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Institutional investor network, analyst public information and extreme risks

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ABSTRACT

This paper builds the institutional investor network on the basis of the common stock holdings of mutual funds with large positions. Institutional investors share and interact private information through social networks. Seen from separating private and public information, the effects of private information sharing in institutional investor networks and the effects of public information diffusion on extreme risks are examined, respectively. Then, the integrated impact of institutional investor information sharing with analyst on extreme risks is analysed. Empirical research has found that analyst public information spread will decrease the probability of extreme risks. The information sharing in social network of institutional investors will restrain stock market extreme risks. The closer network of institutional investors lower the influence of analyst public information on extreme risks. In addition, we also found that stock liquidity has weakened the inhibition of fund network information sharing on extreme risks. The research results provide reference for the authorities to regulate market participant behaviours so as to avoid risks.

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1. Introduction

In the recent years, China's capital market has developed rapidly. As of 2019, there are more than 3,000 listed companies in China, with a total market value of about 60 trillion yuan. The rapid development of capital market has not only brought about the prosperity of capital market but also brought about large volatility in stock markets. Accompanied by this, there have been many extreme events caused by drastic volatility in the capital market in recent years. Moreover, market volatility and extreme risks are occurring more frequently. In particular, due to the shock of the global public health event in 2020, the capital market has shown great uncertainty. Therefore, it is of great importance to examine the relationship between market participants and extreme financial risks.

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The reason why extreme events occur frequently is because stock market highly depends on information shock. Institutional investors and analysts are important market participants. The market is flooded with a lot of information, and analysts issue public forecast reports through investigation and research. Institutional investors can obtain private information through social networks by virtue of their team and their own advantages. Then, how does the spread of private and public information affect the extreme market risks? What is the mutual influence mechanism of different channels of private information and public information spread? What is the effect of various types of information dissemination on extreme risks of stock market? Hence, clarifying these issues will be the focus of this study.

Since institutional investors can obtain private information through social networks, they have information advantages. Therefore, its trading operations in the stock market often trigger herding effects (Galariotis et al., 2015). The impact of institutional investor behaviour on crash risk has received increasing attention (Callen and Fang, 2013). The gather of bad news and the burst of accumulated news often leads to stock price crashes for stocks that have synchronicity (Jin and Myers, 2006). And the information opacity plays an important role in crash risks (Hutton et al., 2009). Since mastering information advantage often results in excessive profits, institutional investors often seek more private information to enhance their information advantage. Existing studies have shown that there is close communication between institutional investors. Colla and Mele (2010) found that there exists obvious correlation among the trading behaviours of closely related institutional investors in the information network. The close information interaction of institutional investors will inevitably affect the information it holds and the investment decisions made. Therefore, study on the influence of institutional investor information sharing on stock volatility is conducive to exploring the role of private information in preventing extreme risks.

The analyst industry in China has developed rapidly, and the forecast report released by analysts has also expanded their influence on the market. However, academics disagree on the authenticity and the role of analyst forecast reports. On the one hand, analyst attention can reduce the information opacity of company, thereby inhibiting the occurrence of stock price crashes (Tusheng et al., 2017). On the other hand, in order to increase trading volume and to earn more commissions, analysts often provide more buying rating reports when recommending stocks and earnings forecasts (Jackson, 2005). Chan et al. (2012) found that analyst optimistic forecast reports add stock extreme risks. If analysts are from investment banks that have underwriting business, its role in increasing collapse risk is more evident. Plentiful research has currently focussed on analyst public information, while lacking studies of the influence of public information from analysts on extreme risk. Furthermore, there have been few studies that considered the impact of private information dissemination in institutional investor social relations networks on analyst forecast, and the comprehensive effect of private information sharing in institutional investor social relations networks and analyst public information on extreme risks.

In summary, the extreme risk may be affected by private information of institutional investor network and public information released by analysts. It is still a difficult problem in current research concerning the separate role of public and private information on extreme risks. And consider the interaction between public information released by analysts and private information of institutional investor social relationship is still a thorny issue. Fortunately, complex network tools provide useful tools in tackling these issues. Through the social network of institutional investors, private information can be separated. Hence, this paper builds an institutional investor network utilising common stock holdings of mutual funds as linkage. Then we investigate whether the positive public information of analysts and the diffusion of private information in networks will affect extreme risks. And we further investigate whether the dissemination of private information in institutional investor networks will enhance or suppress the effect of positive public information on extreme risks.

Specifically, the research content mainly includes the following aspects: Primarily, we investigate whether the spread of analyst public information decreases the extreme risk probability. And whether the dissemination of private information of institutional investor network will also suppress the occurrence of rare risks. Second, we examine the intermediary role of the closeness of the institutional investor network in influencing the effect of analyst public information on tail risk. To be precise, whether the closeness of the institutional investor network weakens or enhances the role of public information released by analysts on tail risks is analysed. Finally, we analyse the intermediary role of stock liquidity in influencing the effect of institutional investor network on stock market tail risk.

The innovative contributions of this study contain the following aspects: primarily, we respectively investigated the influence of public and private information transmission within social network on tail risks. Since there exists conflict of interest between institutional investors and analysts, analysts tend to hide bad news when releasing reports on stocks they heavily invested. As a result, we have examined the effect on stock tail risks when private information of institutional investor and analyst public information are shared. Further, we analyse the impact of private information sharing on the relationship between analyst and tail risks. Different from most previous studies concentrating on the influence of institutional investors on market risk, this paper analyzes the integrated effect of private and public information on tail risk considering the conflict of interest between institutional investor and analyst.

2. Literature review and research hypothesis

2.1. Institutional investor network

The existing literature generally builds the institutional investor network on the basis of three attributes. The first kind of network is the social network constructed according to the attributes of social relations. Pool et al. (2015) found that institutional investors with common social relationships have similar holdings and trading styles. Cohen et al. (2008) found that fund managers prefer to invest in companies having same educational background for company directors, and such investments can get more profits. The second kind of network is an information network formed according to geographic location. Hong et al. (2005) found that trading behaviours of fund managers in the same city are similar. Even if fund manager and related stocks are far apart, this model will manifest itself. The third kind of network is the information network formed according to the investor's asset allocation, such as holding the common stock. Pareek (2012) proposed that there is information exchange between institutional investors who hold the same stock with large positions, and used this method to build an institutional investor network. It has been found that investment performance of institutional investors within the same network shows significant similarity. These studies have constructed information networks between institutional investors from different dimensions. And no matter how institutional investor network is built, frequent information exchanges will occur in the network. The exchange of information in this network will affect the investment performance and returns of investors (Ozsoylev et al., 2014).

