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Institutional investor information network, analyst forecasting and stock price crash risk

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ABSTRACT

In this paper, we construct the information network of fund investors based on the theory of social relationship networks and examine its impact of fund information sharing with analysts on stock price crash risk. Our results show that private information sharing among institutional investors reduces crash risk. Further results show that fund information sharing can alleviate analyst optimism bias and improve analyst forecast accuracy, which further reduces stock price crash risk. Moreover, these identified effects are more pronounced in a bull market than a bear market. Our study contributes to the research on private information transmission in fund information networks, and provides a new perspective for recognizing the relationships among institutional investor behavior, analyst forecasting, and stock price crash risk.

1. Introduction

Previous research provides evidence supporting the theoretical link between information transmission and stock prices incorporating firm-specific information. The market efficiency hypothesis assumes that stock price reflects all of the available information, including the interactions between decision-making individuals. In reality, the availability of information is often asymmetric to market participants (Sims, 2006). There exists private information exchange among the social network of institutional investor, including information sharing and social learning, and these interactions will affect the trading behavior of other participants (Galariotis et al., 2015). Information sharing has led to behavioral contagion among institutional investors, which is closely related to financial risk contagion (Jegadeesh and Kim, 2010). There is often private information exchange between funds holding the same stocks. Research demonstrates that analysts are major transmitter in information channel, and private information sharing of funds will have an important impact on analyst forecasts (Cheng et al., 2016). As the principal clients of analyst research reports, institutional investors also determine these analysts' compensation by voting star analysts (Brown et al., 2015). In addition, Gu et al. (2013) and Bowen et al. (2018) argue that there exists close interest relationship between buyer funds and seller analysts, because analysts have the possibility of issuing biased reports to cater to institutional investors. Under this background, we will address what are the economic consequences of the private information sharing within social network of institutional investors on other market participants, especially on the analysts, and how does this affect the crash risk of stock price?

Industry knowledge is one of the most key determinants of analysts' compensation and the most significant input to both their

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earnings forecasts and their stock recommendations (Green et al., 2014). On the one hand, conflicts of interest often arises when analysts obtain commissions for providing services to their client funds, the existence of interest relationships will affect the accuracy of analyst forecast. Firth et al. (2013) find that analyst recommendation on stock is significantly higher if those stocks are held by the mutual fund of the analyst's brokerage company. It is the existence of this conflict of interest effect that has caused analysts to make biased predictions (Bowen et al., 2018). On the other hand, institutional investors also share information with analysts through the disclosure of information, which increases the comprehensiveness of information on the market.

Institutional investors exchange private information through the same social relationship networks. They observe and exchange information with each other, and the consequences of these interactions ultimately affect stock price volatility (Blocher, 2016). From the perspective of information transmission efficiency, information sharing among institutional investors makes market participants more informed about information regarding listed companies, which is conducive to improving pricing efficiency (Soltes, 2014). Existing research on institutional investor networks has mainly focused on how to introduce social relationship networks into institutional investor behavior. Few studies have considered the impact of fund private information sharing with analysts on stock price volatility risk. When facing conflicts of interest between funds and analysts, analysts tend to issue biased reports to hide the bad news of listed companies whose stocks are held by their client funds. This forecast bias can often lead to a large-scale stock price collapse when bad news is accumulated to a certain extent. And the crash risk of stock price often occurs when the accumulation of negative information reaches a breaking point (Kim et al., 2011a, 2011b).

The difference between this paper and the existing research on institutional investors, analysts and stock price crash risks is mainly manifested in the following two aspects. Firstly, most of the existing studies analyze the impact of institutional investor behavior on stock price crash risk or on analyst interest relationship separately, ignoring how private information dissemination from institutional investors to analysts affects stock price crash risk. In view of this, this paper analyzes the impact of private information sharing within institutional investor network with analyst on the crash risk of stock price with the help of social network tools. Secondly, most studies so far analyze stock price crash risk from the perspective of internal information transparency (Kim et al., 2011a, 2011b). However, most of these studies analyze the factors affecting crash risk from the internal characteristics of company without considering the impacts of external participants, such as institutional investors and analysts, on the stock price crash risk. There exist both information sharing mechanisms within institutional investor social network and conflict of interest mechanisms between fund manager and analysts. Hence, further exploration is required to determine which of these mechanisms dominates when considering the possible interactions between institutional investor private information sharing and analyst behavior on the stock price crash risk. In view of this, our study will examine the economic consequences of analyst interest relationship on crash risk of stock prices. And we will further examine the combined effects of private information sharing within institutional investor social network combined with analyst interest relationship on stock price crash risk.

In recent years, global stock markets experience turbulence and even more since the financial crisis, "the black swan"[1] phenomena appear more frequently globally, and China market is not an exception. For example, several years after the international financial crisis in 2008, thousands of stocks collapsed almost simultaneously in China's stock market in 2015, and the Internet financial default triggered a wave of bond defaults in 2018. Compared to developed capital markets, emerging markets such as China achieves growth, the problems with institutional investors and analysts play a more important role in crash risk. Since China's stock market contains less firm-specific information, and more severe hiding of bad news by the senior management, it makes stock prices in China jump and fall more violently (Piotroski and Wong, 2012), which provides an ideal experimental environment for the study of stock price crash risk. Therefore, we mainly focus on China's market in this study since it share common features with other emerging market. Importantly, information sharing among market actors apply to all active markets. Besides, to enhance the stability of financial market and to promote rational investment, the China Securities Regulatory Commission has vigorously developed fund-based institutional investors. The large presence of institutional investors in Chinese economy provides abundant samples for analysis and are representative to other markets.

Most of the existing research mainly analyzes the impact of the information exchanges between individual institutional investors on the companies that they commonly hold stock from the perspective of corporate governance, while ignoring the impact of private information sharing between analysts and institutional investor on the crash risk of stock price. This study aims to explore the relationships between institutional investor networks, analyst forecasting, and stock price crash risk from the perspective of private information sharing within network. And how the integrated effect of private information sharing in institutional investor network with analysts affects stock price crash risk is examined. Specifically, we first construct the institutional investor information network based on the large holdings of the same shares between funds, and then analyze how private information sharing affects analyst forecasting. Second, we examine the economic consequences of fund information sharing on crash risk. Third, the channel through which how analysts affects the relationship between institutional investor information sharing and crash risk is investigated. In the robustness test, we consider the stock price synchronization to address if the conclusion obtained from stock price crash risk is robust. In the extended analysis, we consider how investor sentiment changes the information transmission mode under different market conditions: bull market and bear market. Our analysis highlights the importance of information acquisition in examining the implications of information networks among institutional investors.

Our study makes several contributions to the extant literature. On the basis of Pareek (2012), primarily, we build the institutional investor information network based on stocks held in common by funds as network ties. We employ the structural characteristics of

[1] "black swan" include subprime mortgage crisis, European sovereign debt crisis stock market crash and so on.

network to measure the information transmission efficiency of information sharing. Specifically, using complex network theory, and Gephi, Ucinet and Pajeck softwares, we calculate the topological structure indicators of institutional investor network. Then the topological feature indicators are employed to measure the efficiency of private information dissemination in fund information network. Unlike prior empirical work, our study disentangle the effects of private information sharing from social interactions. At present, there is relatively little research on the establishment of institutional investor behavior and other market factors via network structure characteristics. Then, we apply the importance of institutional investor network and information sharing with key market players, especially analysts in the information transmission channel. The important innovation of this paper is that we focus on examining the relationships among institutional investor information sharing, analyst conflicts of interest, and crash risk. In particular, we examine the impact channel of private information sharing on stock price crash risk. Explaining the information sharing channels from the perspective of complex network enriches the researches on the impact of institutional investor network structure on analysts and stock price volatility.

Hence, this paper will analyze the interaction between institutional investors and analysts to investigate both the information sharing effect. Specifically, the impacts of fund private information sharing with analyst on the crash risk of stock prices will be examined by virtue of the microstructure of the information network. This paper proceeds as follows. In Section 1, we describe the background of the study, and in Section 2, the literature is reviewed. In Section 3, we propose the research hypotheses and the empirical methodology. The network construction are presented in Section 4. Section 5 explains the empirical results. We show robustness tests in Section 6 and further analysis in Section 7. We conclude with Section 8.

