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Does systemic risk affect fund managers' tail risk-taking?

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ABSTRACT

This paper investigates the impact of systemic risk on the tail risk-taking behavior of fund managers, based on the data from China's mutual funds from 2011 to 2021. We construct a systemic risk indicator by utilizing industry indices and market macro state variables, and find that systemic risk can markedly inhibit the tail risk-taking behavior of fund managers. This inhibition effect is strengthened by the performance ranking of funds. Within the tournament effect framework, fund managers tend to be more risk averse in order to secure the realized return, as the fund's ranking is primarily motivated by compensation incentives rather than career concerns. Moreover, given that the portfolio associated with a fund forms a network, we find that the information mechanism can attenuate the inhibition effect that systemic risk indicators have on the tail risk-taking behavior of fund managers.

1. Introduction

Mutual funds, as one of the major institutional investors in the financial market of China, have a crucial impact on market stability and efficiency. Despite claim to offer diversified investment portfolios and a professional management, mutual fund managers often engage in risk-taking activities in pursuit of higher returns (Boguth and Simutin, 2018; Ma and Tang, 2019; Massa and Patgiri, 2009; Sun et al., 2023); some of them even take tail risks actively for higher expected returns (Karagiannis and Tolikas, 2019). But such a maneuver, if goes excessive, may well incur significant losses of the funds. Therefore, it is crucial to examine the tail risk-taking behavior of mutual fund managers, especially under severe conditions.

Systemic risk may lead to the collapse of the entire financial system, thereby negatively affecting almost all investors in the market, including mutual funds. Particularly, investment of mutual funds is subject to various constraints such as shareholding ratios and adjustment costs, which are usually more severely impacted by systemic risks, meaning that the fund managers have to sell off stocks at low prices to maintain cash flow (Coval and Stafford, 2007; Rakowski, 2010; Shleifer and Vishny, 2011). Consequently, fund managers' tail risk-taking behavior should be constrained by the level of systemic risk. In terms of studying the risk-taking behavior of fund managers, focusing on systemic risk rather than the common types of risks, is more conducive to gaining fresh insights into a proper assessment of the investment strategies and performance involved. In this paper, we innovatively study the impact of systemic risk on fund managers' tail risk-taking behavior and substantiate its underlying mechanisms.

It is well documented that the tournament mechanism can explain the impact of fund performance on the risk-taking behavior of

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fund managers (Chevalier and Ellison, 1997). Specifically, compensation incentives encourage midyear losers to take greater risks so as to catch up with midyear winners, who, in turn, tend to adopt more conservative investment strategies (Brown et al., 1996; Qiu, 2003). Fund managers are subject to career concerns in addition to their incentive compensation. Evidence shows that the probability of a fund manager being dismissed is inversely related to the fund's performance (Hu et al., 2000; Khorana, 1996). In this paper, we aim to further investigate whether the tournament mechanism can affect fund managers' tail risk-taking behavior when subject to systemic risk, and if so, which incentive, compensation or career concerns, is the dominant factor.

Recent studies have highlighted the significant role that information transmission in fund networks plays in affecting the risk-taking behavior of fund managers (Cohen et al., 2005; Rossi et al., 2018). In the stock market, institutional investors may hold specific stocks with large positions as top holding stocks, based on their access to private information (Bushee and Goodman, 2007). Similarly, in the mutual fund market, different fund managers may hold the same top holding stocks, and the resulting fund network can reflect the information owned by these managers to some extent. We conjecture that fund managers who invest in the top holding stocks are privy to specific information about those stocks. By analyzing fund network characteristics, this paper focuses on whether the quality and quantity of information available to fund managers affect their tail risk-taking behavior when subject to systemic risk.

In the measurement of systemic risk indicators, most studies have concentrated on the financial sectors (Billio et al., 2012; Gravelle and Li, 2013; Huang et al., 2009; Lehar, 2005). However, systemic risk can arise from factors external to the financial sector, such as imbalances within the real economy (Smaga, 2014). A downturn in a specific sector can quickly spread through the industry supply chain, leading to correlated stock fluctuations and risk amplification in financial markets, ultimately impacting the overall economy (Aobdia et al., 2014). Based on the real-world input-output linkages among various industries and the closely interconnected supply chain relationships (Costello, 2020), there exists a strong connection between economic sectors. Therefore, this paper incorporates industry indices into the measurement of systemic risk. We employ the method put forward by Amor et al. (2022) and develop an indicator named the Systemic Risk Meter (SRM), to gauge the systemic risk. This indicator is constructed based on the penalty parameter in linear quantile lasso regression, which takes into account the tight supply chain relationships between industries, as well as market macro state conditions.

When evaluating the tail risk of mutual funds, we adopt the Copula-based method proposed by Chabi-Yo et al. (2018). Different from the work of Karagiannis and Tolikas (2019), who employ the method put forward by Kelly and Jiang (2014) which only considers individual assets and is thus incapable of capturing the tail risk dependency across assets, the Copula-based method not only addresses this limitation but also effectively characterizes the time-varying nature of tail risks. As a measure of fund managers' risk adjustment behavior over a given year, we utilize the difference between the tail risks taken by fund managers in the first and second halves of the year.

To assess the impact of systemic risk on fund managers' tail risk-taking behavior, we perform a panel regression analysis using a dataset of Chinese mutual funds spanning from 2011 to 2021. The adjustment in fund tail risk is regressed on the systemic risk indicator, fund-level control variables, and fund-fixed effects. Our results indicate that as the level of systemic risk increases, the tail risk-taking behavior of fund managers will be inhibited.

Within the tournament framework, we then examine the moderating effect of performance ranking on the relationship between systemic risk and fund managers' risk-taking behavior. We find that the performance ranking of funds enhances the inhibition effect of systemic risk on risk-taking behavior. Given the high drawdown level observed in the Chinese mutual funds market, we interpret this effect as a propensity for fund managers to prioritize stability and avoid risk-taking after achieving a good performance in the face of systemic risk, with a mindset of "lying flat and pursuing stability" employed to preserve the realized gains.

Considering another incentive, we further explore the influence of fund managers' career concerns on their risk-taking behavior and compare it with the effect of compensation incentives. Firstly, by conducting descriptive statistics on the reasons behind the departure of mutual fund managers in China, we observe some interesting phenomena: fund managers depart for varied reasons with a relatively high frequency, and in many cases it is just job-hopping within the fund industry. We then perform a logit regression to examine the relationship between fund performance and fund managers' career concerns, the results of which indicate that a fund's performance ranking has no substantial impact on whether there will be a departure or not. Our finding suggests that career concerns are relatively insignificant in the labor market for fund managers in China. In other words, within the framework of tournament, the fund's ranking strengthens the inhibition effect of systemic risk on its managers' risk-taking, primarily driven by compensation incentives rather than career concerns.

We then investigate the impact of the information mechanism on the relationship between systemic risk and tail risk-taking behavior. To this end, we analyze the network characteristics of funds, specifically, the degree centrality and the closeness centrality indicators, based on the network of the top holding stocks of all funds. These metrics gauge the quality and quantity of information accessible to fund managers (Hochberg et al., 2007). The results reveal that these two types of network characteristics weaken the inhibition effect of systemic risk on tail risk-taking behavior. This phenomenon can be attributed to the information mechanism, that fund managers have an incentive to take more tail risks when they possess either a higher quality or quantity of information.

Next, we conduct further analysis of our findings. We observe that systemic risk exerts an inhibitory effect on fund managers' tail risk-taking behavior, irrespective of their working experience. Notably, this inhibitory effect is more pronounced for funds managed with less working experience. Furthermore, systemic risk also exerts an inhibitory effect on the risk-taking behavior of fund managers, with no significant differences observed among fund managers with varying educational backgrounds. Additionally, we investigate the ramifications of the COVID-19 pandemic and find that, fund managers' tail risk-taking behavior is consistently inhibited by systemic risk. This phenomenon becomes even more pronounced post-COVID-19, lending additional credence for our findings.

To ensure the robustness of our findings and to address potential endogeneity, we conduct a series of robustness tests. First, we use lagged terms for all explanatory variables and add additional control variables to alleviate omitted variables bias. Subsequently, we utilize an instrumental variable and apply a two-stage least squares regression to further mitigate endogeneity, which yields results consistent with our main findings. Additionally, we recalculate systemic risk indicators using a new window size and also introduce other systemic risk indicators. After implementing the aforementioned measures, we re-examine the impact of systemic risk on the tail risk-taking behavior of fund managers. These tests provide strong evidence that our study findings are reliable and robust.

The primary contributions of this paper are threefold. First, it enriches the measurement of systemic risk. While current research has mainly focused on systemic risk among financial institutions (Acharya et al., 2017; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017), there is still a need to construct an indicator that considers various sectors within the economy to comprehensively reflect systemic risk. To address this issue, we construct an indicator known as the SRM, based on the work of Amor et al. (2022), to evaluate systemic risk in China. The SRM indicator considers the risk spillover among industries, as well as the dependence of systemic risk on macro state factors. By incorporating these factors, the SRM provides a more comprehensive depiction of the systemic risks in China.

Secondly, this paper augments the extant literature on the tail risk-taking behavior of fund managers. Previous studies have mostly focused on fund managers' behavior towards common risks (Brown et al., 1996; Busse, 2001; Elton et al., 2009; Massa and Patgiri, 2009; Qiu, 2003), whereas our research pays more attention to the risk-taking behavior of fund managers for tail risks. While Lu et al. (2022) examine how fund managers' behavior varies under different market conditions, we focus on how systemic risk affects fund managers' tail risk-taking behavior, and explore the mechanisms that influence their risk preferences under extreme conditions.

Finally, our study extends the understanding of the mechanisms that influence fund managers' risk-taking behavior based on the tournament framework and fund network characteristics. Prior research has suggested that compensation incentives and career concerns can explain the effect of performance ranking (Busse, 2001; Chevalier and Ellison, 1997; Hu et al., 2011). Our findings indicate that compensation incentives, rather than career concerns, constitute the primary mechanism that influences fund managers' tail risk-taking behavior under systemic risk. Additionally, our study shows the fund network characteristics have a moderating effect on fund managers' tail risk-taking behavior.

The rest of this paper is organized as follows: Section 2 reviews previous literature and develops our hypotheses; Section 3 introduces the design of variables and the model setting; Section 4 presents and analyzes the empirical results; Section 5 tests the robustness of these results, and Section 6 concludes the paper.

