of *ISS* is –0.1098, which is significantly negative at the level of 1%.

If both *a* and *b* are significant, it means that the indirect effect is significant. Then carry out the fourth step to test the coefficient *c*′. if *c*′ is significant, it means that the direct effect is also significant. Finally, the fifth step is carried out. The same signs of *ab* and *c*′ are reported as part of the mediating effect, and the amount of mediating effect is $ab/c = 3.4502 \times (-0.1098) / (-0.5011) = 0.7560$. This paper tests the intermediary effect of various in-

Table 12. Mediating effect test of information infection

	(1)	(2)	(3)
Explained variable	$R_{i,t}$	*ISS*	$R_{i,t}$
IZX	**–0.5011*****(*c*)	**3.4502*****(*a*)	**–0.1223*****(*c*′)
	(–61.9474)	(459427.8190)	(–39.1774)
ISS	–	–	**–0.1098*****(*b*)
	–	–	(–49.3476)
$DLXZ_{t-1}$	0.0028***	–0.0059***	0.0021***
	(82.1410)	(–233112.7260)	(86.5041)
$DLXZ_{t-2}$	–0.0056***	0.0140***	–0.0040***
	(–68.8957)	(191025.0510)	(–74.7410)
GXZ_{t-1}	0.0056***	–0.0050***	0.0051***
	(59.2781)	(–56443.2980)	(59.8564)
GXZ_{t-2}	0.0437***	0.0490***	0.0491***
	(55.4513)	(74890.7021)	(56.0618)
SHIBOR	0.0168***	1.0009***	0.1267***
	(4.9821)	(1.36e+07)	(32.4605)
ln *CJL*	0.0070***	0.0000	0.0070***
	(32.6230)	(0.0057)	(32.6230)
Constant	8.2850***	–51.6203***	2.6168***
	(61.0535)	(–408419.4849)	(49.5611)
Individual effect	control	control	control
Time effect	control	control	control
R-square	402307	402307	402307
Observations	0.3290	1.0000	0.3290
Number of Companies	3265	3265	3265

dustries, and the results show that, except for the resident service, repair, and other service industries (O) which cannot estimate the results due to the insufficient sample observation number, other industries have passed the intermediary effect test.

4.4. Robustness test

In order to ensure the reliability of the regression, the company registered in Hubei Province in the existing sample is excluded and the regression is conducted again. Because Hubei Province is the outbreak place of the COVID-19, the impact of the epidemic is stronger than other provinces. As a result, removing the sample of A-share listed companies in Hubei Province can more effectively test the impact of infodemic on the stock market. It can be seen from Table 13 that the regression results of the new samples show that the information epidemic and information infection still have a negative impact on the stock returns of A-share listed companies, and the intermediary effect of information infection is still significant. The empirical results have not changed substantially.

Table 13. Robustness check

	(1)	(2)	(3)
Explained variable	$R_{i,t}$	ISS	$R_{i,t}$
IZX	–0.5020**(c)	3.4500***(a)	–0.1230***(c')
	(0.0082)	(2.06e-05)	(0.0031)
ISS			–0.1100***(b)
			(0.0023)
$DLXZ_{t-1}$	0.0028***	–0.0059***	0.0021***
	(3.40e-05)	(6.97e-08)	(2.46e-05)
$DLXZ_{t-2}$	–0.0056***	0.0140***	–0.0040***
	(8.18e-05)	(2.01e-07)	(5.45e-05)
GXZ_{t-1}	0.0056***	–0.0050***	0.0051***
	(9.58e-05)	(2.42e-07)	(8.56e-05)
GXZ_{t-2}	0.0439***	0.0490***	0.0493***
	(0.0008)	(1.79e-06)	(0.0009)
SHIBOR	0.0179***	1.0010***	0.1280***
	(0.0034)	(2.02e-07)	(0.0040)
ln *CJL*	0.0070***	0	0.0070***
	(0.0002)	(9.02e-09)	(0.0002)
Constant	8.3000***	–51.6200***	2.6230***
	(0.138)	(0.0003)	(0.0534)
Individual effect	control	control	control
Time effect	control	control	control
R-square	391,272	391,272	391,272
Observations	0.3300	1.0000	0.3300
Number of Companies	3,176	3,176	3,176

Conclusions and countermeasures

From the perspective of the infodemic caused by COVID-19, this paper explored the impact of the information level on the stock market. The results show that:

(1) In the research on the impact of infodemic on information infection, it is found that the more serious the infodemic is, the deeper the people's information infection is, which is manifested by the increase in the search frequency of "epidemic situation" related keywords.

(2) In the study of the impact of infodemic and information infection on the stock market, it is found that from the perspective of the overall research of A-share listed companies, the negative impact of infodemic and information infection on the overall stock returns of A-share listed companies is still significant, and the infodemic and information infection hurt all industries.

(3) In the examination of the impact mechanism of the infodemic on the stock market, it is found that the research results confirm that the impact path of the infodemic on the stock returns of A-share listed companies is not only directly affected, but also affected through the information infection intermediary. Based on the impact mechanism of the infodemic on the stock market and the above research conclusions, this paper puts forward suggestions for stabilizing the abnormal fluctuations of the stock market when major public health events occur from the following two aspects:

1) In terms of infodemic and information infection: when major public health events break out, the spread of excessive information should be controlled to reduce people's contact with excessive information and reduce people's degree of information infection. This paper does not distinguish between rumor and nontumor information in the infodemic but focuses on the quantitative study of the relationship between the infodemic and the stock returns. This shows that we should not only control the quality of information released but also pay attention to the quantity of information released. Excessive information is also an important factor causing public panic and anxiety. The infodemic is the source of information infection. All information release platforms should strictly control the information related to the epidemic and pay attention to the quantity and quality of information released. Efficient and accurate information will reduce people's anxiety and panic about the uncertainty of the epidemic.

2) In the aspect of public emotion monitoring, information and emotion spread equally rapidly in the all-media era. Therefore, it is necessary to improve the psychological counseling mechanism for the public to respond to public health emergencies, to avoid the infection of destructive emotions caused by information infection caused by the infodemic, which has a serious negative impact on social order and economic development.

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