2. Literature review

2.1. Institutional investor information network

Social capital theory holds that social network resources owned by individuals exist in interpersonal relationships, and it includes social organization, social network and network grabbing (Coleman, 1999). The signal transmission theory thinks that under the environment of information mismatch, the company transmits internal information to the outside through various channels (Spence, 1973). While corporate private in-house meetings between institutional investors and management are common across the world, there are generally no requirements to disclose anything about these meetings to other stakeholders. It appears that the dissemination of private meeting information could be beneficial for other investors who are unable to attend such meetings. The introduction of social networks into the information interaction behavior of investors can effectively portray information transmission within the network. Pareek (2012) believes that there are information exchanges between fund managers who jointly hold the same stocks. This kind of word-of-mouth communication influences investor decisions on trading stocks. Bushee and Goodman (2007) show that informed trading by institutions is not wide spread and only institutions with large stockholdings possess private information. Although prior studies have constructed institutional investor networks based on the social relationship network method, there are few studies that have analyzed the influence mechanism between information sharing within institutional investor network, analyst forecasting and stock price crash risk.

2.2. Institutional investor information network, analyst forecasting and stock market crash risk

The principal-agent theory holds that in order to maximize their own interests, there is an agency conflict between shareholders and managers (Jensen and Meckling, 1976). Similarly, there exists conflict of interest relationship between the buyer fund and the seller analyst, especially the commission relationship (Ljungqvist et al., 2007). If analysts bring benefits to their client investors by publishing biased forecast reports, there is conflict of interest between them (Mehran and Stulz, 2007; Bowen et al., 2018). On the one hand, institutional investors cast votes for the best analysts in each sector in the all-star poll. A high ranking directly influences the analyst's remuneration and career prospects. On the other hand, the seller analyst obtains transaction commissions by providing research report services and arrangements for buyer institutional investors (Brown et al., 2015). In order to maintain good cooperative relationship with institutional investors and to protect their own benefits, analysts tend not to disclose the negative information of stocks held by institutional investors with a large position in those stocks. Hence, analyst forecasting behavior will be affected by these related interests inevitably (Hovakimian and Saenyasiri, 2010; Gu et al., 2013). This conflict of interest effect has caused analysts to make biased predictions (Bowen et al., 2018). The existence of analyst conflicts of interest indicates that the traditional rational expectation theory has been challenged, and the efficient market theory has been shaken.

The traditional theory of information asymmetry emphasizes the importance of information to the market. As important participants in the market, security analysts have played the role of alleviating market information asymmetry. Prior research contends the informativeness or investment value of analysts' earnings forecasts or stock recommendations. However, subject to conflicts of interest, analysts tend to ignore the damage of negative information (O'Brien et al., 2005). Based on the efficient market hypothesis, research on market-level stock price crash risk mainly includes "volatility feedback" theory. It contends that while the capital market continues to receive news from all quarters, the stock price will reflect the received news, and will fluctuate accordingly. However, it is difficult to satisfy the efficient market hypothesis in reality. By relaxing the conditions, scholars have proposed the "information hiding" theory (Jin and Myers, 2006). It holds that in order to satisfy their own interests, the managers of enterprises often hide the unfavorable news in the enterprises. Kim et al. (2011a, 2011b) argues that the crash risk in stock price often occurs when the accumulation of negative information reaches a breaking point, and the concentrated release of this information causes a great negative shock, which causes the stock price to crash. In addition, Hutton et al. (2009) find that company opacity of information is inversely related to stock price crash risk. Kim et al. (2020) finds that foreign investors help to reduce firms' stock price crash risk through improving local firms' financial reporting quality. Most previous studies mainly focus on analyzing the effects of various accounting characteristics, ownership structures and the institutional infrastructures on stock price crashes (DeFond et al., 2015; Piotroski et al., 2015; An et al., 2018; Liang et al., 2020). Only a few studies have investigated the possible effect of private information interactions between analysts and institutional investors on stock price crash risk.

Valuable private information feedback can be obtained via sharing with others in social network (Crawford et al., 2017). Dong et al. (2016) also find that the reduction in information processing cost reduces stock return synchronicity. Ozsoylev et al. (2014) argue that due to the existence of investor information networks, the proliferation of private information will affect other market participants. Institutional investor information sharing improves the comprehensiveness of market information, especially to analyst. However, analysts often do not objectively take advantage of the private information that they possess and are unwilling to disclose the negative information of listed companies, (O'Brien et al., 2005). Hence, it requires further investigation regarding whether information sharing effect dominates in influencing crash risk.

3. Hypothesis development

3.1. Institutional investor information sharing and analyst forecasting

Concerning private information sharing within institutional investor network, funds disclose research summaries of the listed companies to the seller market through the channels of stock exchanges. This transmission increases both the number of analysts tracking of information and the number of reports being distributed. It attracts more attention from security analysts to the firms and causing more energy to be spent on these forecasted firms (Davis et al., 2015). The disclosure of institutional investor research records provides information channels for analysts, increasing information transparency (Bushee et al., 2011; Soltes, 2014). Mandatory information disclosure enhances the information transparency of listed companies. In other words, institutional investor information sharing has brought increased information to the security analyst industry (Cheng et al., 2013). Hutton et al. (2009), Jin and Myers (2006) argue that with improved transparency more firm-specific information will be available in the market, and it facilitates the incorporation of information into stock prices. When more information is incorporated into the stock price, the stock price is quickly returned to the market equilibrium. Hence, the disclosure and transparency of information can help improve forecast accuracy. The investigation of the transmission routes between institutional investor information sharing with analyst prompts the analysis of the interacting items of network topological indicators and analyst attention. Based on this analysis, we propose our first hypothesis.

H1. Institutional investor information sharing can improve the analyst forecast accuracy and reduce analyst optimism bias.

3.2. Analyst interest relationship and stock price crash risk

Companies exhibit high stock price synchronization in the capital market (Jin and Myers, 2006). An and Zhang (2013) find that the higher the synchronization of stock prices, the higher the frequency of crashes for those stock prices will be. In order to increase trading volume and to earn more commissions, analysts tend to provide more buying rating reports when recommending stocks and forecasting earnings (Jackson, 2005). In other words, for the sake of maintaining their relationship with institutional investors, analysts tend to issue overly optimistic forecast reports (Mola and Guidolin, 2009). Subject to interest relationship, analysts tend to ignore the damage of negative information (O'Brien et al., 2005). Under this circumstance, the analyst optimistic bias about positive information will cause the firm negative information to be hidden. When the accumulated negative information is released, it may cause the resonance effect in the stock market, increasing stock price crash risk. Kim et al. (2011a, 2011b) posit that the crash risk of stock price often occurs when the accumulation of negative information reaches the limit, and the concentrated release causes a great negative shock, causing the stock price to crash. Seen from the perspective of conflicts of interest between buyers and sellers, this phenomenon may cause stock price crash risk by exacerbating analyst optimistic bias. Hence, we made the following assumptions:

H2. Analyst optimistic bias will cause the stock price crash risk of listed companies.

3.3. Institutional investor information sharing and stock price crash risk

Institutional investors have access to valuable private information, and they have expanded the range of asset choices by allowing the portfolio to be fully decentralized through information sharing (Gray et al., 2012). Influenced by external regulation and industry competition, it is often difficult for individual institutional investors to monopolize information, and private information sharing have widened the transmission channels. Within fund information network, the accuracy of information can be verified through direct communication, and cognitive deviations can be corrected through social learning. Information sharing can quickly integrate market information into stock prices, reducing the accumulation intensity of hidden negative information. Moreover, the reduction of the ability of firm management to hide bad news lowers the risk of stock price bubbles and crashes (Callen and Fang, 2013). Communication within social networks improves the pricing efficiency of stocks (Han and Yang, 2013). Those that support institutional investors can stabilize the market propose that professional research teams are able to invest more prudently and rationally, thus playing a role in suppressing stock price volatility. Based on this outcome, the following hypothesis was made:

H3. Institutional investor private information sharing reduces the crash risk of stock price.

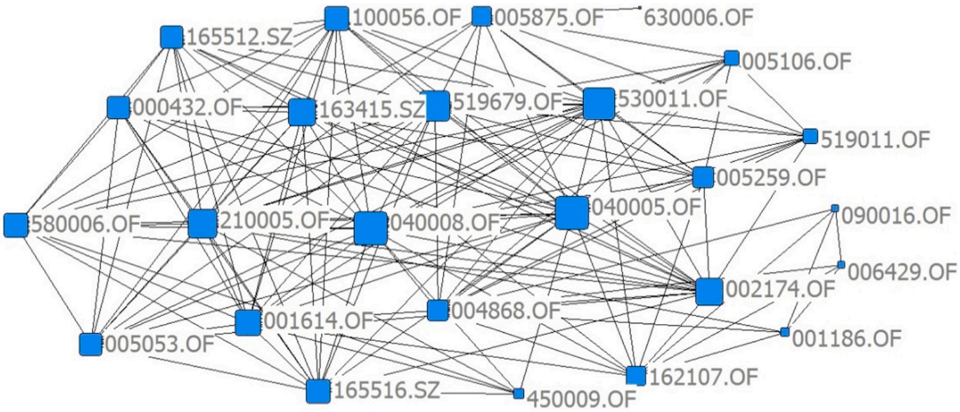

Fig. 1. Mutual fund information network.