2. Literature review and hypothesis development

2.1. *Systemic risk and tail risk taking*

Systemic risk is usually defined as the possibility of breakdowns in the overall system through risk comovements of most sectors caused by a trigger event (Benoit et al., 2017; Billio et al., 2012; De Bandt and Hartmann, 2000; Kaufman and Scott, 2003). The diffusion of systemic risk can lead to investor panic, resulting in a reduction in expectations and aggressive asset sales, which may cause a liquidity crisis and market collapse (Pástor and Veronesi, 2013; Shleifer and Vishny, 2010). The literature of systemic risk measurement of financial institutions abounds (Acharya et al., 2017; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017). Recently, some studies uncover that idiosyncratic shocks at the firm level, particularly within large firms, may precipitate aggregate economic fluctuations (Gabaix, 2011). Acemoglu et al. (2017) employ a multisector general equilibrium model, and find that micro-level shocks, propagating through risk transmission mechanisms across different industries, can amplify GDP volatility and thereby impair long-term economic growth. In light of these findings, we refer to the approach proposed by Amor et al. (2022), by taking into account the fundamental facts of input-output and supply chain relationships between industries, and combining with the current macro state variables and market sentiment, to construct an indicator SRM that can comprehensively reflect the systemic risk.

The tail risk of assets is commonly regarded as the risk of assets suffering great losses. Concerning the measurement of tail risk, the most common method is to adopt the extreme value theory represented by Value-at-Risk (VaR). However, this method is limited to the risk of a single asset and ignores the interrelationships between different assets. Thus, some studies improve tail risk measurement by considering the correlation of extreme risk between aseets (Chabi-Yo et al., 2018; Kelly and Jiang, 2014). Since there are also close interrelationships among assets in the fund market (Agarwal et al., 2017), we employ the method proposed by Chabi-Yo et al. (2018) to evaluate mutual funds' tail risk. This method takes into account the time-varying nature of tail risk while also captures the dependence of tail risk between an individual fund and the market.

Since Rietz (1988) introduce extreme events into the analysis of market collapse, extensive research finds that tail risk can bring positive risk premiums in the stock market (Gabaix, 2012; Huang et al., 2012). In recent years, research on tail risks has been extended to the mutual fund market. Karagiannis and Tolikas (2019) explore the tail risk premium across mutual fund returns and find that fund managers can achieve higher returns by voluntarily taking on tail risk. Nevertheless, there is only limited research on the factors that affect the tail risk-taking behavior of fund managers. Lu et al. (2022) recently investigate fund managers' tail risk-taking behavior under different market conditions. They find that the tournament effect has a more significant impact on fund managers' tail risk behavior in bull markets. Systemic risk can lead to extreme market losses, which usually imply a simultaneous decline in numerous stocks, and this type of risk is difficult to diversify (Poon et al., 2004). In such a case, investors will redeem their investment massively and fund managers have to engage in asset underselling (Coval and Stafford, 2007). Hence, it is unlikely that fund managers will attain more returns by taking on tail risks when the level of systemic risk is high. Instead, they are more likely to incur significant losses. Consequently, fund managers may adopt more cautious investment strategies rather than taking more tail risks. Regardless of whether or not they can achieve excess returns, fund managers should prudently weigh the behavior of tail risk-taking in the context of systemic risk. These arguments therefore lead to the following hypothesis:

H1. : The intensification of systemic risk will inhibit fund managers' risk-taking behavior.

2.2. Compensation incentives and career concerns within tournament framework

The compensation of a mutual fund manager is commonly positively correlated with the size of a fund's assets, and the performance ranking of a fund is the primary determinant that attracts cash inflows. Therefore, fund managers will focus on improving the fund performance ranking driven by compensation incentives. Brown et al. (1996) introduce the tournament theory, which proposes that when the fund manager's compensation is linked to the fund's performance, mid-year losers tend to be more willing to increase fund's volatility than mid-year winners. Motivated by the convexity of the fund flow-performance relation, fund managers who perform poorly at mid-year seek to increase the risk of their portfolios by the end of the year (Chevalier and Ellison, 1997; Dai et al., 2019). Even among mutual funds with good performance, compensation incentives remain a driving factor. Qiu (2003) finds that fund managers with performances closer to top-tier performance levels tend to increase risk-taking. However, some studies have come to different conclusions. Busse (2001) and Elton et al. (2009), using higher frequency data, find no evidence of increased risk-taking by mid-year losers. Huang et al. (2011) also suggest that mid-year losers should not rashly increase their risk-taking, as this could worsen the fund's performance.

Apart from compensation incentives, fund managers are also subject to career concerns, as their poor performance may lead to dismissal if they take excessive risks and cause returns to decline. Research indicates an inverse relationship between the likelihood of a manager's dismissal and fund performance (Hu et al., 2000; Khorana, 1996). Young fund managers (Chevalier and Ellison, 1999), those who work without a team (Bryant, 2012; Dangl et al., 2008), and those who have experienced an economic recession are more likely to decrease risks due to career concerns (Pool et al., 2019). Although poor performance can result in fund manager dismissal, other studies suggest that this punishment mechanism is limited by the fund managers' tenure. Dangl et al. (2008) find that the longer the manager has worked for the company, the less likely they will be dismissed, and Wu et al. (2016) suggest that such punishment for underperforming fund managers is insignificant against the wide backdrop of labor market.

Within the tournament framework, Kempf et al. (2009) suggest that the risk-taking behavior of fund managers largely depends on the relative importance of compensation incentives and career concerns. They point out that in a bull market, mid-year losers may be motivated by compensation incentives to take higher risks. In contrast to their research, considering the fact that Chinese fund managers are less likely to be dismissed, we conjecture that career concerns are not the primary driver influencing Chinese fund managers' cautious decision-making under systemic risk pressures. Additionally, Chinese mutual funds tend to exhibit high levels of drawdown so that most funds may suffer losses under systemic risk. In such circumstances, fund managers tend to prioritize stability and reduce risk-taking activities in order to preserve their current performance and compensation, rather than taking tail risks to achieve high premiums. Based on the above discussion, we develop the following hypothesis:

H2. : The ranking of fund performance enhances the inhibition effect of systemic risk on fund managers' tail risk-taking behaviors, which is mainly driven by compensation incentives rather than career concerns.

2.3. Fund network and information mechanism

Recent work finds that information sharing among investors can generally improve market efficiency (Ozsoylev et al., 2014; Pool et al., 2015). When making investment decisions, investors gather information from various sources, and these information channels form networks. The literature has extensively analyzed the features of these networks from multiple perspectives, including geographic location (Hong et al., 2005; Pool et al., 2015), education background (Butler and Gurun, 2012; Cohen et al., 2008; Kuhnen, 2009), internal governance (Souther, 2018; Spilker, 2022), and shareholding structures (Pareek, 2012). However, few studies have examined the impact of network characteristics on fund managers' risk-taking behavior. Notably, some institutional investors tend to hold significant positions in specific stocks (top holding stocks), and previous literature suggests that this may be due to the acquisition of private information regarding the relevant stocks (Bushee and Goodman, 2007). We conjecture that the top holding stocks held by a fund also contain specific information. Cohen et al. (2005) point out that fund managers who make similar investment decisions possess comparable skills in selecting stocks and acquiring information.

Centrality measures the position of a node in a network and reflects the information that the node possesses. Freeman (1978) proposes several methods for measuring centrality, including degree centrality and closeness centrality. The former reflects the quantity of information available to a node and the latter shows the quality of information the node owns. Rossi et al. (2018) investigate whether centrality affects pension fund managers' risk-taking propensity, and find that managers with higher centrality tend to take more risks. Fund managers at the center of the network usually have significant information advantages and stronger profitability (Ozsoylev et al., 2014). As Lu et al. (2022) discover, the perceived higher level of tail risk for managers with access to sufficient information may not result in them actually taking on more risk. Moreover, the stronger the network centrality of a fund, the greater the impact of the manager's investment decisions on other fund managers through information sharing (Chen et al., 2017). This can lead to other funds to imitate the investment strategy of the fund, thus enhancing their confidence in taking tail risks. Therefore, we propose the following hypothesis:

H3. : The network characteristics of the fund weaken the inhibition effect of systemic risk on fund managers' risk-taking behavior by providing them with access to information.

Table 1
Variable definition.

Variable	Name	Description
$X_{j,t}$	Wind Primary Industry Group Index	Log return of closing prices
$Bond_t$	China bond Composite Index	Log return of closing prices
HSI_t	Hang Seng Index	Log return of closing prices
$MSentiment_t$	Quantitative Statistics of Network News	The variable is obtained by summing the market capitalization-weighted values
$MSearch_t$	Internet Search Index of Listed Companies	The variable is obtained by summing the market capitalization-weighted values

3. Data and methodology

3.1. Data

The stock and bond index data utilized in this research are obtained from Wind. Fund-related data is sourced from the China Stock Market and Accounting Research (CSMAR) database and RESSET financial database. Financial news and Internet search data are derived from the China Research Data Service Platform (CNRDS). Considering the availability and integrity of the data required to calculate systemic risk indicators, we select the sample period of 2011–2021. In this study, actively managed mutual funds should meet a shareholding market capitalization of greater than 60% of the fund's total assets and have been in operation for at least one year by the middle of year t.

3.2. The measurement of systemic risk

We introduce the single-index model (SIM):

$$X_{j,t}^{s} = \alpha_{j,t}^{s} + A_{j,t}^{s\top}\beta_{j}^{s} + \varepsilon_{j,t}^{s} \tag{1}$$

where $A_{j,t}^{s\top} = \begin{bmatrix} M_{t-1}^{s} \\ X_{-j,t}^{s} \end{bmatrix}$, $X_{-j,t}^{s}$ is the log return of all other industry indices except industry index j, and M_{t-1}^{s} denotes variables that reflect macro state characteristics, mainly composed of the China Bond Composite Index, Hang Seng Index, and unstructured data (sentiment data and Internet searching data as shown in Table 1).

$$M_{t-1}^{s} = \begin{bmatrix} Bond_t \\ HSI_t \\ MSentiment_t \\ MSearch_t \end{bmatrix}$$

where

$$MSentiment_t = \sum_{i=1}^{n_t} Weight_{i,t} * \left(Positive_{i,t} - Negative_{i,t}\right) \tag{2}$$

$Weight_{i,t}$ is the proportion of the market value of stock i at time t. $Positive_{i,t}$ ($Negative_{i,t}$) is the number of positive (negative) opinions about stock i at time t. This indicator reflects the sentiment of the media about the current market. To some extent, it represents the confidence of news media coverage in the current market and economic expectations.

$$MSearch_t = \sum_{i=1}^{n_t} Weight_{i,t} * Searchindex_{i,t} \tag{3}$$

The above indicator reflects the attention paid by investors to the current markets. Specifically, it captures the extent to which investors engage in active information acquisition behavior. We normalize the variable considering its relatively larger range of values.