To be precise, the third type of information network based on asset allocation belongs to atypical social relationship network, which avoids the influence of social human relations on network construction. Different from the first two types of social network construction methods, it is more reasonable to express information sharing based on the consistency of transactions and positions between institutional investor nodes in the network. Existing research has also verified that institutional investors are holding stocks because they own the private information of the stocks (Bushee et al., 2011). Therefore, this paper draws on Blocher (2016) and Crane et al. (2019) to build an information network based on the stock common holdings of institutional investors, and measures the degree of information sharing within the network through the characteristics of the network topology. Then the relationship between institutional investor private information sharing, analyst public information and extreme risks is analysed.

2.2. Analyst public information and tail risk

As the professional team in the capital market, analysts have the advantages of rich experience, fast computation, and sufficient information (Hutton et al., 2011). Analyst forecast plays an intermediary role between the quality of information disclosure and the collapse of stock prices (Tusheng et al., 2017). In particular, star analyst ratings can affect stock price volatility (Loh and Stulz, 2011). On the one hand, Clement and Tse (2005) research found that analyst forecast will become bolder as their experience grows, and bold forecast were more accurate than herds. On the other hand, Mehran and Stulz (2007) believe that if analysts bring benefits to their client investors by issuing biased forecast reports, there exist conflict of interest between them. It is the existence of this conflict of interest that has caused analysts to make optimistic forecast (Bowen et al., 2018). Although analysts tend to release biased reports, the more optimistic the analyst forecast, the better the outlook for stock price (Womack, 1996). In addition, China's capital market regulatory system has become stricter, and it has also provided a good environment for the development of companies that analysts pay more attention to. Hence, we make the following hypothesis:

H1a: The issue of analyst public information decreases the probability of tail risks.

However, analyst prediction behaviour is inevitably influenced by related interests (Gu et al., 2013; Hovakimian and Saenyasiri, 2010). Irvine (2004) research found that in the two weeks after the analysts released the forecast, the brokerage company will conduct a large number of transactions on the predicted stock, which proves that the analyst forecast will affect the commission income of brokerage companies. In order to maintain a good cooperative relationship with institutional investors, analysts tend to issue biased research reports (Mola and Guidolin, 2009). Considering this kind of conflicts of interest, analysts tend to ignore the damage of negative information (O'Brien et al., 2005). Analysts tend to hide negative information, however, once the information is accumulated to the limit, it will trigger a chain reaction of bubble burst. Hence, we make the following alternative hypothesis:

H1b: The issue of analyst public information enhances the probability of tail risks.

2.3. Institutional investor network and tail risk

Social relationship networks are the main means of disseminating private information (Han and Yang, 2013). A large number of studies have confirmed the existence of institutional investor information networks. Hong et al. (2005) found that institutional investor of the same city have similar trading behaviours, and they spread information about stocks by word of mouth. An institutional investor information network is formed between institutional investors through social relationship connections to disseminate private information. Private information sharing is the rational choice to maximise self-interest and to obtain valuable information in return (Crawford et al., 2017; Stein, 2008). Research of institutional investor market behaviour on capital market is numerous, and academic and regulatory authorities have yet to form consistent opinion. Verma and Verma (2007) found that investor sentiment displayed significant positive correlation with stock returns volatility. However, An and Zhang (2013) presented that long-term institutional investors had negative correlation with stock price synchronisation and crash risk. This is because institutional investors who hold company stocks for a long time tend to supervise the behaviour of company management, which reduces the accumulation of negative information of the company, thereby reducing the collapse risk of stock price (Xu et al., 2014). Information sharing and exchange in social network may enhance the accuracy and comprehensiveness of information to the market. By improving the market efficiency, the extreme market risk caused by abnormal stock price volatility is reduced (Han and Yang, 2013). In addition, Irvine (2007) found that institutional investors with information advantages and professional capabilities can reduce stock volatility through strategic trading. Hence, we propose the following alternative hypothesis:

H2a: Information sharing in institutional investor network inhibits tail risks.

On the other hand, institutional investors also employ market noise to force stock prices to deviate from their intrinsic value, thereby exacerbating market volatility (Dennis and Strickland, 2002). Studies have shown that herd behaviour among institutional investors will increase the volatility of stock prices and increase the volatility risk of stocks (Tan et al., 2008). The information diffusion in the investor information network disturbs capital market stability (Ozsoylev et al., 2014). Information interaction among institutional investors via their social relationship network leads to the behavioural contagion, which is an important trigger for the financial crisis (Jegadeesh and Kim, 2010). Hence, we propose the following hypothesis:

H2b: Information sharing of institutional investor network will add tail risks.

The exchange of information in social network will enhance the multi-faceted information advantages and enable them to make more correct investment decisions, decreasing stock market tail risks caused by decision mistakes. Meanwhile, the information exchange of institutional investor network may also trigger herding behaviour. Especially during periods of high stock liquidity, institutional investors are active in trading. Through mutual imitation and social learning within the information network, it is easier to form herd behaviour, which exacerbates stock market risk. While during the period of low stock liquidity, institutional investors have less market trading behaviour, which suppresses the herding behaviour generated by mutual imitation in the information network. The reduction of herding behaviour decreases the stock market risk. Therefore, we propose the following hypothesis:

H3: The lower liquidity adds the inhibitory effect of information sharing on tail risks.