3.4. *Institutional investor information sharing, analyst interest relationship and stock price crash risk*

Institutional investors are the major clients of security analysts and important sources of profit for analysts. And analysts usually pay more attention to stocks that institutional investors hold in large positions since they need to employ their research reports as marketing tools (Mola and Guidolin, 2009). Moreover, institutional investors have mastered important ways of advancing the careers of analysts, such as manipulating the selection of the best analysts. It is not easy for analysts to disclose negative firm information while maintaining a cooperative relationship with institutional investors. In addition, private information sharing by institutional investors can make listed companies more transparent. Under the assumption that conflicts of interest between analysts and institutional investor increases crash risk, and private information sharing of funds reduces analyst optimism bias. The impact of private information shared by institutional investors and analysts on crash risk mainly depends on the relationship between institutional investors and crash risk. Considering that fund information sharing will decrease analyst optimistic bias, and analyst optimistic bias is positively correlated with stock price crash risk, we propose our fourth hypothesis accordingly.

H4. Institutional investor information sharing reduces the crash risk of stocks caused by analyst conflicts of interest. In other words, institutional investors spilling private information to analysts contributes to reducing crash risk of stock price.

4. Research design

4.1. *Data and sample*

We obtain the data on analyst forecasts, companies' financial accounts, corporate governance and stock market returns from the CSMAR corporate finance database and the behavioral finance database. The stock-holding funds and the mutual fund data are collected from the Wind special fund database. The selection of mutual funds is limited to equity funds and hybrid funds. In view of the great difference between the management methods of index funds and other funds, the reinforced index funds and the passive index funds are removed. The data covering 2007–2019 as the sample to analyze the relationship between institutional investor information sharing, analyst forecasting and stock price crash risk. We exclude listed companies of the financial industry, ST companies as well as companies with incomplete data. All continuous variables are winsorized at the 1 % and 99 % levels to remove outliers. Our final sample comprises 8219 firm-year observations for the analysis.

4.2. *Variable and model specification*

4.2.1. *Institutional investor information network*

As can be seen from the existing literature, the institutional investor information network generally can be constructed in three ways. The first construction method uses the social network theories based on social relations, in which the alumni relationship network provides fund managers with more private information than is disclosed otherwise (Cohen et al., 2008). Pool et al. (2015) propose that fund managers within the same social networks display similar holdings and trading styles. Other social attributes, such as shared educational backgrounds and working backgrounds are also employed to build social networks (Cici et al., 2017). The second type of information network is mainly formed based on geographic location. Fund managers living in the same city tend to display consistent trading behavior (Hong et al., 2005). There is evidence that the overlaps of funds whose managers reside in the same neighborhood is considerably higher than that of funds whose managers live in different neighborhoods (Pool et al., 2015). The third type of information network is based on the asset allocation of investor portfolios, such as those that hold common stocks. On this basis, Crane et al. (2019) construct an institutional investor network according to the common ownership in the US capital market, and analyze the corporate governance ability of the network clique. There is evidence of coordination between firms that have the same

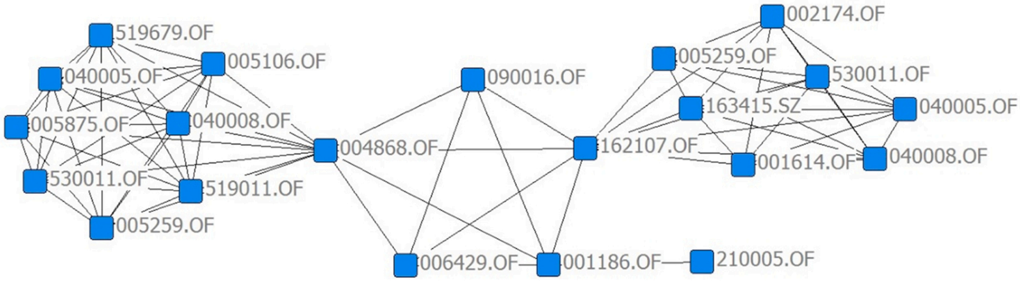

Fig. 2. Stock network example.

owner (e.g., Azar et al., 2018).

The third type of social network, which supports information communication based on the consistency of intra-network transactions and positions, is more reasonable. Therefore, based on Pareek (2012) and Blocher (2016), we can build an information network of institutional investors based on the connection of stocks that they hold in common. Furthermore, we employ the network topology structure to illustrate the efficiency of institutional investor information sharing. Under this circumstance, the network topology structure of funds that hold stocks in large positions are used to represent the efficiency of the information sharing in the network (Crane et al., 2019). Then we use social network tool to analyze the impact of institutional investor information sharing on the relationship between analyst forecast bias and crash risk.

In order to analyze how private information sharing within institutional investor network influence analyst forecast and crash risk, we construct the institutional investor information network primarily. If two funds hold the same stock in large positions, it is defined as the two funds being in the same information network (Pareek, 2012). For the fund holding stocks in large positions, it means that the market value of the stock held by the fund accounts for more than 5 % of the total market value of the fund, and we mainly employ the top ten stock positions announced by the fund reports. The fund information network is the collection of all other funds in the same information network as it. Then we build the fund information network linked by the funds' same holdings.

Based on the semiannual reports issued by the stock exchanges in 2019, we primarily summarized the full picture of the information network of mutual funds in China, as shown in Fig. 1. It is worth noting that the construction approach of the fund information network in other years is similar to that in Fig. 1. Seen from the network topology characteristics, the average path length of the network is 1.7049 and the clustering coefficient is 0.7455. It indicates that Chinese institutional investor network displays small world features, which reflects the rapid speed of information diffusion (Cowan and Jonard, 2004). To more clearly show the connections between stocks in the fund information network, we take the China Inner Mongolia Yili Industrial Group (Yili) as an example, and depict the stock network built around Yili shares in Fig. 2. In Fig. 2, the Yili shares are held by five mutual funds, and the codes of these five funds are respectively 006429. OF, 004868. OF, 162107. OF, 001186. OF, and 090016. OF. Each of these five funds has its own fund information network. And the Yili stock network is the collection of five funds holding its shares and their respective fund information networks. The structural characteristics of stock network also indicate that private information can quickly spread within networks.

4.2.2. *Variable definition and measurement*

4.2.2.1. Institutional investor information sharing. We adopt the centralization indicators of institutional investor network structure. The network topology indicators associated with information dissemination characteristics are used as proxy variables for information sharing efficiency: the degree centralization and clustering coefficient. The degree of institutional investor network (*degree*) describes the overall centrality of network, indicating to what extent the institutional investor information network is built around certain nodes.

$$
\begin{aligned}
degree &= \sum\nolimits_{k-1}^{N} (D(n_{max}) - D(n_k))/(N-2) \\
D(n_k) &= d(n_k)/(N-1)
\end{aligned}
\tag{1}
$$

where $d(n_k)$ represents the degree of node n_k in the network, and $D(n_{max})$ represents the maximum value of $D(n_k)$, N represents the number of nodes in the network. A higher value of degree indicates a more important role played by the key nodes in network information dissemination. These important nodes accelerate the speed of information dissemination in the institutional investor network (Brunetti et al., 2019).

Further, we adopt the clustering coefficient indicator in the institutional investor information network. It is likely that nodes having identical neighbors are connected with each other. Such a tendency can be measured by the clustering coefficient, that is, the clustering coefficient measures the probability that the neighbors of nodes are themselves neighbors. A high value of the clustering coefficient suggests that it is easier to form a clique (Song et al., 2016). The clustering coefficient c_i of node i can be defined as follows.

$$
cluster_i = \frac{\sum_j \sum_k g_{jk,i}}{g_i(g_i - 1)} \tag{2}
$$

where g_i denotes the node degree, $g_{jk,i}$ equals one for j, k if the nodes are connected to each other and are both neighbors of node i, otherwise, it is zero. A high value of the clustering coefficient indicates a close connection between the nodes in the network, and a greater possibility of information spreading between the nodes.

4.2.2.2. Analyst forecasting. Analysts issue more cautious recommendations for those of his or her stocks that are predominantly owned by institutional investors. And pressure from client mutual funds drives analyst optimism. According to the research of Jackson (2005), Hovakimian and Saenyasiri (2014), the measurement of optimistic bias (*fopt*) of analyst earnings forecasts is constructed using the following formula.

$$fopt_{i,j,t} = (feps_{i,j,t} - aeps_{i,t}) / |aeps_{i,t}| \tag{3}$$

where $fopt_{i,j,t}$ denotes the extent of optimistic bias of analyst j for company i's earnings forecast per share in year t. $feps_{i,j,t}$ represents analyst j's prediction of company i's earnings per share in year t. $aeps_{i,t}$ denotes the actual value of earnings per share of company i in year t. When the value of $fopt_{i,j,t}$ is positive, it indicates that there is an upward forecast deviation, and the analyst earnings forecast is more optimistic at this time. The larger the value of $fopt_{i,j,t}$, the higher the optimistic tendency of analyst earnings forecasts, as well as the more optimistic bias of the analyst.