Tibshirani (1996) proposes the LASSO method, based on the research of Bassett Jr and Koenker (1978). This method imposes a penalty term on the coefficient of the variables, thus enabling variable selection. Here, we use the LASSO method to build λ_i (Belloni and Chernozhukov, 2011; Li and Zhu, 2008),

$$\min_{\alpha_j^s, \beta_j^s} \left\{ \frac{1}{n} \sum_{t=s}^{s+(n-1)} \rho_\tau \left(X_{j,t}^{s} - \alpha_j^s - A_{j,t}^{s\top}\beta_j^s \right) + \lambda_j^s \left\| \beta_j^s \right\|_1 \right\} \tag{4}$$

where

$$\rho_\tau(u) = |u|^c \mid \tau - \mathrm{I}_{(u<0)} \mid$$

$I(\cdot)$ is an indicator function, and $\tau \in [0,1]$, c $= 1$, namely L1-norm quantile regression. The L1-norm quantile linear regression can then be used to select relevant covariates (other industries and macro state variables) for each industry j.

Table 2
Control variables.

Notion	Variable name	Description
$Age_{i,t}$	Fund age	The logarithm of days since the fund inception date in the first half of year t
$Size_{i,t}$	Fund size	The logarithm of the fund total net asset in the first half of year t
$Vol_{i,t}$	Fund volatility	The standard deviation of the net return of fund in the first half of year t
$Cashflow_{i,t}$	Fund cash flow	The cash flow of fund in the first half of year t (Sirri and Tufano, 1998)
$Navrtn_{i,t}$	Fund net return	The net return of fund in the first half of year t
$Team_{i,t}$	Fund team	The number of managers of fund in the first half of year t
$FundFamily_{i,t}$	Fund family size	The logarithm of aggregated number of all underlying funds within a certain family in the first half of year t
$Fee_{i,t}$	Fund fees	The sum of all types of fees of fund in the first half of year t

The Generalized Approximate Cross Validation (GACV) criterion (Yuan, 2006) is used to select the model and obtain the optimal λ_j^s

$$min\ GACV\left(\lambda_j^s\right) = min\frac{\sum_{t=s}^{s+(n-1)} \rho\tau\left(X_{j,t}^s - \alpha_j^s - A_{j,t}^{s,\top}\beta_j^s\right)}{n - df} \tag{5}$$

where df is the trace of the hat matrix at time t. The advantage of $GACV$ is that it can be applied even when $p > n$, meaning that when the number of parameters to be evaluated is larger than the window size, model selection can still be performed.

The distribution of the λ_j^s in a moving window gives important information as to the interconnections among different industries. Thus, the SRM is defined as the average of λ_j over the set of J industries for all windows. It is formally written as follows:

$$SRM = J^{-1}\sum_{j=1}^{J}\lambda_j * 100 \tag{6}$$

3.3. Variable definition

Following Chabi-Yo et al. (2018) (Details are listed in Appendix A), we use daily returns of a fund, and daily returns of the CSI 300 index to calculate the left tail risk of a fund for each six month (hereinafter referred to as tail risk). This paper takes the difference between the tail risk in the second half and the first half of year t to reflect the adjustment of a fund's tail risk-taking:

$$Dltr_{i,t} = ltr_{i,t}^{(2)} - ltr_{i,t}^{(1)} \tag{7}$$

$ltr_{i,t}^{(1)}$ refers to the tail risk of fund i in the first half of year t, and $ltr_{i,t}^{(2)}$ refers to the tail risk of fund i in the second half of year t. We use $Dltr_{i,t}$ as the explained variable.

Then we construct two types of moderator variables regarding fund performance and its network characteristics. By sorting the net return of funds in the first half of year t in ascending order, the original ranking, $Rank_{i,t} = 1, 2, \dots, N_t$ can be obtained. Considering different scales of funds in each year, we normalize the ranking:

$$Rank_{i,t=t^*} = \frac{rank_{i,t=t^*} - min\left(rank_{i,t=t^*}\right)}{max\left(rank_{i,t=t^*}\right) - min\left(rank_{i,t=t^*}\right)} \tag{8}$$

where $t = t^*$ means that we normalize the ranking in the year of t^*.

According to Pareek (2012), a fund network is constructed based on the top holding stocks of the fund in the first half of the year (the market value of the stocks accounts for more than 5% of the total stock market value of the fund). If two funds are observed to hold one or more stocks heavily at the same time, it is considered that there are connections between them. An example is provided in Appendix B (see Fig. B.1) to illustrate these connections within the network. Based on the constructed fund network, we calculate the network centrality of each fund in the first half of year t.

As defined by Freeman (1978), degree centrality is calculated as follows:

$$Degree_{i,t} = \frac{\sum_{i=1, i\neq j}^{N_t}\alpha\left(f_i, f_j\right)}{N_t - 1} \tag{9}$$

In period t, when fund i is directly related to fund j, $\alpha\left(f_i, f_j\right)$ equals 1, otherwise, it is 0. $N_t - 1$ indicates the maximum centrality that the fund i can achieve, and its role is to eliminate the impact of changes in network scale. The degree centrality reflects the amount of information that fund managers have.

Similarly, the closeness centrality (Freeman, 1978) is defined by the inverse of the average length of the shortest paths to all the other vertices in the network as follows:

Table 3
Summary statistics.

Variables	Mean	SD	Min	Median	Max
$Dltr_{i,t}$	−0.058	0.250	−0.602	−0.053	0.514
SRM	0.284	0.045	0.149	0.286	0.404
$Degree_{i,t}$	0	1.000	−1.557	−0.109	3.975
$Closeness_{i,t}$	0	1.000	−3.827	0.088	6.563
$Age_{i,t}$	7.470	0.694	5.966	7.514	8.727
$Size_{i,t}$	0.016	0.005	0.006	0.015	0.028
$Vol_{i,t}$	20.093	1.609	16.130	20.216	23.206
$Fee_{i,t}$	3.068	0.548	1.450	3.263	3.917
$Cashflow_{i,t}$	0.035	0.819	−0.929	−0.094	5.374
$Navrtn_{i,t}$	0.121	0.192	−0.220	0.093	0.714
$Team_{i,t}$	1.433	0.659	1.000	1.000	6.000
$FundFamily_{i,t}$	3.356	1.218	0.693	3.258	6.157

Table 4
Tail risk-taking adjustment and SRM.

	(1)	(2)
	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−0.831***	−1.780***
	(−16.275)	(−19.954)
$Age_{i,t}$		−0.010
		(−1.011)
$Vol_{i,t}$		−5.214***
		(−7.225)
$Size_{i,t}$		−0.025***
		(−6.507)
$Fee_{i,t}$		0.002
		(0.152)
$Cashflow_{i,t}$		−0.007*
		(−1.706)
$Nartm_{i,t}$		0.466***
		(26.644)
$Team_{i,t}$		−0.004
		(−0.804)
$FundFamily_{i,t}$		0.076***
		(7.619)
Fund FE	Yes	Yes
N	8578	8578
adj. R^2	−0.009	0.111

Note: The dependent variable is the tail risk adjustment of mutual funds. No control variables are added in column (1), and control variables of fund characteristics are added in column (2). The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. Note that all variables except the explanatory variables are based on the first half-year. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

$$Closeness_{i,t} = \frac{N_t - 1}{\sum_{i=1, i \neq j}^{N_t} d(f_i, f_j)} \tag{10}$$

Since the closeness centrality reflects the position of a fund within the network, the more it is in the geometric center, the more important the information about it is. We use closeness centrality to represent the information quality of the fund (Hochberg et al., 2007). To render the annual network centrality indices of different periods comparable, we standardize all network centrality indices (Chen et al., 2020; D'Arcangelis et al., 2021).

As shown in Table 2, refer to previous research (Chen et al., 2004; Cohen et al., 2008; Karagiannis and Tolikas, 2019; Lu et al., 2022), we control funds' age ($Age_{i,t}$), size ($Size_{i,t}$), volatility ($Vol_{i,t}$), cash flow ($Cashflow_{i,t}$), net return ($Navrtn_{i,t}$), family size ($FundFamily_{i,t}$), team ($Team_{i,t}$) and fees ($Fee_{i,t}$). To mitigate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

Table 5
Mechanism analysis from the perspective of performance ranking.

	(1)	(2)	(3)	(4)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−0.346***	−1.409***	−0.422***	−1.347***
	(−3.082)	(−11.085)	(−3.833)	(−10.530)
$SRM \times Rank_{i,t}$	−0.978***	−1.923***		
	(−4.745)	(−8.605)		
$Rank_{i,t}$	0.257***	0.310***		
	(4.410)	(5.030)		
$SRM \times Rank^{sp}_{i,t}$			−0.833***	−1.726***
			(−4.059)	(−7.945)
$Rank^{sp}_{i,t}$			0.224***	0.287***
			(3.848)	(4.746)
$Age_{i,t}$		−0.006		−0.010
		(−0.661)		(−1.021)
$Vol_{i,t}$		−3.404***		−4.764***
		(−4.719)		(−6.573)
$Size_{i,t}$		−0.021***		−0.021***
		(−5.491)		(−5.583)
$Fee_{i,t}$		−0.001		−0.001
		(−0.111)		(−0.063)
$Cashflow_{i,t}$		0.002		0.000
		(0.649)		(0.001)
$Nartm_{i,t}$		0.688***		0.647***
		(32.303)		(31.450)
$Team_{i,t}$		−0.008		−0.007
		(−1.591)		(−1.411)
$FundFamily_{i,t}$		0.074***		0.077***
		(7.659)		(7.833)
Fund FE	Yes	Yes	Yes	Yes
N	8578	8578	8578	8578
adj. R^2	−0.007	0.161	−0.008	0.151

Note: This table reports the moderating effect of ranking. Notice that all variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4. Model design

This paper explores whether the systemic risk significantly affects the tail risk taking behaviors of funds. Therefore, we construct the following regression model to test H1:

$$Dltr_{i,t} = \alpha + \beta SRM_t + \lambda Control_{i,t} + \alpha_i + \varepsilon_{i,t} \tag{11}$$

where $Dltr_{i,t}$ is the adjustment of fund i's tail risk in the second half of year t to the first half of year t. SRM_t is the systemic risk indicator in the first half of year t, and $Control_{i,t}$ are the control variables of fund i in the first half of year t. α_i refers to fund fixed effects, and $\varepsilon_{i,t}$ is the random error term.[1] The standard errors are clustered at the fund level.

An extended model is built to explore the effect of fund performance ranking:

$$Dltr_{i,t} = \alpha + \beta_1 SRM_t + \beta_2 Rank_{i,t} + \beta_3 SRM_t Rank_{i,t} + \lambda Control_{i,t} + a_i + \varepsilon_{i,t} \tag{12}$$

where $Rank_{i,t}$ is the performance ranking of the fund i in the first half of year t. It can be seen that coefficient β_3 on the interaction term reflects the variation in the intensity for SRM_t with each unit change in the performance ranking. We include fund fixed effects in the panel regression, and the standard errors are clustered by fund.