2.4. Institutional investors networks, analyst public information and tail risks

To sustain customer relationships with institutional investors as well as obtaining commission income, analysts will make optimistic and biased forecasts about the stocks held by institutional investors due to the existence of conflict of interest (Mola and Guidolin, 2009; O'Brien et al., 2005). The larger the holding positions of institutional investor and the more commission income generated from the institutional investor, the higher the analyst optimistic forecasts about the stock (Firth et al., 2013; Gu et al., 2013). Jackson (2005) also verified that analyst optimistic forecast would increase the trading volume of their brokerage firms. Wei et al. (2015) found that analyst forecast have an important impact on institutional investor herding effects. The higher the consensus of analyst expectations, the stronger the herd effect of institutional investors. In addition, the herding effect caused by information sharing of institutional investors may affect the analyst rating report through the interest relationship with the analyst (Brown et al., 2014). Theoretically, the closer the institutional investor network is, the more stocks the institutional investors jointly hold, and the more conflict of interest the analysts will face. Furthermore, this will lead to greater bias in the forecast reports made by analysts, which will affect the inhibitory effect of analyst public information on tail risks. Hence, we present the following hypothesis:

H4: Information sharing of institutional investor network decreases the influence of analyst public information on tail risk.

3. Research design

3.1. Institutional investor network

For the sake of analysing how information sharing within institutional investor network influences tail risk, we build the institutional investor network primarily. If two funds buy same stocks in large positions, it is defined in the same network (Pareek,

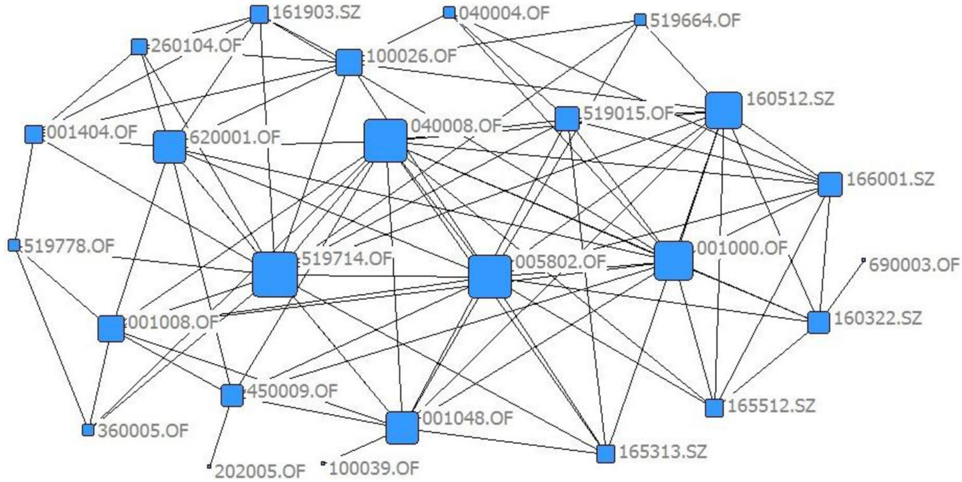

Figure 1. Institutional investor information network.
Source: the authors.

2012). For the fund buying stocks in large positions means that the capital market value of stocks held by the funds occupies more than 5% of the total value. And we mainly employ the top ten stock positions announced by the fund reports. Referring to Pareek (2012), we set the position of funds having larger than 5% as large positions, and there exists information exchange between funds who hold the same shares in large positions. If the fund holding of a stock exceeds 5% of all positions held by it, then all the funds that hold the same stock in large positions have information exchange with the original fund. The fund network is the collection of all other funds in the same network as it. Then we build the fund network linked through the funds' same holdings.

Based on the annual report data, we construct the mutual fund network of China in Figure 1. The Chinese institutional investor information network in Figure 1 is built on the top ten glamour stocks. We define the existence of information exchange for funds that share the same stock in large positions and connect them by a line. In Figure 1, taking the fund 165512.SZ as an example, the fund 165512.SZ hold the common stock together with funds 040008.OF and 160512.SZ as well as other six funds in large positions. Then the fund 165512.SZ in the fund network exhibits a total of six lines connected to the fund with common holdings in large positions. Based on the above principles, we have constructed the Chinese institutional investor information network. Through calculating the average path length and the clustering coefficient of fund network, it is found that Chinese institutional investor network displays small world characteristics.

3.2. Network topology indicators

We choose the network degree centrality and network clustering coefficient indicators to measure information spread efficiency of fund network. The degree centrality in the network describes the total centrality of network, indicating to what extent the fund network is built around certain network nodes. The network centrality measures some nodes in the network that play a special role in the information dissemination. The larger the value, the greater the role these nodes play, and the faster the speed of information propagation in the network.

$$\begin{gathered} degree = \sum_{k-1}^{N}(D(n_{max}) - D(n_k))/(N-2) \\ D(n_k) = d(n_k)/(N-1) \end{gathered} \tag{1}$$

where $d(n_k)$ is the degree of node n_k, and $D(n_{max})$ is the maximum value of $D(n_k)$.

The nodes that directly connected to the node n_i may also be connected other nodes. The clustering coefficient $cluster_i$ of node n_i measures the degree of connectivity between k_i nodes directly connected to the node n_i. The higher value of the clustering coefficient is, the higher the efficiency of information transmission within the institutional investor network displays. And the calculation formula is shown as follows:

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

where $g_{jk,i}$ is used to determine whether the k_{th} node that directly connected to the node is also connected to the j_{th} node.

3.3. Extreme risk

Value at risk (VaR) and Conditional value at risk (CVaR) are commonly emplyed risk measure index. VaR refers to the maximum loss faced by a certain asset portfolio in a certain period of time under a certain level of confidence α under normal circumstances. In other words, in a certain holding period under a given confidence level, the maximum loss of the asset portfolio will not exceed VaR.

$$VaR(\alpha) = -F_r^{-1}(1-\alpha) \tag{3}$$

where $F_r(.)$ is the cumulative distribution function of returns.

Because VaR does not satisfy sub-additivity, VaR of asset portfolio can surpass the weighted average VaR of individual asset. Hence, CVaR satisfying sub-additivity is employed to weigh portfolio risk. CVaR represents the average loss value of the investment portfolio under the condition that the loss of the investment portfolio exceeds a given VaR value. In extreme cases, the expected loss CVaR of the financial system can also be used to measure the state of crisis, as shown in Eq.(5).

$$CVaR(\alpha) = -\frac{\int_{-\infty}^{-VaR} x f_r(x)dx}{1-\alpha} \tag{4}$$

$$CVaR_{m,t-1}(C) = E_{t-1}(r_{mt}|r_{mt} < C) = \sum_{i=1}^{N} w_{it}E_{t-1}(r_{it}|r_{mt} < C) \tag{5}$$

where $f_r(.)$ is probability density function of returns, C is the threshold.