We define the accuracy of the analyst prediction (*accu*) as the inverse of the forecast error (*err*), which is calculated by dividing the absolute value of analyst's prediction of the stock earnings per share minus the actual stock earnings per share by the absolute value of $aeps_{i,t}$. In general, the greater the forecast error, the lower the analyst forecast accuracy. And forecasts errors $err_{j,t}$ are specified below.

$$\begin{aligned} Err_{i,j,t} &= |feps_{i,j,t} - aeps_{i,t}| / |aeps_{i,t}| \\ err_{j,t} &= \sum_{i=1}^{n} Err_{i,j,t} \Big/ n \end{aligned} \tag{4}$$

where j denotes the number of analysts, i represents the number of companies, t is the forecast year.

4.2.2.3. Stock price crash risk and stock price synchronization. Stock price crash risk is primarily proposed by Chen et al. (2001) and is later employed to capture firm-specific crash risk. To characterize the stock price crash risk, we adopt two measurement indicators as used in Hutton et al. (2009), Kim et al. (2011a, 2011b), and Kim and Zhang (2016): the negative conditional return skewness (*ncskew*), and the down-to-up volatility (*duvol*). The calculation of the indicators is carried out using the two-step method. Firstly, the market-adjusted returns residuals at the firm level are obtained according to the following Eq.(5).

$$r_{it} = \alpha + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_4 r_{m,t+2} + \varepsilon_{it} \tag{5}$$

where r_{it} denotes the returns of company i after considering dividend reinvestment at time t, and r_{mt} represents the average returns of company i weighted by the market capitalization at time t. The inclusion of lagging items and leading items were to adjust the asynchronous trading of listed company stocks. We measure the firm-specific weekly return for firm i at week t as the logarithm of the residual term $W_{it}=log(1 + \varepsilon_{it})$.

Secondly, two variable indicators of negative conditional return skewness (*ncskew*) and down-to-up volatility (*duvol*) are constructed based on W_{it}. The first proxy is based on skewness to capture the asymmetry of returns distribution (Zaman et al., 2021). To do so, we calculate the negative third moment of firm-specific weekly returns for the individual sample over the standard deviation of firm-specific weekly returns raised to the third power in Eq.(6). The second proxy is based on the down-to-up volatility since the absence of the third moment avoids the overly influence of extreme week returns. We calculate the standard deviation of the firm-specific returns for individual groups. And then the natural logarithm is applied to the ratio of standard deviation in the down weeks to standard deviation of up weeks to capture the down-to-up volatility in Eq. (7).

$$ncskew_{it} = -\frac{n(n-1)^{3/2}\sum W_{it}^3}{(n-1)(n-2)\left(\sum W_{it}^2\right)^{3/2}} \tag{6}$$

$$duvol_{it} = \log\frac{(n_{up}-1)\sum_{down} W_{it}^2}{(n_{down}-1)\sum_{up} W_{it}^2} \tag{7}$$

where n is the number of stock transactions of listed companies during the year, and n_{up} (n_{down}) is the number of times that the holding returns of stocks are greater than (less than) the average returns. The greater the value of *ncskew*, the higher the firm stock price deviates from the market negatively, as well as greater crash risk. Similarly, the greater the value of *duvol*, the greater the degree of left skewness in returns distribution, and hence greater crash risk. A higher value of *ncskew* and *duvol* implies a more "crash-prone" stock price.

Concerning the measurement of stock price synchronization, we used the definition given by Durnev et al. (2003). Morck et al. (2000) gives the measurement of stock price synchronicity, but it does not include industry returns to explain stock returns in the regression model. Although Gul et al. (2010) derive two alternative measures of synchronicity, the samples they use are very different from our study. The given method in Durnev et al. (2003) uses the following formula to estimate R^2 of the individual stocks to measure stock price synchronization. A growing body of literature has used this common measure of stock price synchronicity as a proxy for stock price informativeness. According to the different measurement methods, the measurement methods of stock price synchronization include the equal-weight average method of submarkets (*SYND*) and the equal-weighted average method of comprehensive markets (*SYNS*).

$$r_{i,k,t} = \alpha_i + \beta_i r_{m,t} + \gamma_i r_{k,t} + \varepsilon_{i,t} \tag{8}$$

where $r_{i,k,t}$ represents the returns of individual stocks i in industry k in week t. $r_{m,t}$ denotes the value-weighted returns of the market index in week t. r_{lt} is the value-weighted returns of industry k in week t. Industry dummies are applied to estimations, and the industry classification uses the categories issued by the China Securities Regulatory Commission.

To avoid firms that go public are delisted, or experienced trading halts, we follow Jin and Myers (2006) and exclude firms whose shares trade for less than 26 weeks over a fiscal year. Because R^2 is highly skewed and bounded between unit and zero, the logistic transformation is applied to obtain nearly normally distributed variable.

4.2.2.4. Control variables. The control variables mainly consist of three types of variables. The first type is the operational variables of listed companies, including the asset-liability ratio (*asslia*), the shareholding ratio of the top ten major shareholders (*holder*), the market capitalization (*lncap*), the net returns on equity (*roe*), the ratio of earnings to market (*em*), the price earnings ratio (*pe*), and the book-to-market ratio (*bm*). The second type is the characteristic variables of listed firms at the market level, including the individual stock returns (*returns*), the turnover rate (*turnove*r), and the individual stock illiquidity (*Amihud*). These variables are used to control herding effects. The third kind of variable is the control variables related to analyst forecasting, which mainly includes analyst rating (*rate*) and analyst attention (*analyst*) variables. Particularly, analyst rating is commonly used in the literature as a proxy variable for public information of listed companies. Finally, we control the influencing factors at the industry level.

4.2.3. Model specification

4.2.3.1. Institutional investor information sharing and analyst forecasting. The business relations between mutual funds and brokerage firms influence sell-side analyst recommendations. This section mainly consists of the testing of hypothesis H1 and the analysis of the impact of private information sharing of fund on analyst forecasting. The model specification is shown below, focusing on the coefficients of key variables.

$$Conflicts_{it} = \beta_0 + \beta_1 degree_{i,t-1} + \beta_2 cluster_{i,t-1} + \gamma Control_{i,t-1} + \sum Industry + \varepsilon_{it} \tag{9}$$

in which the analyst forecasting is measured by the optimistic bias (*fopt*) and the forecast accuracy (*accu*), and $Control_{it}$ represents a set of control variables.

4.2.3.2. Analyst forecasting and stock price crash risk. Analysts are concerned about their reputations among institutional investors in general. They might bow to pressure from their institutional investor clients and become overly optimistic in stock recommendations. Hence, we will investigate whether analyst forecast bias causes stock price crash risk.

$$Crashrisk_{it} = \beta_0 + \beta_1 fopt_{i,t-1} + \beta_2 accu_{i,t-1} + \gamma Control_{i,t-1} + \sum Industry + \varepsilon_{it} \tag{10}$$

where $Crashrisk_{it}$ is measured by *ncskew* and *duvol*, respectively. In the robustness test, the explanatory variable $Crashrisk_{it}$ is replaced by stock price synchronization indicators. Significantly negative coefficients of β_1 and β_2 would indicate support for hypothesis H2.

4.2.3.3. Institutional investor information sharing and stock price crash risk. Information sharing by institutional investors affects market pricing efficiency, which generates an important impact on stock price crash risk. Using the topology structure indicators of social network to measure the efficiency of information sharing, we used Eq. (11) to examine whether the information sharing of institutional investors affects the stock price crash risk. If the hypothesis H3a holds, the coefficients of β_1 and β_2 should be significantly negative.

$$Crashrisk_{it} = \beta_0 + \beta_1 degree_{i,t-1} + \beta_2 cluster_{i,t-1} + \gamma Control_{i,t-1} + \sum Industry + \varepsilon_{it} \tag{11}$$

In particular, the stock price crash risk is often accompanied by liquidity risk. Taking this factor into account, the Amihud indicator reflecting liquidity risk and its interaction items with the network topology indicator are added to the model so as to investigate this mechanism.

4.2.3.4. Institutional investor information sharing, analyst forecasting and stock price crash risk. Although institutional investors value unbiased, high-quality research reports, institutional investor clients may pressure business-related analysts into issuing overly optimistic stock recommendations. Institutional investors share private information within social networks, while spilling private information further to analysts at the same time. To examine the influence mechanism of the combined effect of information sharing and conflicts of interest on stock price crash risk, Eq. (12) is used to test the relationship between these variables.