Our second hypothesis posits that the moderating effect of a given ranking is more attributable to compensation incentives than to career concerns. Therefore, the following logit regression is employed to further verify this intuition:

$$DPT_{i,t} = \alpha + \beta_1 Rank_{i,t} + \lambda Control_{i,t} + a_i + v_t + \varepsilon_{i,t} \tag{13}$$

$$DPT_{i,t} = \begin{cases} 1\ ,\ a\ departure\ from\ a\ fund\ occurs \\ 0\ ,\ others \end{cases} \tag{14}$$

[1] The value of SRM varies with year t but not with fund i. This means we cannot include time fixed effects (year FEs) in the models because it will absorb all the explanatory power of SRM.

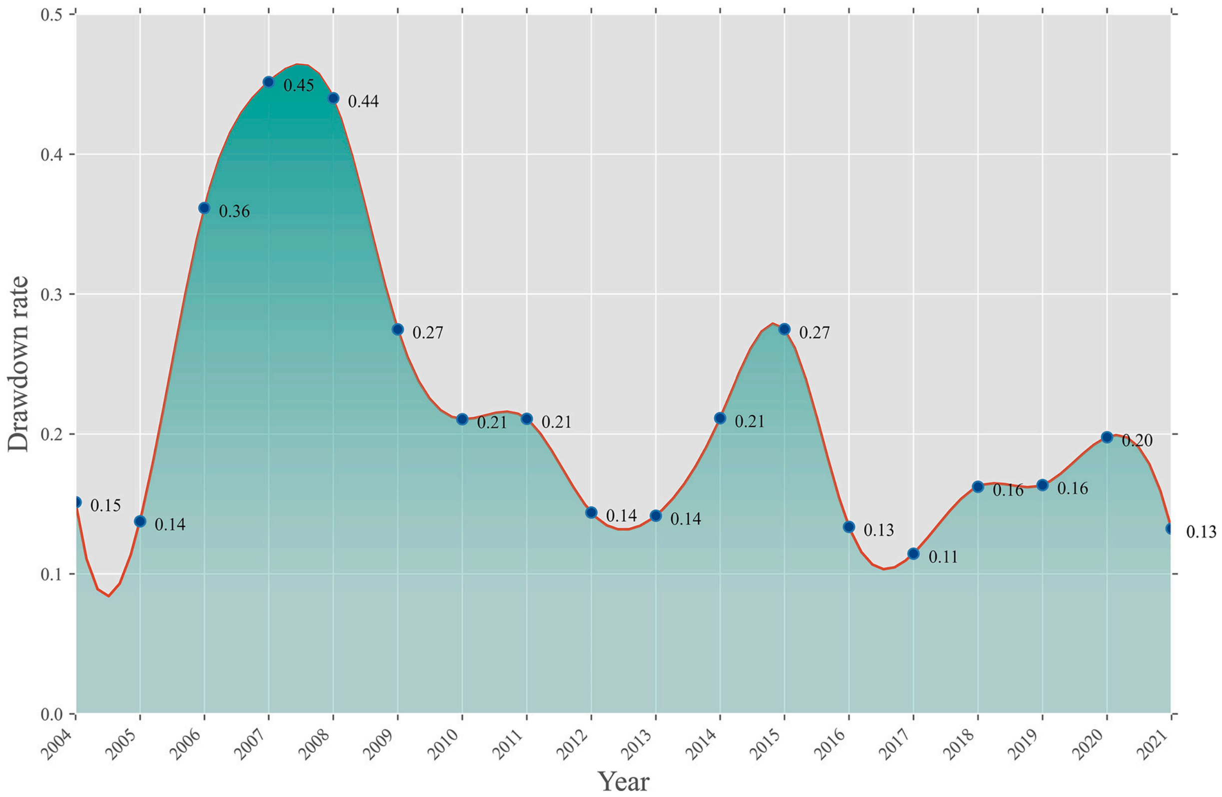

Fig. 1. Average drawdown rate of mutual funds in China. This figure illustrates the average drawdown rate of all mutual funds in China, spanning the period from 2004 to 2021.

where $DPT_{i,t}$ is a dummy variable, which equals 1 if a fund departs from fund i in period t, and 0 otherwise. We include fund fixed effects and year fixed effects in this panel regression. If the coefficient β_1 is significantly negative, it implies that an improvement in a fund's ranking does inhibit the departure of fund managers. That is, the higher the performance ranking of the fund, the more stable the position of fund managers. Conversely, if the coefficient β_1 is not statistically significant, it suggests that the decisive factor influencing the departure of fund managers may not be performance ranking in China's fund human resources market, indicating career concerns are comparatively minor among these professionals. Consequently, the primary mechanism that affects the tail risk-taking behavior of fund managers should be the compensation incentives.

To test hypothesis 3, an extended model is built to explore the effect of a fund's network structure:

$$Dltr_{i,t} = \alpha + \beta_1 SRM_t + \beta_2 Centrality_{i,t} + \beta_3 SRM_t Centrality_{i,t} + \lambda Control_{i,t} + a_i + \varepsilon_{i,t} \tag{15}$$

$Centrality_{i,t}$ is the network centrality of fund i in the first half of year t. We include fund fixed effects in the panel regression, and the standard errors are clustered by funds.

4. Empirical results

4.1. Summary statistics

The sample includes 8578 observations, with 1792 distinct funds. Table 3 shows the descriptive statistics of the main variables. The mean value of the fund's tail risk adjustment is −0.058, with the minimum value of −0.602 and the maximum value of 0.514.[2]

4.2. The fund's tail risk adjustment and SRM

As illustrated in Table 4, the coefficient of SRM is significantly negative, which remains significant with the inclusion of the control variables. Hypothesis 1 is thus verified, and it can be seen that there is a negative relationship between SRM and the fund managers'

[2] In order to save space, the specific results of the variable correlation coefficient matrix are not reported here, but can be obtained from the authors if required.

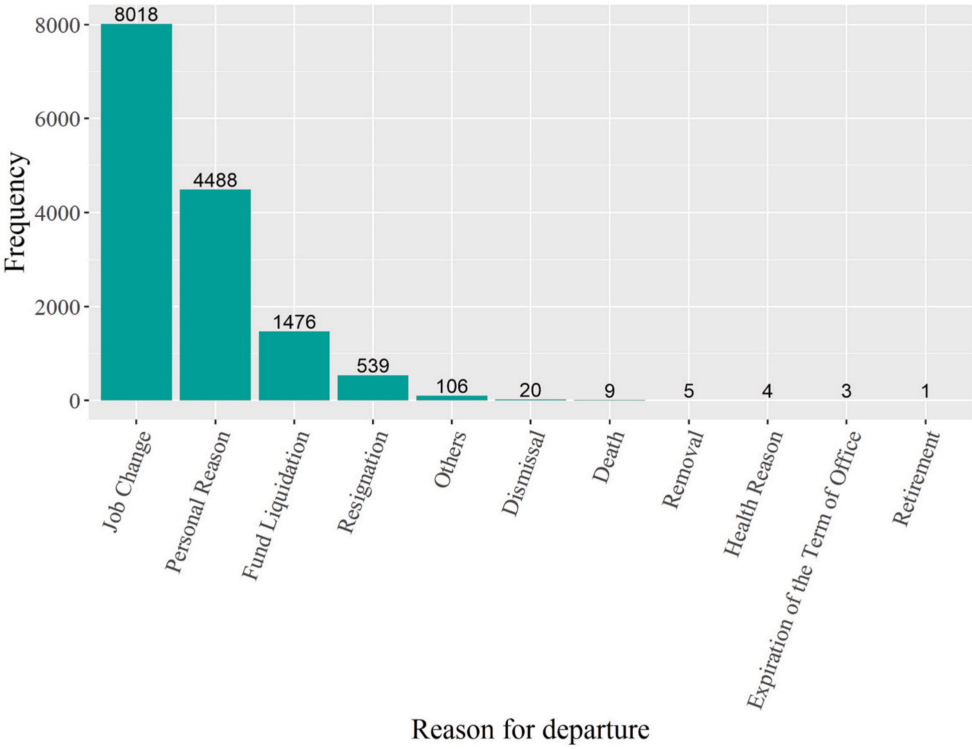

Fig. 2. Histogram of the cause for fund managers' departures. This figure depicts the reasons why fund managers experience departure. The causes can be categorized as either active (e.g., voluntary resignation) or passive (e.g., dismissal). The data covers the period from August 31, 2001 to December 31, 2021.

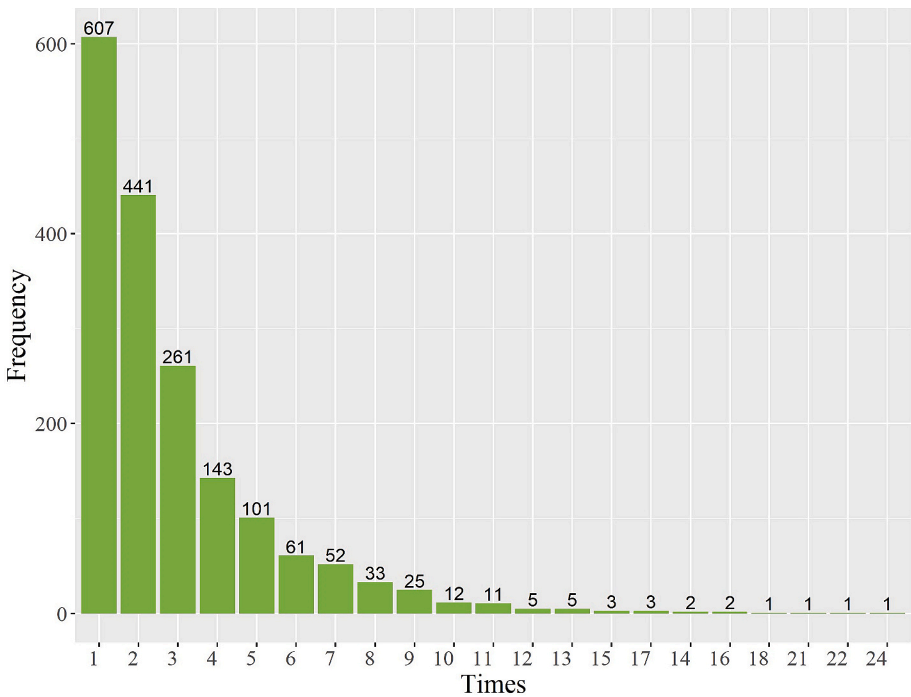

Fig. 3. Histogram of the frequency distribution of fund managers' departures. This figure shows the frequency of departure experienced by fund managers throughout their careers. The data covers the period from August 31, 2001 to December 31, 2021.