However, tail events have occurred more often recently. Due to the existence of tail risk, financial assets returns features leptokurtosis and fat tails, which contradicts normal distribution. Hence, it is better to use extreme value theory on the basis of generalised Pareto distribution (Gpd) to compute VaR and CVaR. Then, the returns larger than critical value K is defined as the extreme value X_{max}, and we number the returns series larger than the critical value K as $y_1, y_2, \ldots, y_n$. There exist n values from N sample that are larger than the critical value K. Moreover, the extreme value series $z_1, z_2, \ldots, z_n$, $z_1=y_1\text{-}K$, $z_2=y_2\text{-}K$, $\ldots$, $z_n=y_n\text{-}K$, are defined. $F(x)$ denotes the returns distribution function, then it can be computed in the following.

$$F_{max}(z_t) = \frac{F(K+z_t)-F(K)}{1-F(K)} \tag{6}$$

If K becomes high, then $F_{max}(z_t)$ reaches generalised Pareto distribution. Further, VaR and CVaR under Gpd can be computed.

$$VaR_z^{Gpd}(\alpha) = \mu + \frac{\sigma}{\xi}\left\{[(1-\alpha)N/n]^{-\xi} - 1\right\} \tag{7}$$

$$VaR_r(\alpha) = VaR_z^{Gpd}(\alpha) + K \tag{8}$$

$$CVaR_r(\alpha) = K + \frac{1}{1-\alpha}\int_0^{1-\alpha} VaR_z^{Gpd} x dx \tag{9}$$

It requires a backtest to assess the accuracy of results on the basis of normal distribution and generalised Pareto distribution. It can investigate the coverage of real loss through the model, and can test if the real loss and expected loss are efficient. The Kupiec failure rate LR test in Eq. (10) is the most commonly used test.

$$LR = -2\ln\left((1-p^*)^{T-N}(p^*)^N\right) + 2\ln\left((1-p)^{T-N}p^N\right) \tag{10}$$

4. Model specification

4.1. Analyst public information and extreme risk

As mentioned above, on the one hand, high-quality public information will guide investors to make proper investment decisions, so that more promising stocks are held by more investors. Moreover, the more optimistic the forecast report of analysts is, the more attention it will attract investor, thereby reducing the extreme risk caused by large-scale flight of investors. In the recent years, as China's capital market supervision has become stricter, most of the listed companies have entered a stage of benign development. More investment opportunities have further promoted the stock market, decreasing the emergence of extreme market risks.

However, in order to increase trading volume and to obtain more commission income, analysts tend to issue optimistic earnings forecasts and ratings. Under this conflict of interest situation, analysts tend to ignore the damage of negative information. The accumulation of negative news increases the risk of market collapse, which in turn may exacerbate extreme risks. To verify this hypothesis, we specify the following model.

$$Risk_{it} = \alpha + \beta rank_{it} + \gamma controls_{it} + \varepsilon_{it} \tag{11}$$

where $Risk_{it}$ represents the extreme risk variable of the stock market, which is measured by VaR and CVaR. $rank_{it}$ denotes analyst rating, which represents public information variables. $controls_{it}$ represents control variable.

4.2. Institutional investor network, analyst public information, and extreme risk

There exists conflict of interest between institutional investor and analyst. The denser the institutional investor network, the more severe this kind of conflict of interest will be. It will eventually affect the influence of analyst's forecasting reports, which causes analysts to make untrue report statements under the influence of conflict of interest, and thus affecting the tail risks. To verify this hypothesis, we specify the following model:

$$Risk_{it} = \alpha + \beta rank_{it} + \phi rank_{it} * net_{it} + \delta net_{it} + \gamma controls + \varepsilon_{it} \tag{12}$$

where net_{it} represents the topological indicator variable of institutional investor information network, which is measured by the network degree indicator and the network clustering coefficient indicator. $rank_{it}{}^{*}net_{it}$ denotes the interaction term of analyst rating $rank_{it}$ and network topology indicator net_{it}.

4.3. Institutional investor network and tail risks

On the one hand, information exchange in institutional investor network will improve the accuracy of information in the market. By improving the dissemination efficiency of market information, the extreme risk caused by abnormal stock price volatility is reduced. On the other hand, the herd effects exhibited by fund managers in the same network is more obvious. Studies have shown that herd behaviour among institutional investors will increase the volatility of stock prices and increase the market risk. The diffusion of information in the investor information network disturbs the stability of capital market. To verify this hypothesis, we specify the following model. In the specified model, by examining the regression results of the network topology indicator net_{it} on tail risk $Risk_{it}$, we analyse the effect of fund network on tail risk.

$$Risk_{it} = \alpha + \beta net_{it} + \gamma controls_{it} + \varepsilon_{it} \tag{13}$$

Further, we examine the role of liquidity in tail risk by institutional investor networks. As mentioned earlier, the worse the liquidity, the less likely it is to produce herd behaviour, which has an impact on the relationship of institutional investors and tail risk. Then we specify the following model:

$$Risk_{it} = \alpha + \beta net_{it} + \phi net_{it} * amihud_{it} + \delta amihud_{it} + \gamma controls + \varepsilon_{it} \tag{14}$$

where $amihud_{it}$ denotes illiquidity, which represents liquidity variable. $net_{it}{}^{*}amihud_{it}$ denotes the interaction item between network topology indicator net_{it} and liquidity indicator $amihud_{it}$.

4.4. Variable selection

5. Empirical analysis

5.1. Data and descriptive statistics

We use mutual funds and A-share listed stocks as samples to build the fund information network (Tables 1 and 2). The sample period covers data from 2007 to 2018, and the data come from *Wind*. The mutual fund selects the stock data including all common stock funds, the partial stock mixed funds and the balanced mixed funds. Especially, the stock holdings in large positions refer to the stock in the top ten

Table 1. Variable selection.