Table 1
Descriptive statistics.

variable	mean	sd	min	p50	max
SYN	0.379	0.186	0.0429	0.385	0.763
ncskew	-0.093	0.598	-1.842	-0.114	2.020
rate	0.900	0.049	0.679	0.912	0.974
analyst	35.350	13.290	6	36.500	66
accu	1.053	3.024	0.032	0.561	41.667
fopt	0.013	0.026	-0.096	0.009	0.123
degree	8.843	2.619	5.280	7.920	13.200
cluster	0.739	0.074	0.622	0.730	0.854
asslia	0.471	0.253	0.000	0.480	0.876
holder	56.480	17.520	21.390	60.470	89.360
lncap	17.960	0.886	15.580	18.030	20.590
roe	0.173	0.109	-0.377	0.183	0.395
em	6.064	4.615	-7.573	5.052	23.240
pe	25.890	29.840	-120	21.070	200
bm	0.594	0.321	0.104	0.541	1.407
turnover	250	160	47.300	200	940
returns	26.760	35.800	-41	22.210	150
Amihud	0.010	0.023	0.001	0.004	0.207

Table 2
Institutional investor information sharing and analyst forecast.

	Forecast accuracy				Analyst optimism bias			
degree		0.1346** (2.35)		0.8649** (1.39)	-0.0036* (−1.71)		-0.0028*** (−1.53)	
cluster	1.2733*		2.0195*			-0.0582***		-0.0174***
	(0.89)		(0.56)			(−5.49)		(−1.47)
analyst	0.0355***	0.0389***	0.0215 * **	0.0201**	-0.0612***	-0.0353**	-0.0622***	-0.0396***
	(3.49)	(3.68)	(2.94)	(3.30)	(−4.78)	(−4.64)	(−5.48)	(−5.24)
degree analyst*				2.3588*			-0.0158**	
				(0.42)			(−1.12)	
*cluster * analyst*			1.9746*					-0.0249**
			(0.62)					(−1.01)
fopt	-0.0072	-0.0081	-0.0194	-0.0052				
	(−0.23)	(−0.27)	(−0.42)	(−0.16)				
accu					-0.0067**	-0.0089**	-0.0081**	-0.0022**
					(−0.64)	(−0.76)	(−0.72)	(−0.23)
rate	8.0218**	9.2136***	7.2688**	9.3611***	-0.0551*	-0.0835**	-0.0429*	-0.0716**
	(1.91)	(2.02)	(1.88)	(2.24)	(−1.73)	(−2.15)	(−1.38)	(−2.04)
asslia	-1.4765**	-2.6612*	-2.1782**	-1.5207*	0.0214**	0.0166**	0.0152	0.0146
	(−1.36)	(−1.67)	(−1.34)	(−1.39)	(1.83)	(1.65)	(1.54)	(1.45)
holder	-0.0455*	-0.012	-0.0529**	-0.0321	0.0001	0.0001	0.0001	0.0001
	(−1.72)	(−0.99)	(−1.98)	(−1.66)	(0.61)	(0.75)	(0.89)	(0.96)
lncap	0.8735**	0.1317	0.9217**	0.1895	-0.01025*	-0.0045*	-0.0133*	-0.0164*
	(2.07)	(0.21)	(2.21)	(0.24)	(−3.31)	(−1.59)	(−3.76)	(−3.98)
roe	-0.5211*	-1.8826*	-0.5284*	-1.8835	-0.0716*	-0.0255*	-0.0326**	-0.0515**
	(−0.15)	(−0.69)	(−0.12)	(−0.83)	(−2.68)	(−1.53)	(−1.75)	(−1.98)
em	-0.0166*	0.0084*	-0.0197	0.0157	0.0022*	0.0047*	0.0019**	0.0012**
	(−0.29)	(0.11)	(−0.14)	(0.19)	(2.86)	(3.01)	(2.64)	(2.77)
pe	0.0049*	0.0056*	0.0045*	0.0267*	-0.0001	-0.0001	-0.0001	-0.0001
	(0.32)	(0.98)	(0.36)	(1.21)	(−0.27)	(−0.29)	(−0.61)	(−0.67)
bm	-0.2166*	-1.2351*	0.4519*	-1.5299*	-0.0168	-0.0147	-0.0588*	-0.0419
	(−0.08)	(−0.79)	(0.13)	(−0.77)	(−1.36)	(−0.86)	(−1.96)	(−1.61)
returns	0.0077	0.0263**	0.0062	0.0138***	-0.0001	-0.0001	-0.0001	-0.0001
	(0.71)	(2.36)	(0.71)	(2.68)	(−1.11)	(−1.21)	(−1.49)	(−1.64)
Industry/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3648	3290	3390	3588	3720	3187	3526	3314

Note: * ** , * *, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 3
Analyst optimistic bias and stock price crash risk.

	Stock price crash risk			
	ncskew	*ncskew*	*duvol*	*duvol*
fopt	0.0125*	0.0134*	0.0121**	0.0138**
	(1.66)	(1.73)	(2.18)	(2.39)
analyst	-0.0158***	-0.0095	-0.0075*	-0.0064
	(−2.94)	(−1.36)	(−1.90)	(−1.24)
accu		-0.0422**		-0.0252*
		(−2.38)		(−1.91)
asslia		0.1845*		0.2978*
		(0.53)		(1.15)
holder		0.0038*		0.0028*
		(0.88)		(0.88)
lncap		-0.1443*		-0.0313*
		(−1.13)		(−0.33)
roe		-2.1148**		-1.2502*
		(−2.45)		(−1.93)
em		0.0073*		0.0031*
		(0.42)		(0.23)
pe		0.0002		-0.0000
		(0.11)		(−0.00)
bm		-0.4007*		-0.2052*
		(−0.59)		(−0.41)
returns		0.0046*		0.0033*
		(1.98)		(1.92)
turnover		0.0002		0.0001
		(0.39)		(0.33)
Amihud		0.3497*		-1.2217
		(0.15)		(−0.72)
Industry/Year	Yes	Yes	Yes	Yes
N	3886	3731	3886	3731

$$\begin{aligned} Crashrisk_{it} = \beta_0 + \beta_1 network_{i,t-1} + \beta_2 conflicts_{i,t-1} + \beta_3 network_{i,t-1} \times conflicts_{i,t-1} \\ + \gamma Control_{i,t-1} + \sum Industry + \varepsilon_{it} \end{aligned} \tag{12}$$

where $network_{it}$ uses the network topology indicators characterized by degree and clustering coefficient; $conflicts_{it}$ represents the optimistic bias (*fopt*) and the prediction accuracy (*err*).

5. Empirical findings and discussions

In the empirical research section, we first examine the relationship between institutional investor private information sharing and stock price crash risk. Then, we examine how analysts forecasting will affect the relationship between private information sharing of funds and crash risk. Because stock price synchronization and stock price crash risk are similar in risk formation mechanism, the robustness test used for these variables chooses stock price synchronization as proxy variable. Taking into account the external market situation and the high degree of irrationality of individual investors in the Chinese stock market, we expand our analysis employing investor sentiment and bull market information to reexamine the above issues. We present evidence with regard to how institutional investor private information spread within network influence the consequences of analyst forecast bias.

5.1. Descriptive statistics

The descriptive statistics results of the fund information network, analyst forecast bias and stock price crash risk are shown in Table 1. The statistics of Table 1 show that, the quarterly average of the proportion of the funds holding stocks with a large position in all funds is 41.4 %, which indicates that the fund information network has important impacts on stock volatility. The size of the fund information network increases year by year. The average path length and the clustering coefficient of the network for each year indicate that Chinese institutional investor network displays small world features, which reflects rapid speed of information diffusion.

5.2. Institutional investor information sharing and analyst forecasting

Table 2 reports the regression results of institutional investor information sharing and analyst forecasting, including the results of forecast accuracy in the left panel and optimism bias in the right panel. The first row and the second row report results of the degree indicator and clustering coefficient indicator, respectively. The fourth row and fifth row report the interaction items of degree and clustering coefficient with analyst attention respectively.

As seen in the left panel of Table 2, the coefficient values of *degree* and *cluster* are respectively 0.1346 and 1.2733, the results are

Table 4
Institutional investor information sharing and stock price crash risk.