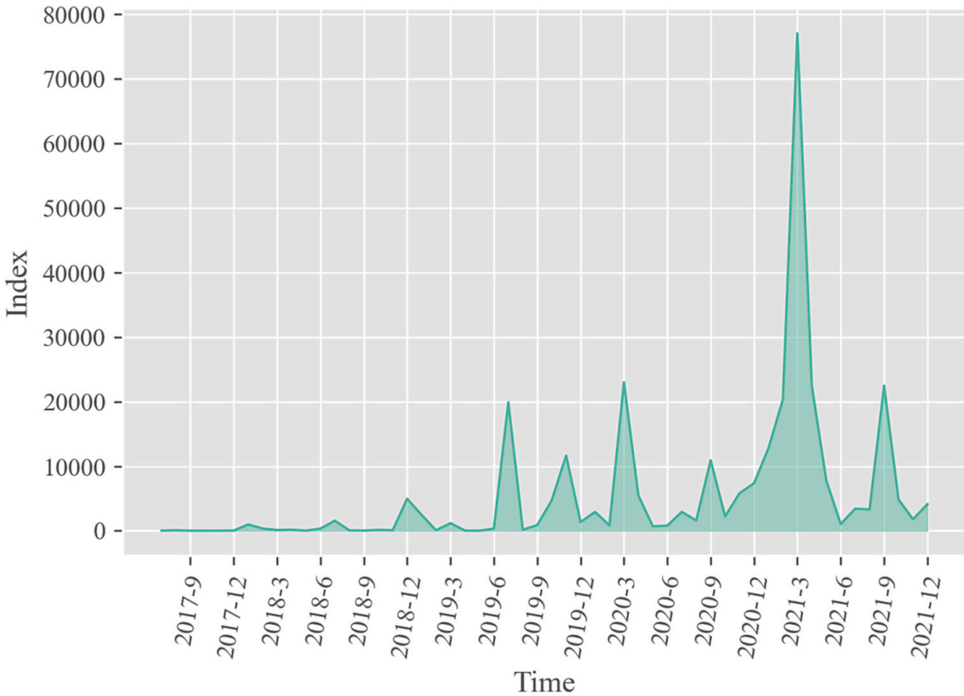

Fig. 4. Baidu index. The corresponding time interval is from July 3, 2017 to December 31, 2021. The data is collected from the Baidu search index page using a Python web crawler program. The keyword used for the search is "top holding stocks of funds / heavy position stocks of funds". The data collection begins on July 3, 2017, which aligns with the start time of Baidu search indices for the specified keyword.

tail risk-taking behavior. As systemic risk increases, fund managers will choose to take less tail risks. On average, fund managers tend to lower the tail risk by 1.78 units for every 1 unit increase in systemic risk.

4.3. The moderating effect of rankings

In Table 5, we examine the impact of rankings on the relationship between fund managers' tail risk-taking behavior and systemic risks. According to these results, the fundamental conclusion that SRM has a negative impact on the fund managers' tail risk-taking behavior remains unchanged.

The regression results presented in columns (1)–(2) of Table 5 show that the coefficients of interaction terms between SRM and $Rank_{i,t}$ are all negatively significant at 1%. This suggests that as $Rank_{i,t}$ improves, the inhibition effect of SRM on the risk-taking behavior of fund managers strengthens. When ranking funds by performance, we only consider the funds' returns, whereas in most cases, investors also need to seek a balance between returns and volatility by using a popular indicator such as the Sharpe ratio. In columns (3)–(4), we use $Rank^{sp}_{i,t}$, which represents the ranking according to the Sharpe ratio, to replace $Rank_{i,t}$ and obtain the same conclusion. As mentioned previously, as systemic risk increases, fund managers tend to adopt a "lying flat" mentality and pursue stability, indicating their unwillingness to bear more tail risk during this period. Therefore, the inhibition effect of systemic risk on tail risk-taking behavior is strengthened.

We propose a potential explanation that compensation incentives may drive midyear winners to curtail risk-taking, thereby contributing to SRM's inhibitory influence on tail risk-taking behavior.While this may appear counterintuitive, the phenomenon of drawdown provides an explanation for this behavior. When systemic risks break out, funds that have achieved higher earnings in the early stages of the year which are more likely to experience a drawdown, while those performing relatively poorly are less affected. This will result in a reversal of the fund ranking, thereby deteriorating the status of the initial winner. As shown in Fig. 1, the drawdown rate of Chinese mutual funds is perennially higher than 10%, with an annual average of 21.74%. The drawdown rate experienced a sharp increase during the two bull markets in 2007 and 2015, indicating that many funds with a stronger prior performance are unable to preserve their profits. A higher drawdown rate will result in a decrease in the main component of the fund manager's compensation, specifically, the performance incentive portion.[3] Therefore, refraining from taking additional tail risks as systemic risk increases is an effective approach to safeguarding achieved gains. This behavior can be explained by the compensation incentives within the tournament framework. Fund managers tend to seek stability and pursue a smooth landing to preserve the realized returns when the

[3] In China, the compensation contracts of fund managers are not published.According to a report by the Wall Street Journal, in China, the compensation structure for fund managers primarily includes a base salary and performance-based incentives.

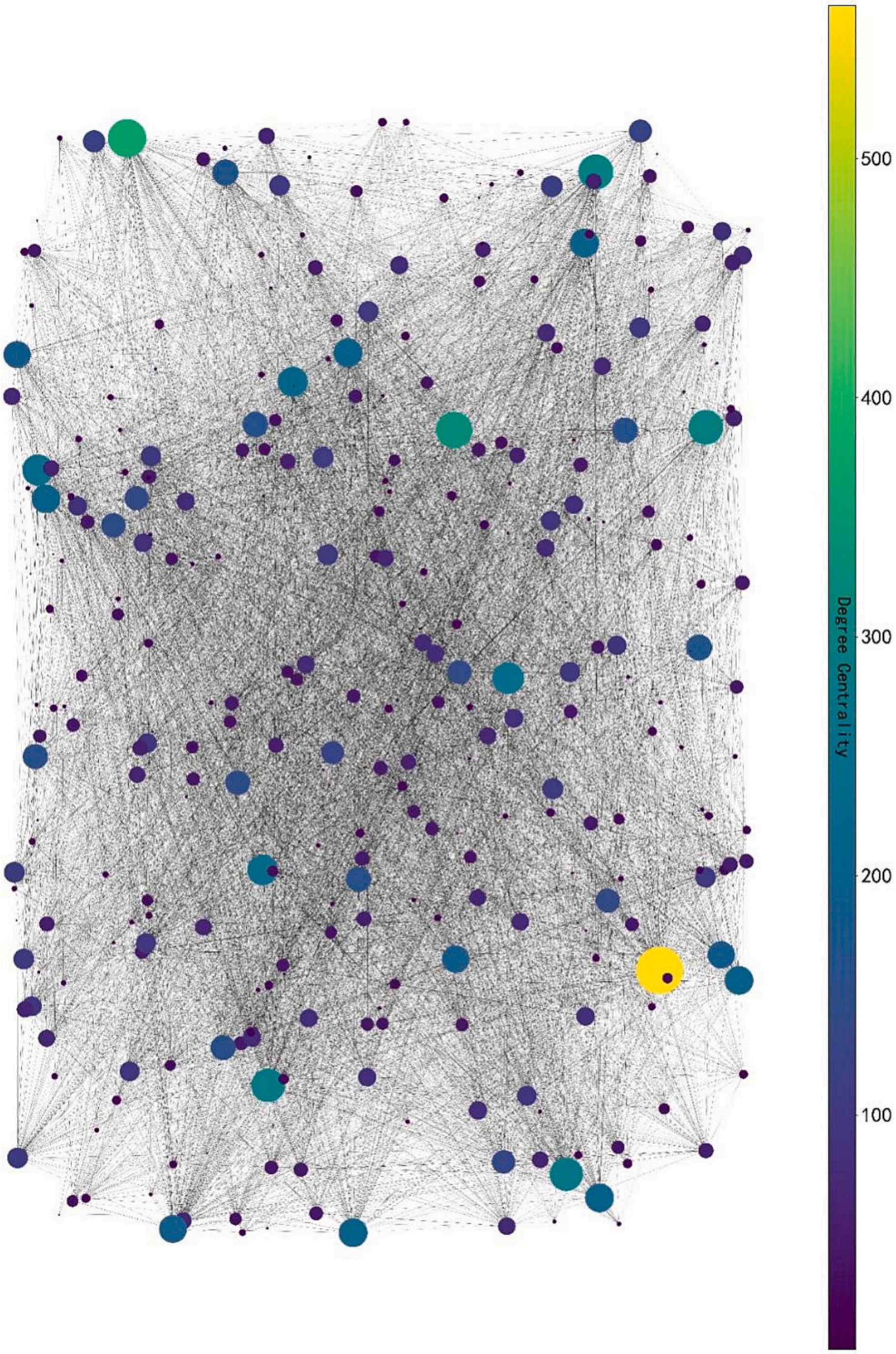

Fig. 5. A Network of Mutual Funds on June 30, 2011. Due to the extremely large number of funds, a cross-section of the sample on June 30, 2011 is selected to illustrate the network relationships of the funds in order to present the facts clearly. The network structure of the fund is visualized based on its degree centrality. The radius of the node corresponds to the brightness of the color, reflecting the magnitude of the fund's degree centrality.

market is experiencing systemic risk.