Dependent variable	VaR	Value at risk, indicating the magnitude of extreme risk
	CVaR	Conditional value at risk, indicating the magnitude of extreme risk
Independent variable	*rank*	Analyst rating, which is the average value that analysts rate stocks
	degree	Degree centrality
	cluster	Clustering coefficient
	rank degree*	Interaction term between analyst rating and degree centrality
	rank cluster*	Interaction term between analyst rating and clustering coefficient
	*degree*amihud*	Interaction term between degree centrality and illiquidity
	cluster amihud*	Interaction term between clustering coefficient and illiquidity
Control variable	*ReportAttention*	Research report attention, the number of research reports that track and analyse the company during the year
	lnm	Log market value, logarithm of the total market value of company stocks
	ForecastAccuracy	Analyst forecast accuracy
	froe	Return on equity
	fpe	Price earnings ratio
	amihud	Illiquidity
	PIT	Kurtosis
	beta	Beta in the CAPM model
	AGARCHT	AGARCH model with Student *t* distribution
	lever	Ratio of liabilities to assets
	em	Returns-to-market ratio
	mr	Annualized returns
	optimism	Analyst optimism bias
	forecastoptimism	Analyst forecast optimism
	turnover	Turnover rate
	bm	Book to market ratio

Source: calculated by the authors.

Table 2. Descriptive statistics.

Variable	Mean	SD	Min	p50	Max
VaR	0.010	0.010	−0.007	0.008	0.042
CVaR	0.011	0.012	−0.007	0.009	0.048
rank	0.900	0.049	0.679	0.912	0.974
degree	8.843	2.619	5.280	7.920	13.200
cluster	0.739	0.074	0.622	0.730	0.854
*rank*degree*	7.970	2.428	4.121	7.228	12.380
*rank*cluster*	0.664	0.069	0.487	0.660	0.810
degree**amihud*	0.089	0.265	0.004	0.034	2.733
cluster**amihud*	0.007	0.019	0.0004	0.003	0.177
ReportAttention	0.893	0.460	0.110	0.845	2.190
lnm	0.180	0.009	0.156	0.180	0.206
ForecastAccuracy	0.905	3.023	0.024	0.301	31.080
froe	0.173	0.109	−0.377	0.183	0.395
fpe	0.259	0.298	−1.162	0.211	1.958
amihud	0.010	0.023	0.001	0.004	0.207
PIT	1.796	1.865	−0.534	1.308	10.060
beta	0.368	0.350	0.024	0.217	1.454
AGARCHT	0.212	0.141	0.026	0.171	0.697
lever	0.471	0.253	0.0001	0.480	0.876
em	0.603	0.463	−0.757	0.504	2.324
mr	0.268	0.358	−0.407	0.222	1.512
optisim	0.106	0.636	−0.098	0.037	7.520
forecastoptimism	0.013	0.026	−0.096	0.009	0.124
turnover	2.476	1.644	0	1.990	9.449
bm	0.594	0.321	0.104	0.541	1.407

Source: calculated by the authors.

positions announced by the fund's quarterly report. According to statistics, the quarterly average value of the funds holding stocks in large positions in all funds is 40.6%.

5.2. Analyst public information and tail risk

We use the analyst rating indicator *rank* to measure analyst public information, and calculate the influence of analyst public information on tail risk VaR and CVaR, respectively. Seen from the regression results shown in Table 3, the analyst public information displays an obvious negative effect on tail risk. Specifically, for the independent variable regression results in the first column and the second column without control variables, the analyst rating coefficients are significantly negative. It shows that when the analyst rating increases by 1 percentage, the extreme risk measured by VaR will decrease by 0.0864 units, and the extreme risk measured by CVaR will decrease by 0.0976 units. Subsequently, we examine the regression results with the addition of control variables. After adding a series of control variables, the analyst rating coefficient has been reduced, but it is still obviously negative. The hypothesis that the analyst public information will suppress the extreme risks of stock market in Hypothesis 1a has been proved. It is due to the orderly development of China's capital market under a strict regulatory environment, and more investment in listed companies has further promoted the development of the capital market, decreasing the emergence of extreme market risks.

5.3. Institutional investor network and tail risk

We use degree and clustering coefficient indicators of fund network to measure network closeness, and use network indicators to regress with tail risk. It can be seen

Table 3. Analyst public information and tail risk.

	(1) VaR	(2) CVaR	(3) VaR	(4) CVaR
rank	−0.0864***	−0.0976***	−0.0602***	−0.0648***
	(−5.28)	(−5.34)	(−2.94)	(−2.83)
ReportAttention			0.0054**	0.0061**
			(2.06)	(2.05)
turnover			−0.0010*	−0.0010
			(−1.73)	(−1.64)
ForecastAccuracy			−0.0002	−0.0002
			(−0.69)	(−0.66)
froe			−0.0179*	−0.0196
			(−1.67)	(−1.63)
fpe			−0.0102***	−0.0113***
			(−3.29)	(−3.25)
amihud			−0.0608*	−0.0653*
			(−1.75)	(−1.68)
PIT			0.0001	0.0001
			(0.23)	(0.20)
beta			0.0113***	0.0133***
			(3.45)	(3.62)
cons	0.0876***	0.0992***	0.0637***	0.0689***
	(5.95)	(6.02)	(3.35)	(3.23)
R^2	0.0329	0.0424	0.0982	0.1017

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

from the results in Table 4 that the regression coefficients of network degree and clustering coefficient in the first to fourth columns are significantly negative. It indicates that the more institutional investors exchange information, the closer the network is, and the lower the probability of tail risk is. Besides, when the fund network increases by one unit, the tail risk VaR decreases by 0.0013 units. Institutional investor information network clustering coefficient increase by 1 unit will reduce the stock market extreme risk VaR by 0.023 units. Institutional investor network degree and clustering coefficient can reduce tail risk, and the network clustering coefficient can reduce extreme risk to a greater extent.

5.4. Institutional investor network, analyst public information and tail risk

In order to test the interactivity between fund network and analyst public information on tail risk, we use the interaction item between the analyst public information and institutional investor information network topology indicators to verify Hypothesis 4. The regression results are shown in Table 5. It can be concluded that the regression results strongly verify the proposed hypothesis. In the first to fourth columns, the interaction coefficients of analyst public information and network degree and clustering coefficient are significantly greater than 0. It shows that the existence of fund network will affect the inhibitory effect of analyst public information on tail risk. And the larger value of topology indicator of the fund network is, the more efficient the private information dissemination is. In addition, larger value of topology indicator of fund network means denser network density. And efficient private information dissemination will decrease the role of analysts in disclosing information to suppress tail

Table 4. Institutional investor information network and stock market tail risk.