	Stock price crash risk			
degree	-0.0326**		-0.0448***	
	(−2.35)		(−2.65)	
cluster		-0.8611*		-1.0248*
		(−1.73)		(−1.80)
analyst			0.0010*	0.0045*
			(0.21)	(1.00)
asslia			0.5150*	0.5194*
			(1.84)	(1.83)
holder			0.0048*	0.0054*
			(1.43)	(1.58)
lncap			0.0059	-0.0272
			(0.10)	(−0.44)
roe			-1.4214**	-1.3322*
			(−2.09)	(−1.94)
em			0.0033	0.0039
			(0.23)	(0.27)
pe			0.0015	0.0017
			(0.85)	(0.96)
bm			0.4039*	0.2842*
			(0.93)	(0.64)
turnover			-0.0001	0.0002
			(−0.46)	(0.51)
returns			0.0025*	0.0015*
			(1.62)	(0.98)
Amihud			0.8348*	1.2547*
			(0.44)	(0.65)
Industry/Year	Yes	Yes	Yes	Yes
N	4367	4421	4321	4412

significant at the levels of 5 % and 10 %, respectively. Institutional investor information sharing increases the accuracy of analyst forecasts in term of both the degree indicator of the fund information network and the clustering coefficient indicator. Moreover, the greater the analyst attention is, the higher the accuracy of the forecast becomes. This outcome is mainly due to the information sharing through following other analysts. The coefficients of the interaction items between the degree of fund information network and analyst attention and the interaction items between the clustering coefficient of fund information network and the analyst attention are significantly positive (2.3588 and 1.9746). Our further results on interactive items of the network topology indicator with analyst attention show that institutional investor information sharing can increase forecast accuracy by enhancing the information transparency of listed companies. With respect to the control variables, it can be seen that analyst public information enhances forecast accuracy since the results of analyst rating reveals a more comprehensive reflection of analyst public information.

The right panel in Table 2 reports the results of analyst optimism bias. The results show that the topological indicators of the fund information network are negatively correlated with analyst optimistic bias. The coefficient values of degree and clustering are respectively − 0.0036 and − 0.0582, and the results are significant at the levels of 1 % and 10 %, respectively. It indicates that the information sharing reduces analyst optimistic bias. Due to the information spread among analysts, a greater degree of analyst attention results in a lower degree of optimism bias. The coefficients of the interaction term between topological indicators and analyst attention are negative, indicating that institutional investor information sharing reduces analyst optimism bias by influencing analyst attention. From the perspective of control variables, positive public information decreases analysts' optimistic bias. Hence, the results of Table 2 verify hypothesis H1. The information sharing between institutional investors and analysts has improved the accuracy of analyst forecasts and has reduced analyst optimism bias.

5.3. Analyst optimistic bias and stock price crash risk

Table 3 shows the regression results of analyst optimism bias and stock price crash risk, measured by two indicators, negative conditional return skewness (*ncskew*) in columns 1 and 2 and down-to-up volatility (*duvol*) in columns 3 and 4 as specified in Eqs.(6)–(7). The results show that analyst optimistic bias significantly increases the stock price crash risk, indicating that the conflicts of interest faced by analysts will enhance the tendency toward optimistic bias. This result is consistent with the hidden theory that when analysts release biased reports, they hide the company's negative information and increase the crash risk caused by the release of negative information. Moreover, when using analyst attention as the key variable in columns 1 and 3, the coefficient of the analyst optimistic bias is also positive and significant at the 10 % level.

5.4. Institutional investor information sharing and stock price crash risk

Table 4 shows the regression results of institutional investor information sharing and stock price crash risk using the network

Table 5
Fund information sharing with analyst, and stock price crash risk.

	Stock price crash risk			
degree	-0.0562*		-0.2482***	
	(−1.97)		(−3.68)	
*degree*accu*	-1.3798**		-1.9693**	
	(−2.03)		(−2.21)	
cluster		-1.9671**		-5.8275***
		(−2.16)		(−3.56)
*cluster*accu*		-0.0161*		-0.0217**
		(−1.96)		(−2.57)
accu			-0.0532**	-0.0395**
			(−2.51)	(−2.50)
analyst			0.0024*	0.0048*
			(0.25)	(0.66)
asslia			0.1198*	0.3910*
			(0.33)	(1.45)
holder			0.0025	0.0035
			(0.57)	(1.10)
lncap			-0.1253	0.0144
			(−0.98)	(0.15)
roe			-1.6177*	-1.1930*
			(−1.81)	(−1.82)
em			0.0056*	0.0031*
			(0.31)	(0.23)
pe			0.0006	0.0004
			(0.27)	(0.23)
bm			-0.2134*	-0.0623*
			(−0.31)	(−0.12)
turnover			0.0002	0.0001
			(0.31)	(0.26)
returns			0.0058**	0.0045**
			(2.41)	(2.51)
Amihud			0.4226*	-0.9485
			(0.19)	(−0.57)
Industry/Year	Yes	Yes	Yes	Yes
N	4011	3926	3975	3857

Table 6
Information sharing effect, conflict of interest effect and stock price crash risk.

	ncskew	*ncskew*	*ncskew*	*ncskew*	*duvol*	*duvol*	*duvol*	*duvol*
degree	-0.2354*		-0.2012***		-0.1288*			-0.0330**
	(−3.18)		(−3.01)		(−2.56)			(−0.84)
cluster	-14.7340**			-0.8011*	-9.5179**		-0.9030*	
	(−4.04)			(−0.35)	(−2.81)		(−0.39)	
fopt		0.0141*	0.0142*	0.0136*		0.0146**	0.0148***	0.0149***
		(0.07)	(0.08)	(0.06)		(0.07)	(0.08)	(0.08)
accu		-0.0422**	-0.0425**	-0.0394**		-0.0269*	-0.0300**	-0.0291**
		(−0.32)	(−0.29)	(−0.75)		(−0.89)	(−0.68)	(−0.57)
Control	*Control*	*Control*	*Control*	*Control*	*Control*	*Control*	*Control*	*Control*
Industry/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3536	3218	3322	3465	3617	3588	3691	3107

topology indicator. The results show that private information sharing of institutional investor has a significantly negative impact on stock price crash risk in column 1 and 2, and the impact remain consistent after adding other control variables in column 3 and 4. An increase per unit of the institutional investor information network degree indicator leads to a reduction in the stock price crash risk by 0.0448 units. An increase per unit in the network clustering coefficient results in 1.0248 unit decrease in the crash risk of stocks.

5.5. *Institutional investor information sharing, analyst forecasting and stock price crash risk*

Institutional investors exchange private information within social networks. Through business cooperation with analysts, private information of fund spills over to analysts, which will affect the forecasts of analysts. In order to examine the impact of fund information sharing with analyst on stock price crash risk, this section introduces the interactive items of network topology indicators and analyst forecast accuracy to analyze the underlying mechanism. The results are reported in Table 5. As is shown in the table, the interaction items respectively use degree indicator and clustering coefficient indicator to interact with forecast accuracy variable. Then the impact of fund information sharing with analyst on stock price crash risk can be examined. The regression results of the key

Table 7
Stock price synchronization.

	Analyst optimistic bias and stock price synchronization				Fund information sharing and stock price synchronization			
	SYND		*SYNS*					
cluster						-0.4556**		-0.3481*
						(−2.38)		(−1.74)
fopt	0.9886*	2.1408***	1.0050*	2.2671***				
	(1.71)	(3.20)	(1.76)	(3.35)				
analyst	0.0022*	0.0010*	0.0026**	0.0016*			0.0038**	0.0050***
	(1.95)	(0.56)	(2.40)	(0.87)			(2.27)	(3.13)
accu		-0.0119**		-0.0121**				
		(−2.17)		(−2.19)				
asslia		-0.5346***		-0.4992***			-0.4548***	-0.4532***
		(−5.64)		(−5.21)			(−4.62)	(−4.54)
holder		-0.0021*		-0.0019*			-0.0017	-0.0015
		(−1.83)		(−1.67)			(−1.45)	(−1.28)
lncap		0.0646*		0.0578*			-0.0566**	-0.0680***
		(1.89)		(1.68)			(−2.61)	(−3.14)
roe		-0.1071*		-0.1241*			-0.6620***	-0.6314**
		(−0.45)		(−0.52)			(−2.77)	(−2.61)
em		-0.0009		0.0001			0.0055*	0.0057*
		(−0.18)		(0.03)			(1.10)	(1.13)
pe		0.0004		0.0005			0.0004	0.0005
		(0.63)		(0.83)			(0.72)	(0.83)
bm		0.3502*		0.3003*			-0.1194*	-0.1599*
		(1.92)		(1.63)			(−0.78)	(−1.02)
returns		0.0005*		0.0006*			-0.0002*	-0.0001*
		(0.87)		(0.98)			(−1.86)	(−0.97)
turnover		0.0001		0.0001			0.0006	0.0002
		(0.42)		(0.65)			(1.01)	(0.35)
Amihud		-0.8724*		-0.7722*			-0.9954*	-0.8511*
		(−1.45)		(−1.27)			(−1.49)	(−1.26)
Industry/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4002	3976	3884	3918	4001	3884	3926	3801

variables are listed in columns 1 and 2, and the regression results after adding other control variables are reported in columns 3 and 4.