Next, we delve into the question of whether the career concerns of fund managers are significant in China. In Fig. 3, it is evident that the frequency of fund managers who have experienced departure once during their careers is as high as 607, and there are even managers who have changed the fund they are managing more than 10 times. Over 61.55% of fund managers have experienced departure at some point during their careers, however, those who have been summarily fired are in the minority. A more detailed analysis of Fig. 2 shows that among all fund managers, 4488 of them leave the funds they manage for personal reasons. Since the

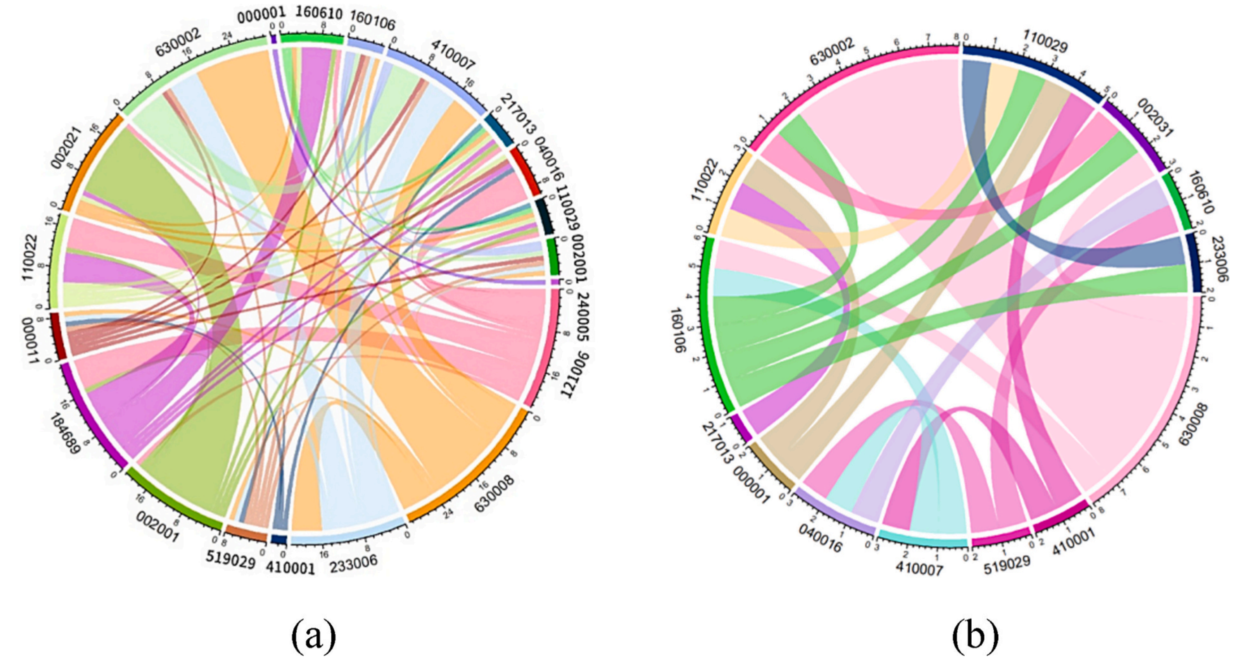

Fig. 6. a. The relationship between top holding stocks held by 20 funds in June 2011. We select 20 funds from the network in Fig. 5 and draw a chord graph for them. The outermost label is the fund name code. The value on the coordinate axis refers to the number of links among funds. The bands connect each block in the center, which refers to the degree of correlation among the funds. The more connections, the wider the band. b. The relationship between top holding stocks held by 20 funds in June 2021. For comparison, we map the network of the same 20 funds in Fig. 6 in 2021.

establishment of the fund market, only 20 managers have been dismissed, and 5 have been removed from their positions, which accounts for a mere 0.5% of the total. Despite the fact that 539 managers have voluntarily resigned from their funds, a more comprehensive analysis reveals that 315 of these have resigned twice or more times, indicating that nearly two-thirds of them find a new job after resigning. Based on these findings, we can conclude that career concerns should be regarded as a relatively insignificant cost in China's fund manager labor market.

Based on the descriptive analysis conducted above, it can be tentatively concluded that career concerns may not influence the effect of ranking on the relationship between SRM and fund managers' tail risk-taking behavior. This is due to the relatively low probability of a fund manager being completely dismissed.

To substantiate our argument with stronger evidence, we employ a logit regression to test our findings. Table 6 shows that the ranking of a fund, whether based on return or the Sharpe ratio, does not have a significant impact on the occurrence of departures. Wu et al. (2016) substantiate this claim, stating that the punishment for poor performance is insufficient. As an emerging market, even the most experienced fund managers in China have an average tenure of fewer than 25 years. Additionally, financial professionals such as fund managers are comparatively scarce, which further undermines the effectiveness of this punishment mechanism. As demonstrated by Ma and Tang (2019), there exists a significant asymmetry in the reward structure of fund performance. Fund managers who achieve outstanding performance receive substantial bonuses, while those with poor performance do not suffer deserved punishment. The aforementioned analysis further confirms that the fund managers' tail risk-taking behavior is mainly influenced by the compensation incentives within the tournament framework, rather than career concerns.

4.4. Mechanisms of the network

In recent years, China's fund market has exhibited a "clique" phenomenon, characterized by a large number of funds holding top holding stocks and exhibiting similar trading behaviors. This phenomenon attracts extensive attention. Fig. 4 illustrates that the attention of fund "cliques" began to rise after 2019, reaching their peak in 2021.

We construct a fund network based on its top holding stocks for a specific year in the sample.[4] Fig. 5 shows that funds holding a larger number of top holding stocks are more likely to form connections with other funds. We assign a higher weight to such funds (i.e., larger radius of its nodes) in the graph to indicate the richness of their information. It is evident that there is a complex network relationship among funds, where a few funds (i.e., nodes with a larger radius) are more strongly connected to others.

[4] Constrained by the article's length limit, it is challenging to provide a comprehensive representation of the complete fund network over the sample period, so we have to select a single year from the samples to construct the fund network based on its top holding stocks.

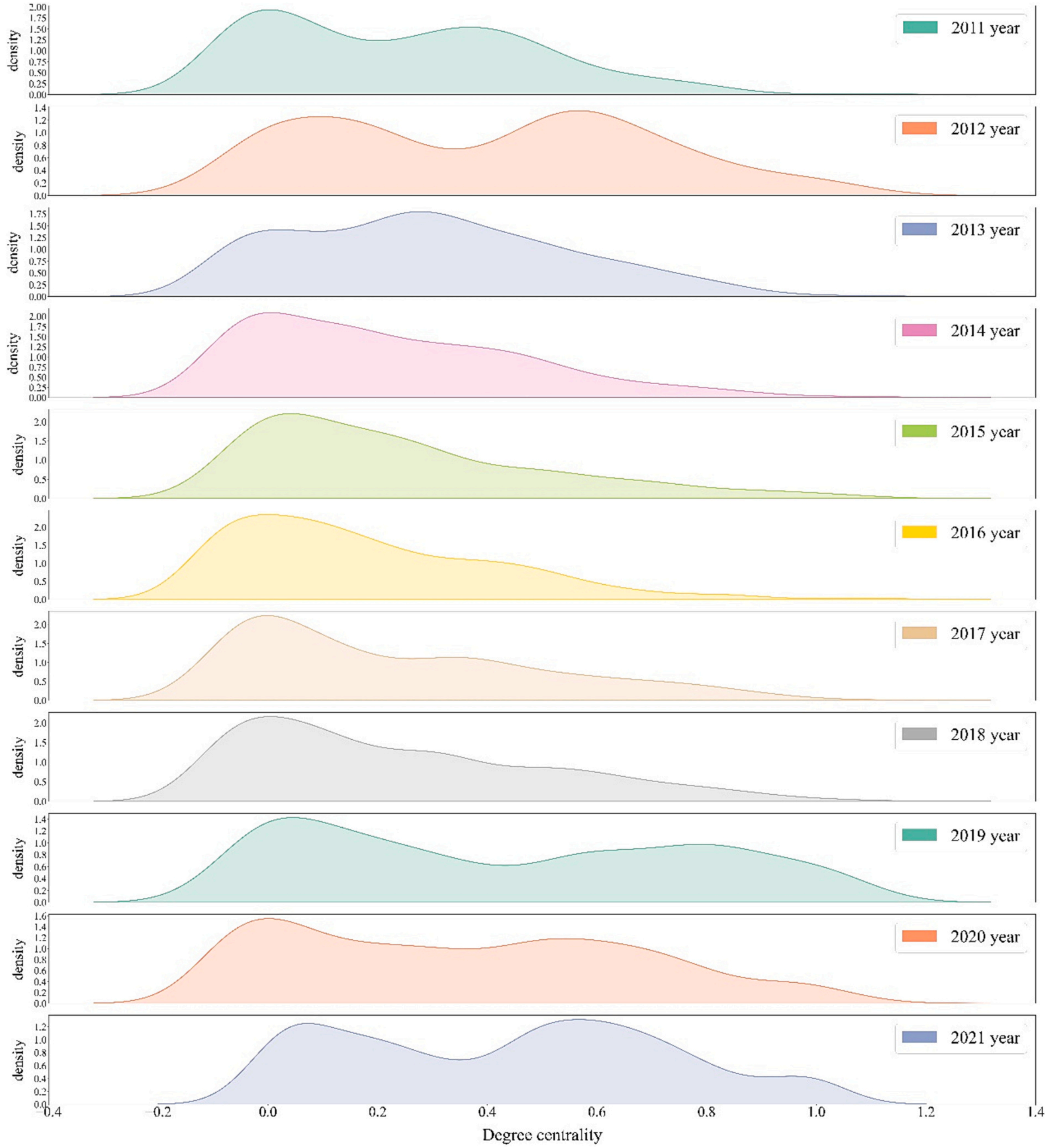

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Fig. 7. Density function curve of the degree centrality of the funds in the sample over the sample period. To better compare the degree distribution of each year, we standardize the degree centrality.

To visually illustrate the connection among funds more effectively, we select 20 funds and make chord graphs in 2011 and 2021 in Fig. 6.

Fig. 6a and b illustrate that these 20 funds form a network by top holding stocks, and this phenomenon is more pronounced in 2021. Despite a decrease in the number of interconnected funds, the links between some of the funds notably increase.

To better analyze the fund network structure, we draw the density function graph of degree centrality for the whole sample interval from the time dimension. In Fig. 7, we find that from 2019 to 2021, the degree centrality of the fund increases significantly compared to the previous years, which is consistent with the trend of the Baidu search index illustrated in Fig. 5. To a certain extent, the degree

Table 6
The effect of performance ranking on fund manger's departure.

	(1)	(2)
	$DPT_{i,t}$	$DPT_{i,t}$
$Rank_{i,t}$	0.013	
	(0.346)	
$Rank^{sp}_{i,t}$		−0.011
		(−0.240)
$Age_{i,t}$	0.047	0.047*
	(1.632)	(1.738)
$Vol_{i,t}$	−3.424	−3.501
	(−1.078)	(−1.230)
$Size_{i,t}$	−0.042***	−0.042***
	(−4.853)	(−6.453)
$Fee_{i,t}$	−0.004	−0.004
	(−0.123)	(−0.130)
$Cashflow_{i,t}$	0.008	0.007
	(0.865)	(0.806)
$Nartm_{i,t}$	−0.270**	−0.210*
	(−2.346)	(−1.723)
$Team_{i,t}$	0.425***	0.424***
	(22.436)	(16.016)
$FundFamily_{i,t}$	0.047	0.046
	(1.392)	(1.555)
Fund FE	Yes	Yes
Year FE	Yes	Yes
N	6814	6814
Pseudo R^2	0.393	0.393

Note: All variables except the explanatory variables are based on the first half-year. The fund fixed effects and year fixed effects are controlled. Standard errors estimated by bootstrap are reported in parentheses. The results for intercept and fixed effects are not reported for brevity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

centrality reflects the "clique" phenomenon.