	(1) VaR	(2) CVaR	(3) VaR	(4) CVaR
degree	−0.0013***	−0.0014***		
	(−4.51)	(−4.37)		
cluster			−0.0230**	−0.0246*
			(−1.99)	(−1.90)
lnm	−0.5123***	−0.5810***	−0.6437***	−0.7241***
	(−4.00)	(−4.04)	(−4.87)	(−4.88)
em	−0.0046*	−0.0053*	−0.0045*	−0.0051*
	(−1.85)	(−1.89)	(−1.70)	(−1.74)
optisim	−0.0002	−0.0002	−0.0001	−0.0001
	(−0.18)	(−0.15)	(−0.09)	(−0.06)
turnover	−0.0008	−0.0009	−0.0003	−0.0003
	(−1.48)	(−1.41)	(−0.44)	(−0.41)
ForecastAccuracy	−0.0002	−0.0002	−0.0001	−0.0002
	(−0.54)	(−0.54)	(−0.45)	(−0.46)
ReportAttention	0.0013	0.0014	0.0041	0.0045
	(0.48)	(0.47)	(1.47)	(1.43)
bm	−0.0110	−0.0133*	−0.0132*	−0.0157*
	(−1.63)	(−1.75)	(−1.79)	(−1.88)
fpe	−0.0100***	−0.0111***	−0.0114***	−0.0127***
	(−3.03)	(−3.00)	(−3.27)	(−3.24)
cons	0.1266***	0.1437***	0.1531***	0.1721***
	(5.32)	(5.36)	(5.65)	(5.66)
R^2	0.1547	0.1893	0.1604	0.1962

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

Table 5. Institutional investor information network, analyst public information and stock market extreme risk.

	(1) VaR	(2) CVaR	(3) VaR	(4) CVaR
rank	−0.1059***	−0.1195***	−0.3920***	−0.4441***
	(−4.73)	(−4.71)	(−2.78)	(−2.78)
*rank**degree	0.0041*	0.0047**		
	(1.97)	(1.98)		
degree	−0.0397**	−0.0452**		
	(−2.45)	(−2.46)		
*rank*cluster*			0.4071**	0.4629**
			(2.17)	(2.18)
cluster			−0.3795**	−0.4308**
			(−2.26)	(−2.26)
lever	0.0012	0.0016	0.0031	0.0037
	(0.20)	(0.22)	(0.49)	(0.52)
froe	0.0058	0.0063	0.0130	0.0142
	(0.53)	(0.50)	(1.15)	(1.12)
em	−0.0055**	−0.0063**	−0.0061**	−0.0070**
	(−2.40)	(−2.43)	(−2.59)	(−2.61)
fpe	−0.0055*	−0.0063*	−0.0048	−0.0055
	(−1.84)	(−1.86)	(−1.57)	(−1.58)
mr	−0.0094***	−0.0097***	−0.0104***	−0.0108***
	(−3.69)	(−3.36)	(−4.13)	(−3.80)
PIT	−0.0001	−0.0001	−0.0003	−0.0003
	(−0.19)	(−0.21)	(−0.65)	(−0.67)
cons	0.1629***	0.1841***	0.3772***	0.4268***
	(4.64)	(4.62)	(2.99)	(2.98)
R^2	0.0959	0.1022	0.0841	0.0975

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

Table 6. Liquidity, institutional investor network and tail risk.

	(1) VaR	(2) CVaR	(3) VaR	(4) CVaR
degree	−0.0007**	−0.0007**		
	(−2.09)	(−2.03)		
degree*amihud*	−0.0277**	−0.0321**		
	(−2.20)	(−2.25)		
cluster			0.0037	0.0051
			(0.30)	(0.37)
*cluster*amihud*			−1.4809***	−1.6978***
			(−3.03)	(−3.07)
amihud	0.3010**	0.3491**	1.2171***	1.3956***
	(2.08)	(2.13)	(3.00)	(3.04)
froe	−0.0141	−0.0161	−0.0092	−0.0105
	(−1.17)	(−1.18)	(−0.75)	(−0.75)
PIT	0.0002	0.0002	−0.0001	−0.0001
	(0.55)	(0.53)	(−0.21)	(−0.24)
lnm	−0.5196***	−0.5821***	−0.4935***	−0.5497***
	(−4.20)	(−4.15)	(−3.73)	(−3.67)
em	−0.0013	−0.0016	−0.0015	−0.0018
	(−0.50)	(−0.54)	(−0.56)	(−0.60)
fpe	−0.0076**	−0.0087**	−0.0081***	−0.0092***
	(−2.54)	(−2.56)	(−2.68)	(−2.70)
mr	−0.0099***	−0.0103***	−0.0133***	−0.0142***
	(−3.69)	(−3.38)	(−5.20)	(−4.87)
bm	−0.0275***	−0.0310***	−0.0291***	−0.0327***
	(−3.64)	(−3.63)	(−3.68)	(−3.65)
cons	0.1324***	0.1487***	0.1206***	0.1341***
	(5.56)	(5.51)	(4.04)	(3.97)
R^2	0.1128	0.1342	0.1583	0.1677

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

risk. Therefore, the previous hypothesis has been proved that the closer the fund network is, the more it will reduce the inhibitory effect of analyst public information on tail risk. In other words, the dissemination of private information will weaken the inhibitory effect of analyst public information on tail risk. That is, there is a substitution relationship between fund information network and analyst public information. The denser the fund information network, the more severe this kind of conflict of interest will be. It will eventually affect the impact of analyst forecasting reports, which causes analysts to make untrue report statements under the influence of conflicts of interest, and thus affecting the stock market extreme risks.

In order to examine the influence of stock liquidity on institutional investor information networks and stock market extreme risks, the interactive items of the information network topology indicators (network degree and network clustering coefficient) and the stock liquidity indicator *amihud* are constructed. To examine the interaction impact of stock liquidity on extreme risks, the regression results are shown in Table 6. In the first to fourth columns, the interaction term coefficients of *amihud* and information network indicators containing degree and clustering coefficient are significantly negative. It shows that stock liquidity plays an intermediary role in the inhibition of extreme risks by institutional investor information networks. The worse the stock liquidity, the stronger the inhibitory effect of the fund network on tail risk. Hence, the hypothesis in H3 that the worse the stock liquidity, the

Table 7. Analyst public information and tail risk (GpdVaR and GpdCVaR).