It can be seen from Table 5 that the interaction effects between network topology indicator and analyst forecast accuracy are significant using both *degree* and *cluster* interacting with analyst forecast accuracy in columns 1 and 2. The results with the addition of control variables and those without adding control variables both indicate that fund information sharing with external analysts reduces the crash risk of stocks. In conclusion, fund information sharing reduces stock price crash risk by improving analyst forecast accuracy. With the improvement in the accuracy of analysts' forecasts, the inhibitory effect of institutional investor information sharing on stock price crash risk has been strengthened. After adding control variables in columns 3 and 4, the coefficient sign of the interaction term remains unchanged, and the value gets larger, with the significance level also improved.

Further, we respectively investigate the impact of information sharing effect and conflict of interest effect on stock price crash risk, and the regression results are presented in Table 6. The first two columns in Table 6 are the regression results calculated using the *ncskew* indicator, and the last two columns are the results calculated using the *duvol* indicator. Institutional investor information sharing is mainly measured by the two network topological indicators of degree and clustering coefficient, and the analyst conflicts of interest are mainly measured by two indicators of analyst optimism bias and analyst forecast accuracy.

The coefficients between crash risk and fund information network topology indicators are negative, and the coefficients of analyst optimism bias are positive. The results of the comprehensive effects of information sharing on crash risk show that private information sharing helps to reduce the crash risk through analyst forecasting. Although the conflicts of interest faced by analysts can lead to crash risk, improved information sharing among institutional investors in social network can reduce stock price crash risk by reducing analyst optimism bias or improving analyst forecast accuracy.

6. Robustness tests

6.1. Institutional investor information sharing, analyst forecasting and stock price synchronicity

Financial theories posit that the heterogeneity of information in stock price adds noise hence the individual volatility of stock price, while the stock price synchronization characterizes the correlation between individual stock price variation and the average market variation. And a lower level of heterogeneous information about firm characteristics in stock prices results in a higher level of synchronization in stock prices. An and Zhang (2013) argue that higher level of synchronization in stock prices results in stronger resonance effect and higher frequency of stock price crashes. Different from the phenomenon of stock price rising, the simultaneous plunge in stock prices is more likely to trigger systemic financial risks (Callen and Fang, 2013). The synchronicity of stock prices and

Table 8
Institutional investor information network, analyst forecasting and stock price synchronization.

	Stock price synchronization			
fopt	0.0003	0.0002	0.0015	0.0018
	(0.15)	(0.10)	(0.69)	(0.80)
degree	-0.0190***		-0.0215***	
	(−3.40)		(−3.32)	
*degree*fopt*	0.0994*		0.1645**	
	(1.79)		(2.53)	
cluster		-0.4783**		-0.4951**
		(−2.36)		(−2.31)
*cluster*fopt*		1.2947*		1.8815*
		(1.62)		(1.97)
accu			-0.0157***	-0.0134**
			(−2.66)	(−2.25)
analyst			0.0079***	0.0091***
			(3.43)	(3.86)
asslia			-0.2150***	-0.2015***
			(−3.16)	(−2.90)
holder			-0.0023**	-0.0021**
			(−2.53)	(−2.24)
lncap			-0.0220	-0.0378*
			(−0.99)	(−1.73)
roe			-0.6078***	-0.5299**
			(−2.76)	(−2.34)
em			0.0117**	0.0118**
			(2.44)	(2.40)
pe			0.0005	0.0007
			(0.89)	(1.22)
bm			-0.0154	-0.0358
			(−0.19)	(−0.44)
turnover			-0.0002**	-0.0001*
			(−2.11)	(−0.86)
returns			0.0010*	0.0005
			(1.73)	(0.93)
Amihud			-0.8420*	-0.6644*
			(−1.27)	(−0.98)
Industry/Year	Yes	Yes	Yes	Yes
N	2216	2133	2059	2247

the crash risk of stocks are closely related, both of which stem from the concealment of bad news by management for their self-driven interest. In the case of asymmetric information, the accumulation of bad news and its instantaneous release will lead to stock price collapse (Jin and Myers, 2006), and opaque information is an important reason for this sort of collapse (Hutton et al., 2009). Similar to the studies on stock price crash risk, existing studies find that stock price synchronization can also be affected by market players such as institutional investors and analysts by virtue of information spreading (Xu et al., 2013). Therefore, in this section we use stock price synchronization to test the robustness.

Table 7 shows the regression results of analyst optimistic bias and stock price synchronization in the left panel and the regression results using the topology indicators for institutional investor network and stock price synchronization in the right panel. The first column and the second column of the left panel are the *SYND* calculated by the equal-weight average method of the sub-market, and the third column and the fourth column of the left panel are the *SYNS* calculated by the equal-weight average method of the integrated market. The results show that the coefficients of the optimism bias of analyst earnings forecasts are all positive and statistically significant, which indicates that analyst optimistic bias brings about stock price synchronization. As can be seen in the table, analysts pay more attention to stocks held by institutional investors in large positions, and the interest relationship between funds and analysts enhances optimistic bias. More analyst attention conveys more information about the stock to market investors, which is likely to trigger herd effect among investors. If investors in the market follow one another consistently, the stock price synchronization in the market will also be higher.

The results of the right panel in Table 7 show that institutional investor information network generates a significantly negative impact on the synchronization of stock prices, and this impact remains after we add the set of control variables. Specifically, after controlling the related influencing factors, an increase of fund information network per unit leads to a decrease of 0.0154 units in stock price synchronization. Each additional unit of the network clustering coefficient results in a decrease in stock price synchronization by 0.3481 units. This decrease indicates that private information dissemination of funds helps reduce stock price synchronization by improving the transparency of information of listed companies.

Subsequently, we introduce the interactive items of network topology indicators and analyst optimism bias to see how the joined force of fund information sharing and analyst interest relationship may impact stock price synchronization. The results are reported in Table 8. It can be seen that the interaction effects of both *degree* and *cluster* with analyst optimism bias are positive and significant. It suggests that analyst optimism bias moderates the inhibitory effect of institutional investor information sharing on stock price

Table 9
Regression results of crash risk and stock price synchronization under bull market.

	Stock price crash risk				Stock price synchronization			
Explained variable	*fopt*	crash risk	crash risk	crash risk	*fopt*	synchronization	synchronization	synchronization
degree	0.0021*		-0.0839***	-0.0577*	0.0021*		-0.0287***	-0.0186***
	(1.69)		(−2.77)	(−1.90)	(1.69)		(−2.71)	(−2.86)
fopt		4.6054*		4.3692*		1.8414**		-0.0009
		(1.65)		(1.91)		(2.26)		(−0.4)
*degree*fopt*				1.7584*				0.1347**
				(1.84)				(2.07)
analyst	0.0230***	0.0872*	0.2504*	0.0536	0.0230***	-0.0232	-0.0005	0.0024*
	(2.72)	(0.36)	(1.23)	(0.29)	(2.72)	(−0.49)	(−0.25)	(1.71)
accu	-0.0042***	-0.0635***	-0.0548***	-0.0533***	-0.0042***	-0.0163**	-0.0065	-0.0152**
	(−5.14)	(−2.90)	(−2.79)	(−2.69)	(−5.14)	(−2.14)	(−1.06)	(−2.46)
rate	-0.2219**	1.7454*	1.9080*	2.0704*	-0.2219**	-0.0678	-0.5954	-0.5027
	(−2.27)	(0.69)	(0.81)	(0.99)	(−2.27)	(−0.09)	(−0.82)	(−1.41)
asslia	0.0264	0.2826*	0.4094*	0.3717*	0.0264	-0.3018***	-0.2607***	-0.2524***
	(1.44)	(0.66)	(0.93)	(0.97)	(1.44)	(−3.45)	(−3.18)	(−3.67)
holder	0.0002	0.0025	0.0041	0.0023	0.0002	-0.0036**	-0.0029**	-0.0029***
	(1.01)	(0.43)	(0.73)	(0.47)	(1.01)	(−2.55)	(−2.10)	(−3.12)
lncap	-0.0105	0.1599*	0.1951*	0.2881*	-0.0105	0.0858*	0.0661	-0.0236
	(−1.51)	(0.92)	(1.17)	(1.99)	(−1.51)	(1.81)	(1.39)	(−0.97)
roe	-0.1176*	-1.1573*	-1.5056*	0.6441	-0.1176*	-0.7457*	-1.0959***	-0.5739**
	(−1.90)	(−0.80)	(−1.01)	(0.47)	(−1.90)	(−1.93)	(−2.96)	(−2.51)
em	0.0049***	0.0181	0.0177*	0.0023	0.0049***	0.0163**	0.0198***	0.0102**
	(4.19)	(0.61)	(0.63)	(0.08)	(4.19)	(2.39)	(3.00)	(2.08)
pe	-0.0000	0.0027*	0.0033	0.0035*	-0.0000	-0.0001	-0.0001	0.0004
	(−0.01)	(1.14)	(1.26)	(1.58)	(−0.01)	(−0.18)	(−0.14)	(0.75)
bm	-0.1378***	1.9826*	1.2132	1.9867*	-0.1378***	-0.1107*	-0.2442*	-0.0499
	(−3.01)	(1.60)	(1.11)	(1.96)	(−3.01)	(−0.82)	(−1.95)	(−0.62)
returns	-0.0003*	0.0118***	0.0090**	0.0068*	-0.0003*	-0.0008	-0.0008*	0.0010*
	(−1.88)	(2.67)	(2.07)	(1.74)	(−1.88)	(−0.60)	(−0.61)	(1.72)
turnover	0.0001**	-0.0006	-0.0005	-0.0001**	0.0001**	-0.0002*	-0.0000	-0.0002**
	(2.09)	(−0.71)	(−0.68)	(−0.07)	(2.09)	(−0.92)	(−0.06)	(−1.98)
Amihud	-0.6901	3.5640***	3.2778***	6.6855**	-0.6901*	11.3805*	-0.9112*	-0.9540*
	(−0.53)	(3.33)	(3.28)	(2.46)	(−0.53)	(1.26)	(−0.10)	(−1.40)
Industry/Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1278	1107	1231	1106	1038	1115	1089	1234