Columns (1)–(2) in Table 7 show that the coefficients of interaction terms exhibit positively significant at the 1% level of significance, indicating that the network centrality weakens the inhibition effect of SRM on the fund managers' tail risk-taking behavior. Being able to access more information provides them with confidence in their investment decisions. This explanation is supported by the idea that "great minds think alike". Despite the abundance of investment opportunities in China's stock market, identifying high-quality stocks worthy of long-term holding still poses a significant challenge to fund managers. Nevertheless, if a fund manager holds a stock that other outstanding managers also hold, it is a validation to their capabilities. As Lu et al. (2022) have suggested, for those fund managers who have access to adequate information, even if the market seems to be plagued by crises, the actual risks they need to take are not nearly as high as it appears. Another alternative explanation is that fund managers will not only receive information but also serve as information sources for other colleagues, thus influencing their investment behaviors in turn. This bi-directional exchange of information could potentially affect the risk-taking behavior of other fund managers. Our analysis provides an explanation for why some fund managers tend to hold portfolios consisting of similar stocks.

Degree centrality measures the amount of information available to fund managers, while closeness centrality reflects the quality of information (Hochberg et al., 2007). The more central a fund is located within the network, the more critical the information the fund manager will receive. The results in columns (4) of Table 7 show that SRM still has a significant inhibition effect on the fund managers' tail risk-taking behavior, and that the quality of information will weaken this inhibition.

4.5. Additional analysis

To develop a deeper understanding of how fund managers' behavior regarding tail risk-taking responds to systemic risk, we extend our empirical analysis to assess the impact of fund managers' experience, educational background, and the COVID-19 pandemic.

The tenure of fund managers may affect their risk-taking behavior. Fund managers with longer tenures, in contrast to their less experienced counterparts, have already established a good reputation and are less concerned about losing their job (Chevalier and Ellison, 1999). Consequently, they may be more willing to take risks. We investigate whether fund managers' tenure influences their attitude towards tail risk exposure in the face of systemic risk. We differentiate fund managers based on their work experience. Fund manager tenure is defined as the duration since they entered the fund industry, serving as an indicator of their experience level (Kempf et al., 2009). For mutual funds with multiple managers, we quantify the team's experience by calculating the average tenure. Funds are classified as "young" if the average experience is below the overall average across all funds, and as "mature" if above.

The results are listed in Table 8. As systemic risk escalates, fund managers tend to curb tail risk taking behavior irrespective of their

Table 7
Centrality and the effect of SRM on tail risk-taking.

	(1)	(2)	(3)	(4)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−0.832***	−1.788***	−0.832***	−1.782***
	(−16.519)	(−20.428)	(−16.407)	(−20.122)
$SRM \times Degree_{i,t}$	0.131**	0.249***		
	(2.170)	(3.901)		
$Degree_{i,t}$	−0.029*	−0.066***		
	(−1.647)	(−3.628)		
$SRM \times Closeness_{i,t}$			0.082	0.166***
			(1.433)	(2.772)
$Closeness_{i,t}$			−0.016	−0.043**
			(−0.980)	(−2.508)
$Age_{i,t}$		−0.010		−0.010
		(−1.006)		(−1.028)
$Vol_{i,t}$		−5.287***		−5.279***
		(−7.304)		(−7.308)
$Size_{i,t}$		−0.025***		−0.025***
		(−6.463)		(−6.475)
$Fee_{i,t}$		0.001		0.001
		(0.071)		(0.062)
$Cashflow_{i,t}$		−0.007		−0.007*
		(−1.644)		(−1.692)
$Nartm_{i,t}$		0.471***		0.468***
		(26.903)		(26.744)
$Team_{i,t}$		−0.004		−0.004
		(−0.806)		(−0.820)
$FundFamily_{i,t}$		0.075***		0.076***
		(7.626)		(7.642)
Fund FE	Yes	Yes	Yes	Yes
N	8578	8578	8578	8578
adj. R^2	−0.008	0.113	−0.009	0.112

Note: This table explores the moderating effect of degree centrality and closeness centrality. Note that all variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

tenure. However, less experienced fund managers are more sensitive to systemic risk, exhibiting a more pronounced reduction in their tail risk-taking behavior. This phenomenon can be attributed to the fact that fund managers with shorter tenures are typically in the early stages of their careers and have not yet established a strong reputation in the market. Consequently, when faced with systemic risk, their risk-taking behavior appears more conservative compared to their more experienced peers.

Next, we examine the potential influence of fund managers' educational qualifications on their tail risk-taking behavior. The relationship between educational attainment and risk attitudes is contentious in existing literature. Some studies associate higher education with reduced risk aversion (Black et al., 2018; Dwyer et al., 2002), while others point to fund managers holding multiple degrees tend to be less risk-seeking (Andreu and Puetz, 2017). Given the stringent barriers to entry in the fund industry, we classify funds managed by individuals holding a Ph.D. or higher degrees as the highly educated group, while those managed by individuals without such advanced degrees are categorized as the less educated group.

As reported in Table 9, results reveal that educational background does not significantly alter the impact of SRM on fund managers' tail risk-taking behavior. A plausible explanation for this finding is that, in contrast to retail investors, fund managers, characterized as sophisticated market participants, appear to maintain a consistent risk attitude towards tail risks in the face of systemic risk, regardless of their educational levels.

The COVID-19 pandemic provides a valuable shock for studying the behavior of fund managers' tail risk-taking. First, we employ the following model specification to examine the impacts of the COVID-19 pandemic:

$$Dltr_{i,t} = \alpha + \beta SRM_t + \gamma SRM_t{}^*Post + \delta Post + \lambda Control_{i,t} + \alpha_i + \varepsilon_{i,t} \quad (16)$$

Columns (1)–(2) of Table 10 report the results of eq. (16), where the coefficient of the interaction term between SRM and Post is significantly negative. This suggests that post-pandemic, the inhibitory effect of systemic risk on tail risk-taking has further strengthened. Then, we conduct a subsample test to examine the impacts of the pandemic shock. As presented in Columns (3)–(4) of Table 10, the results show that both pre- and post- the pandemic, systemic risk has an inhibitory effect on tail risk-taking behavior. The tests of the differences in coefficients indicate that this inhibitory effect has been strengthened after the outbreak of COVID-19.

Table 8
Experience and the effect of SRM on tail risk-taking.

	(1)	(2)	(3)	(4)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−0.867***	−0.779***	−2.013***	−1.615***
	(−11.536)	(−8.825)	(−14.183)	(−12.098)
$Age_{i,t}$			0.011	−0.040**
			(0.747)	(−2.218)
$Vol_{i,t}$			−1.550	−8.508***
			(−1.437)	(−7.076)
$Size_{i,t}$			−0.032***	−0.019***
			(−5.434)	(−2.894)
$Fee_{i,t}$			−0.000	−0.014
			(−0.011)	(−0.644)
$Cashflow_{i,t}$			−0.004	−0.007
			(−0.654)	(−1.020)
$Nartm_{i,t}$			0.466***	0.526***
			(18.073)	(18.608)
$Team_{i,t}$			−0.002	−0.010
			(−0.207)	(−1.170)
$FundFamily_{i,t}$			0.055***	0.095***
			(3.412)	(5.784)
Diff	(1) vs. (2)		(3) vs. (4)	
p value	0.020		0.000	
Fund FE	Yes	Yes	Yes	Yes
N	4023	3978	4023	3978
adj. R^2	−0.010	−0.028	0.106	0.109

Note: The table shows the results of whether the relationship between systemic risk and tail risk-taking varies with the experience of fund managers. Columns (1) and (3) present the regression results for young funds, while columns (2) and (4) present the regression results for mature funds. Notice that all variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept, and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9
Educational qualifications and the effect of SRM on tail risk-taking.

	(1)	(2)	(3)	(4)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−0.811***	−0.851***	−1.801***	−1.798***
	(−13.900)	(−5.741)	(−18.015)	(−7.087)
$Age_{i,t}$			−0.006	−0.029
			(−0.504)	(−0.896)
$Vol_{i,t}$			−4.130***	−7.028***
			(−4.990)	(−3.583)
$Size_{i,t}$			−0.027***	−0.024**
			(−5.940)	(−2.151)
$Fee_{i,t}$			0.006	−0.013
			(0.379)	(−0.306)
$Cashflow_{i,t}$			−0.003	−0.012
			(−0.742)	(−1.189)
$Nartm_{i,t}$			0.463***	0.530***
			(23.878)	(10.664)
$Team_{i,t}$			−0.008	0.002
			(−1.200)	(0.146)
$FundFamily_{i,t}$			0.071***	0.066**
			(6.095)	(2.064)
Diff	(1) vs. (2)		(3) vs. (4)	
p value	0.170		0.370	
Fund FE	Yes	Yes	Yes	Yes
N	6947	1422	6947	1422
adj. R^2	−0.010	−0.043	0.106	0.091

Note: This table shows the results of the heterogeneity analysis with different educational qualifications. Columns (1) and (3) display the results for the less educated group, while columns (2) and (4) display the results for the highly educated group. Note that all variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10
The Covid-19 shock.

	(1)	(2)	(3)	(4)	(5)	(5)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−0.667***	−1.374***	−0.632***	−7.940***	−1.576***	−5.496***
	(−13.030)	(−14.770)	(−12.339)	(−18.288)	(−17.269)	(−5.266)
SRM × *Post*	−6.983***	−5.434***				
	(−16.454)	(−11.265)				
Post	2.075***	1.523***				
	(16.501)	(10.685)				
$Age_{i,t}$		0.026**			0.034***	−0.054
		(2.577)			(3.071)	(−0.873)
$Vol_{i,t}$		−6.743***			−4.639***	−13.281***
		(−9.032)			(−6.160)	(−4.850)
$Size_{i,t}$		−0.008**			−0.011**	−0.021*
		(−2.141)			(−2.293)	(−1.871)
$Fee_{i,t}$		−0.028**			−0.039***	0.004
		(−2.046)			(−2.610)	(0.082)
$Cashflow_{i,t}$		−0.007*			−0.011**	0.002
		(−1.804)			(−2.374)	(0.312)
$Nartm_{i,t}$		0.370***			0.398***	0.437***
		(19.748)			(21.386)	(7.002)
$Team_{i,t}$		−0.008			−0.008	0.016
		(−1.477)			(−1.425)	(1.107)
$FundFamily_{i,t}$		0.116***			0.086***	0.070
		(11.201)			(7.470)	(1.195)
Diff			(3) vs. (4)		(5) vs. (6)	
p value			0.000		0.000	
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8578	8578	6624	3010	6624	3010
adj. R^2	0.034	0.140	0.006	−0.003	0.155	0.040

Note: This table shows how the effect of systemic risk on tail risk-taking is influenced by COVID-19. all variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11
Endogeneity test.