	(1) GpdVaR	(2) GpdCVaR	(3) GpdVaR	(4) GpdCVaR
rank	−3.9725***	−3.1258***	−3.5431**	−2.8531*
	(−3.55)	(−2.68)	(−2.67)	(−1.74)
ReportAttention			0.4006*	0.4116*
			(1.97)	(1.86)
turnover			−0.0884***	−0.1208**
			(−2.78)	(−2.64)
forecastoptimism			−0.0072*	−0.0045*
			(−0.43)	(−0.22)
froe			−1.4629**	−1.8527**
			(−2.35)	(−2.33)
fpe			−0.6239***	−0.7461***
			(−2.94)	(−2.77)
amihud			0.3239	1.6507
			(0.21)	(0.73)
PIT			0.0179	0.0282
			(0.58)	(0.64)
beta			0.4766*	0.5117**
			(1.73)	(1.74)
cons	3.1837***	3.8976***	3.4562***	3.1624**
	(3.83)	(3.98)	(2.79)	(2.23)
R^2	0.0388	0.0496	0.1136	0.1235

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

stronger the inhibitory effect of the institutional investor information network on extreme risks has been proved.

6. Robustness test

6.1. Robustness test

The GpdVaR and GpdCVaR utilising generalised Pareto extreme value distribution is chosen to measure tail risk more accurately. The results are reported in Tables 7 and 8. Compared with VaR and CVaR based on normal distribution, the consequences of GpdVaR and GpdCVaR show better fitting effect.

Primarily, we calculate GpdVaR and GpdCVaR on the basis of the generalised Pareto extreme value distribution. We respectively regress the fund network and analyst public information with tail risk GpdVaR and GpdCVaR. In Table 7, in the first and second columns, the regression results of analyst rating indicator *rank* with GpdVaR and GpdCVaR are shown separately, and the results after the addition of control variables are shown in the third and fourth columns. It can be seen from the table that the results of adding the control variable and that without are significantly negative, which shows that the analyst public information has suppressed the extreme risk. It also proves to a certain extent that the assumption analyst public information will suppress tail risk is robust. From the results of the control variables, analysts' public information has attracted the attention of investors through the analyst's optimistic and biased research reports, which has promoted the company's stock trading and thereby reduced risks.

Table 8. Institutional investor network and tail risk.

	(1) GpdVaR	(2) GpdCVaR	(3) GpdVaR	(4) GpdCVaR
degree	−0.0786***	−0.0895***		
	(−3.92)	(−3.39)		
cluster			−2.4527***	−2.5217***
			(−3.55)	(−2.67)
lnm	−7.6409***	−5.3544**	−7.2609***	−8.1506***
	(−2.56)	(−2.75)	(−3.25)	(−2.68)
froe	−3.2306**	−2.0718*	−1.4683**	−1.7318**
	(−1.47)	(−1.48)	(−2.48)	(−2.26)
bm	−0.1621	−0.1827	−0.4217	−0.4113
	(−0.25)	(−0.44)	(−1.36)	(−1.38)
optisim	−0.0389*	−0.0407*	−0.0359*	−0.0376*
	(−0.27)	(−0.15)	(−0.16)	(−0.11)
forecastoptimism	−1.1659*	−1.1764*	−1.3306*	−1.5742*
	(0.48)	(0.76)	(0.31)	(0.53)
lever	−0.3906	−0.2885	−0.2822	−0.5873
	(−0.85)	(−0.59)	(−0.24)	(−0.29)
cons	5.2114***	5.1622***	6.8896***	5.1643***
	(2.88)	(2.58)	(3.0055)	(3.85)
R^2	0.2136	0.2879	0.2018	0.2741

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

The results in Table 8 show that the regression coefficient of fund network degree and clustering coefficient with GpdVaR and GpdCVaR are significantly negative, respectively. It shows that the private information sharing in fund network can restrain the tail risk. It also proves that the conclusion of Hypothesis 2a is robust, that is, private information sharing in network can reduce the occurrence of tail risk. From the results of the control variables, the existence of conflict of interest between institutional investor and analyst has weakened the impact of analysts' public information on the tail risk.

Then we have constructed the interactive items of private information sharing in fund network and analyst public information dissemination to examine the effects of interactive effects on tail risk. We use the interactive item *rank*net* of analyst public information and network private information sharing to regress GpdVaR and GpdCVaR, respectively, and the results obtained are significantly positive. It illustrates that the conclusion of Hypothesis 4 is robust. The closer the fund network is, the more it will reduce the inhibitory effect of analyst public information spread on tail risk. Further, we examine the influence of the interactive item *net*amihud* of network private information sharing and liquidity on GpdVaR and GpdCVaR. The results of regression are significantly negative, which proves that the conclusion of Hypothesis 3 is robust. The worse the liquidity, the more beneficial it is for institutional investor information networks to suppress extreme risks.

6.2. Bull market and bear market

After replacing the variable indicators for robustness test, we divide the sample period into the bull market and the bear market for test. Especially, we specify the market in

Table 9. Analyst public information and tail risk in the bull and bear markets.