synchronization. That is to say, as the analyst's optimism bias decreases, the inhibitory effect of institutional investors on stock price synchronicity increases. After adding the control variables in columns 3 and 4, the coefficient sign of the interaction term remains unchanged, and the value gets larger, with the significance level also improved.

7. Extended analysis

7.1. Different market trends: bull vs. bear market

External market situations are important factors in stock price crash risk. Security analysts are also affected by macro-level and market factors when making forecasts. In particular, the investment style of fund managers is affected much more by the market as their career goes on. Hence, we further investigate the impacts of external factors such as the market status and the investor sentiment in the expansion study. For the division of the bull market and the bear market, we refer to the method of Pagan and Sossounov (2003) and select the macro-variable indicators that reflect the real economy with the HS 300 index returns to determine the bull and bear markets.

Table 9 shows the regression results of the crash risk under the bull market in the left panel, and the right panel shows the regression results of stock price synchronization under the bull situation. In the left panel of the table, the effect of fund information sharing on analyst optimistic bias is reported in the first column; and the effect of optimistic bias on stock price crash risk is reported in the second column; the third column lists the influence of fund information sharing on stock price crash risk; then the fourth column lists the interactive effect of information sharing and forecast bias on stock price crash risk. In the right panel, the influence of optimism bias on stock price synchronization is shown in the second column; the third column reports the effect of fund information sharing on stock price synchronization; and the fourth column lists the interactive effect of information sharing and conflicts of interest on stock price synchronization. Since the regression results under the bear market situation are similar, and the bear market results are not significant, the analysis results are not reported.

The results display that the coefficients of analyst forecasting become increasingly significant. This outcome indicates that institutional investors rely more on analysts under better economic situations, and the interest relationship between buyers and sellers are closer, resulting in more obvious conflicts of interest. The stock price crash risk caused by analyst conflicts of interest is different under

Table 10
Regression results of endogeneity test.

	Stock price crash risk			
fopt	3.6125**	0.5233	1.5133**	1.7234
	(1.15)	(1.33)	(0.94)	(1.27)
degree	-0.0471**		-0.3104**	
	(−2.76)		(−2.09)	
*degree*fopt*	1.4606**		1.6259**	
	(2.01)		(2.46)	
cluster		-1.8533*		-4.9746**
		(−1.10)		(−1.68)
*cluster*fopt*		0.0207*		0.0316**
		(0.02)		(0.01)
accu			-0.0199**	-0.0619**
			(−0.26)	(−0.77)
analyst			-0.0300**	-0.0291**
			(−2.24)	(−2.20)
asslia			0.1921*	0.2833*
			(0.89)	(1.47)
holder			0.0717	0.0741
			(0.41)	(0.43)
lncap			-0.0017	-0.0019
			(−0.73)	(−0.84)
roe			-1.0525*	-1.0447*
			(−0.90)	(−0.76)
em			0.8940	0.0823*
			(1.59)	(1.92)
pe			0.0007	0.0009
			(0.51)	(0.67)
bm			-0.3718*	-0.3526*
			(−1.82)	(−1.73)
turnover			0.0009	0.0015
			(0.64)	(1.05)
returns			0.0004*	0.0006**
			(1.53)	(2.25)
Amihud			-0.8478	-1.0727
			(−0.49)	(−0.62)
Industry/Year	Yes	Yes	Yes	Yes
N	3772	3885	3664	3804

different market situations. This is just contrary to the conclusion obtained by Loh and Stulz (2018). Furthermore, when examining the differences between analyst optimism bias and stock price crash risk in the bull and bear markets, we find that the relationship between analyst optimistic bias and stock price crash risk is more significant during the bull market. It shows that the same ups and downs of stock prices caused by the close interest relationship between institutional investors and analysts are more obvious when the economy is in a boom. This is mainly due to the large trading volume and financing volume of listed companies in the bull market stage. In order to help their employers obtain more underwriting opportunities and commission income, analysts will release more optimistic reports. In addition, the interactive effect of information sharing and conflicts of interest on crash risk is also more significant in the bull market situation.

7.2. Endogeneity control

Endogeneity-related problems are unlikely to be a major concern for our research findings for two reasons. First, we have controlled for the potential effect of the firm-level and the industry-level variables that have an effect on stock price crash risk, and thus reducing the omitted variables concern to the minimum. Second, we have regressed the dependent variable on the lagged independent variable, while controlling the control variables. As pointed out by Chung et al. (2010), regressions using changes in variables are less subject to spurious correlations and provide a stronger test of causal relations than those using levels of variables.

To further control reverse causality or self-selection biased concern, we further use the propensity score matching method to re-examine the relationship between institutional investor network, analyst conflict of interest and stock price crash risk. We convert the topological structure characteristic variables (degree, clustering coefficient) of the fund information network into the 0–1 binary variables: 1 represents the fund whose indicator value is in the first half, and is used as the treatment group; 0 represents the fund whose indicator value is in the latter half, and is used as the control group. The propensity score of the fund is calculated based on the fitting value of the logit model, and the most commonly used one-to-one matching is employed to determine the control sample. After the matching is completed, the average treatment effect on the stock price crash risk of the treatment group and the control group are calculated, respectively. Then the regression results are listed in Table 10. Seen from the re-examination results, it is consistent with the previous conclusion. Under the condition that analyst optimism bias increases the crash risk of stock price, institutional investors sharing private information with analysts can help reduce the crash risk.

8. Conclusion

This paper analyses the detailed data of mutual funds holding stocks in China, and builds the institutional investor information network based on the social network theories. We aim to explore the relationship among fund information sharing, analyst forecast and crash risk, focusing on the impact of fund information sharing with analysts on stock price crash risk.

We find that institutional investor information sharing improves the accuracy of analyst forecasts and reduces analyst optimistic bias via improving the transparency of information in the market. Private information sharing of fund can integrate information into stock prices and reduces stock price crash risk as well as stock price synchronization. And this effect is more significant in the bull market. Although the conflicts of interest faced by analysts can cause crash risk and synchronization of stock prices of listed companies, the increase in the efficiency of information sharing generates mitigating effect on the crash risk of stock price caused by analyst optimistic bias. Through the sharing of information regarding listed companies by institutional investors with analysts, stock prices can reflect more individual information, and thus reduces crash risk. The robustness test supports that information sharing by institutional investors reduces the stock price synchronicity which is caused by analyst forecast bias.

We believe that the results of our study are beneficial to academic researchers, institutional investors, and analysts. Although we use Chinese data, the results of the study are internationally versatile. The conclusion of the study has important practical significance and helps to better understand the role of institutional investors, so as to strengthen market risk management, and to enrich investment strategies. It can also help institutional investors investigate their interactions with analysts and the crash risk they face. These results also prompt the regulatory authorities to take measures to expand the sharing of fund information so that the information of listed companies is made open and transparent. By alleviating the phenomenon of stock price synchronization and crash risk caused by analyst forecast bias, it improves the efficiency of capital allocation. In addition, it instructs the security regulatory authorities to take timely measures when the market is in a frenzy to mitigate against the crash risk.

CRediT authorship contribution statement

I have made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work. I have drafted the work critically for important intellectual content. And I have approved the version to be published. I agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Besides, all persons who have made substantial contributions to the work reported in the manuscript.

Data Availability

Data will be made available on request.

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