	(1) GpdVaR bull	(2) GpdCVaR bull	(3) GpdVaR bear	(4) GpdCVaR bear
rank	−3.2753***	−3.1683***	−2.5741*	−1.0852
	(−2.48)	(−4.65)	(−1.46)	(−1.23)
ReportAttention	−0.0125*	−0.0106*	−0.1523	−0.4545*
	(−0.04)	(−0.07)	(−0.94)	(−0.63)
turnover	−0.0441***	−0.0763***	−0.0628*	−0.0714*
	(−1.39)	(−1.31)	(−0.88)	(−0.63)
forecastoptimism	−0.0225*	−0.0214*	−0.0079	−0.0089
	(−1.42)	(−1.47)	(−0.24)	(−0.18)
froe	−0.2786	−0.2498	0.6214	0.8225
	(−0.42)	(−0.55)	(0.48)	(0.76)
fpe	−0.1998*	−0.2754*	−0.5772	−0.5889
	(−1.23)	(−1.66)	(−0.48)	(−0.88)
amihud	−3.1538***	−3.2206***	6.5006***	7.4926***
	(−2.89)	(−2.76)	(2.38)	(2.55)
PIT	0.0123	0.0119	0.0825	0.0903
	(0.37)	(0.32)	(1.17)	(1.25)
beta	−0.3535**	−0.4221**	−0.7436*	−0.6126*
	(−2.46)	(−2.69)	(−1.26)	(−1.44)
cons	2.3572***	4.1776***	2.3616	0.8472
	(5.23)	(5.15)	(0.38)	(0.19)
R^2	0.0876	0.0914	0.0536	0.0697

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

the year of 2008, 2009, 2015 and 2018 as bear markets, and the rest years as bull markets. In the sub-sample, we continue to use the tail risk indicators GpdVaR and GpdCVaR on the basis of generalised Pareto extreme value distribution as the dependent variables. And the regression results with analyst public information *rank*, fund network topology indicators degree and *cluster* are shown in Table 9. It can be shown that during the bull market, the analyst rating coefficient is significantly negative, which confirms our previous conclusion. Or to say, the public information of analyst has a suppressive effect on tail risk. While in the bear market, although the coefficient of *rank* is also negative, it is not significant. It shows that the inhibitory effect of analyst public information on tail risk is obvious in the bull market, while not obvious in the bear market. From the results of the control variables, this transmission mechanism is effective in the bull market, but the transmission mechanism is not obvious in the bear market.

In Table 10, we obtain the same conclusion. In the bull market, the regression coefficients of degree and *cluster* are both significantly negative, which validates our previous conclusions. The private information sharing of fund network generates restraining effects on tail risk. However, in the bear market, the coefficients of degree and *cluster* are not significant. It indicates that the institutional investor private information sharing generates significant effects on suppressing the stock extreme risks in the bull market, but not significant in the bear market. The results of the control variables also show that the transmission mechanism is obvious in the bull market but not in the bear market.

Table 10. Institutional investor network and tail risk under bull and bear markets.

	(1) GpdVaR bull	(2) GpdCVaR bull	(3) GpdVaR bull	(4) GpdCVaR bull	(5) GpdVaR bear	(6) GpdCVaR bear	(7) GpdVaR bear	(8) GpdCVaR bear
degree	−0.068***	−0.074***			−0.134	−0.238		
	(−3.62)	(−3.13)			(−0.76)	(−0.74)		
cluster			−0.996*	−0.736*			−1.004	−1.725
			(−1.36)	(−1.32)			(−0.26)	(−0.54)
lnm	6.355**	7.363**	6.313*	6.611*	−8.495**	−8.003**	−7.626**	−9.262**
	(4.26)	(3.16)	(0.62)	(0.75)	(−1.34)	(−1.46)	(−1.39)	(−1.08)
froe	−0.573	−0.648	−0.515	−0.553	−0.389	−0.428	−0.837	−0.663
	(−1.24)	(−1.28)	(−1.09)	(−1.08)	(−0.45)	(−0.45)	(−0.26)	(−0.27)
bm	0.884***	0.675***	0.619***	0.408***	−1.122*	−1.447	−1.006	−1.115
	(2.62)	(2.38)	(1.43)	(1.56)	(−1.28)	(−1.19)	(−1.42)	(−1.32)
optisim	0.189**	0.429**	0.111**	0.266**	0.023	0.047	0.038	0.023
	(2.62)	(1.89)	(1.15)	(1.22)	(0.43)	(0.15)	(0.19)	(0.11)
ReportAttention	0.003	0.004	0.129*	0.118*	0.309	0.267	0.157	0.101
	(0.04)	(0.05)	(1.17)	(1.36)	(0.28)	(0.47)	(0.45)	(0.22)
forecastoptimism	2.266**	2.397**	2.455**	2.418**	5.633	6.108	5.783	5.266
	(3.22)	(3.28)	(3.17)	(3.11)	(3.54)	(2.26)	(1.62)	(1.33)
lever	−0.189	−0.238	−0.229	−0.216	0.282	0.186	0.167	0.079
	(−0.65)	(−0.44)	(−0.53)	(−0.31)	(0.18)	(0.22)	(0.11)	(0.02)
cons	−1.183*	−1.189*	−0.513	−0.234	8.492***	7.324**	6.243***	4.234**
	(−1.79)	(−1.78)	(−0.21)	(−0.23)	(2.34)	(1.48)	(1.34)	(1.34)
R^2	0.1347	0.1529	0.1211	0.1633	0.1225	0.1407	0.1336	0.1594

Note: *means significant at the 10% confidence level, **means significant at the 5% confidence level, and ***means significant at the 1% confidence level.
Source: calculated by the authors.

7. Conclusion

This paper studies the impact of public information released by analysts and private information dissemination in fund network on extreme risk. We also examine whether the private information sharing in the fund network will affect the inhibitory effect of analyst public information on extreme risk. Further, this paper analyzes whether the deterioration of liquidity will affect private information sharing on extreme risk. The empirical research found that: primarily, there exists mutual relationship between the analyst public information spread and extreme risk. When the analyst public information is more optimistic (that is, the higher the analyst rating), the lower the probability of tail risk is. The higher the efficiency of private information transmission in fund network (that is, the greater the centrality and clustering coefficient), the lower the probability of extreme risk. Secondly, both the public information of analysts and the private information sharing will inhibit the occurrence of tail risk. In addition, the closer the fund network is, the more it will reduce the inhibitory effect of analyst public information on tail risk. Thirdly, when the market liquidity deteriorates, private information sharing in social network will enhance the suppression effect of extreme risk.

The research in this paper has important practical significance. Since both analyst public information spread and private information sharing will inhibit the occurrence of extreme risk. It indicates that the regulatory authorities should further strengthen the market leading role of analysts and institutional investors. It helps to promote the integration of information into stock prices, so that stock prices can return to the true value. In addition, this paper considers the public information transmission and private information dissemination comprehensively, and finds that the closer the fund network is, the less the analyst public information will reduce extreme risk.

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