	(1)	(2)	(3)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−1.663***	−1.196***	−2.796***
	(−18.919)	(−12.449)	(−12.731)
$Drawdown_{i,t}$	−0.423***	−0.363***	
	(−8.136)	(−6.893)	
$Turnover_{i,t}$	0.001	0.001	
	(0.886)	(1.360)	
$M2_t$		0.063	
		(1.612)	
Gdp_t		−0.249***	
		(−5.476)	
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
N	8578	8578	8578
adj. R^2	0.118	0.129	0.126

Note: This table shows the result of endogeneity tests. All variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

5. Robustness

5.1. Endogeneity

Since the SRM indicator reflects the overall systemic risk, SRM is hardly to be affected by the individual tail risk-taking behavior of fund managers. However, one might argue that it is still difficult to completely avoid potential endogeneity due to omitted variables

Table 12
Robustness check with different window size.

	(1)	(2)	(3)	(4)	(5)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
$SRM^{(ws=126)}$	−1.423***	−1.709***	−1.600***	−1.441***	−1.431***
	(−26.377)	(−21.610)	(−19.041)	(−27.712)	(−26.951)
$SRM^{(ws=126)} \times Rank_{i,t}$		−0.856***			
		(−7.035)			
$Rank_{i,t}$		−0.112***			
		(−3.384)			
$SRM^{(ws=126)} \times Rank^{sp}_{i,t}$			−0.724***		
			(−5.714)		
$Rank^{sp}_{i,t}$			−0.094***		
			(−2.697)		
$SRM^{(ws=126)} \times Degree_{i,t}$				0.161***	
				(4.371)	
$Degree_{i,t}$				−0.042***	
				(−3.810)	
$SRM^{(ws=126)} \times Closeness_{i,t}$					0.102***
					(3.365)
$Closeness_{i,t}$					−0.025***
					(−2.750)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
N	8578	8578	8578	8578	8578
adj. R^2	0.154	0.242	0.223	0.157	0.155

Note: This table shows the effect of SRM with different window size on tail risk-taking. All variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 13
Robustness check with CoESSR.

	(1)	(2)	(3)	(4)	(5)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
$CoESSR$	−2.344***	−1.123***	−1.274***	−1.236***	−1.238***
	(−21.447)	(−5.297)	(−6.119)	(−9.516)	(−9.523)
$CoESSR \times Rank_{i,t}$		−2.669***		−2.467***	−2.460***
		(−8.059)		(−14.139)	(−14.095)
$CoESSR \times Rank^{sp}_{i,t}$		0.020			
		(0.856)			
$Rank_{i,t}$			−2.290***		
			(−6.942)		
$Rank^{sp}_{i,t}$			0.012		
			(0.499)		
$CoESSR \times Degree_{i,t}$					
$CoESSR \times Closeness_{i,t}$				0.009***	
				(2.613)	
$Degree_{i,t}$					
$Closeness_{i,t}$					0.008**
					(2.277)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
N	8578	8578	8578	8578	8578
adj. R^2	0.112	0.142	0.136	0.143	0.143

Note: This table shows the effect of CoESS on tail risk-taking. All variables except the explanatory variables are based on the first half-year. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

bias. Therefore, in addition to lagged control variables, we include four additional control variables. Two fund-level variables, the turnover ratio (Massa and Patgiri, 2009) and the drawdown ratio (Li et al., 2017) are included, as well as two macroeconomic variables, the growth rate of GDP and the growth rate of M2, following Zhang et al. (2021). The results are presented in columns (1) and (2) of Table 11 and our main conclusions remain unchanged.

Table 14
Robustness check with more centralities.

	(1)	(2)	(3)
	$Dltr_{i,t}$	$Dltr_{i,t}$	$Dltr_{i,t}$
SRM	−1.797***	−1.793***	−1.784***
	(−20.794)	(−20.642)	(−20.239)
SRM × *Eigen*	0.321***		
	(4.573)		
SRM × *Coreness*		0.287***	
		(4.077)	
SRM × *Pagerank*			0.201***
			(3.273)
Eigen	−0.090***		
	(−4.461)		
Coreness		−0.082***	
		(−4.065)	
Pagerank			−0.053***
			(−3.010)
Controls	No	Yes	No
Fund FE	Yes	Yes	Yes
adj. R^2	8578	8578	8578
N	0.115	0.114	0.112

Note: This table presents the results with additional centrality measures. Columns (1)–(3) respectively display the impact of eigenvector centrality, coreness centrality, and pagerank centrality on the relationship between SRM and tail risk-taking. All variables except the explanatory variables are based on the first half-year. To save space, we do not report estimates of control variables. The fund fixed effects are controlled and the standard errors are clustered at the fund level. The results for intercept and fund fixed effects are not reported for brevity. T-statistics are reported in parentheses, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Another approach to mitigating endogeneity concerns is to employ an instrumental variable. The U.S. economic policy uncertainty (EPU) (Baker et al., 2016) can affect the normal operation of enterprises in various industries in China, thereby influencing the systemic risk indicator constructed by industry indices. Hence, following Shen and Hou (2021), we select the U.S. EPU index as the instrumental variable of SRM and perform a two-stage least squares (2SLS) regression. The findings, as reported in columns (3) of Table 11, are consistent with the results presented in Table 4.

5.2. Different window size

When constructing the SRM indicator, we set the rolling window size as 63. In order to avoid the impact of different window sizes on the results, referring to the research of Diebold and Yilmaz (2014), we adopt a window size of 126 to build the SRM indicator. We then conduct further tests on the main assumptions.

The results in Table 12 demonstrate that the negative correlation between systemic risk and fund managers' tail risk-taking is still significant, even when a window size of 126 is utilized to construct an SRM indicator. The effect of fund performance ranking and network centrality remains unchanged, suggesting that the choice of window size does not affect the robustness of our conclusions.

5.3. Different systemic risk indicators

In the realm of systemic risk measurement, the conditional expected shortfall (CoES) is a widely accepted metric (Adrian and Brunnermeier, 2016; Gu et al., 2022; Li et al., 2019). In our study, we calculate the CoES using industry returns and integrate it with the corresponding input/output matrix (Amor et al., 2022), known as CoES Systemic Risk Indicator (CoESSR). We employ CoESSR in lieu of SRM to describe the systemic risk again.

It is evident from Table 13 that when CoESSR is employed to measure systemic risk, our main conclusion, that the relationship between systemic risk and tail risk-taking of fund managers is negatively correlated, remains unchanged. Furthermore, the moderating effect of ranking and network centrality is consistent with our previous results. These findings suggest that the selection of systemic risk measurement methods does not impact the robustness of our conclusion.

5.4. Different centrality metrics

In the extant literature, there are other indicators which reflect the network relationship among individuals. To ensure the robustness of our conclusions, this study also employs indicators such as eigenvector centrality (Bonacich, 1987), the coreness centrality (Seidman, 1983), and the pagerank centrality (Page et al., 1999).

In Table 14, we find that substituting the measurement of centrality indicators does not change the conclusion that centrality indicators can attenuate the inhibition effect of SRM on fund managers' tail risk-taking behavior.

6. Conclusion

This paper investigates the impact of systemic risk on fund managers' tail risk-taking behavior. The analyses suggest that tail risk-taking behavior of fund managers is restrained by the level of systemic risk. Furthermore, we find that the performance ranking of the fund can strengthen this inhibition. As fund ranking increases, fund managers tend to control their impulse to take tail risks and instead pursue a smooth landing, and this is primarily motivated by compensation incentives. Additionally, when considering both the quantity and quality of information, network characteristics demonstrate a notable negative impact on this inhibition. Fund managers with access to abundant and high-quality information are more likely to take tail risks. Therefore, preventing the excessive aggregation of the network may be a feasible strategy for risk prevention in the fund market going forward.

For investors, the findings of this study suggest that risk-averse investors should be cautious when investing in funds exhibiting high centrality characteristics. For funds characterized by this investment style, one strategy is to redeem midyear winners and redirect these investments towards midyear loser to chase higher returns. Alternatively, investors could choose to short funds that are midyear winners in order to keep their profits.

For regulators, our research recommends that a sound exit mechanism for fund managers is necessary to ensure the healthy development of the fund market. Our analysis suggests that compensation incentives are still the most potent mechanism to restrict the risk-taking behavior of fund managers, whereas the relatively low career concerns of Chinese fund managers attenuate the effect of negative incentives on their behavior compared to other kinds of funds (such as private equity funds). However, at this stage we do not know whether the apparent low levels of career concerns are a peculiar phenomenon of mutual funds. Furthermore, it is also worth deliberating whether this phenomenon is instigated by the absence of an exit mechanism, or the rigidity of the labor market of fund managers. An attempt will be made to explore this problem in future research.

CRediT authorship contribution statement

Quansheng Xuan: Conceptualization, Data curation, Methodology, Writing – original draft. **Zhiyong Li:** Conceptualization, Formal analysis, Writing – original draft. **Tianyu Zhao:** Formal analysis, Writing – original draft, Writing – review & editing.

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Appendix A

We use mixed copula to model the tail risk of individual funds and market indicies to reflect the overall dependency structure. The principle of the method is as follows

A.1. Step 1

First, we calculate the log return of fund i and the log return of the market index. We construct scaled empirical distribution function using the log return.

$$\widehat{F_{fr}}(x) = \frac{1}{n+1}\sum_{k=1}^{n} I(FR_k \leq x), \widehat{F_{mr}}(x) = \frac{1}{n+1}\sum_{k=1}^{n} I(MR_k \leq x) \tag{A1}$$

where $I(\cdot)$ is an indicator function.

A.2. Step 2

The copula function we use is defined as follows:

$$C(u_1, u_2, \Theta) = w_1 \times C_{LTD}(u_1, u_2; \theta_1) + w_2 \times C_{NTD}(u_1, u_2; \theta_2) + (w_3) \times C_{UTD}(u_1, u_2; \theta_3) \tag{A2}$$

notice that $\sum w_i = 1, i = 1, 2, 3.$

The specific forms of NTD, LTD, and UTD are shown in the following table:

Table A.1
copula functions.

NTD	LTD	UTD
The Gauss copula	the Clayton copula	the Gumbel copula

(*continued on next page*)

Table A.1 (*continued*)

NTD	LTD	UTD
The Frank copula	the rotated Gumbel copula	the Joe copula
The FGM copula	the rotated Joe copula	the Galambos copula
The Plackett copula	the rotated Galambos copula	the rotated Clayton copula

The estimation of the set of copula parameters are $\Theta_j = \{\theta_1, \theta_2, \theta_3, w_1, w_2, w_3\}$, and we use the canonical maximum-likelihood procedure (Genest, Ghoudi, and Rivest (1995)) to estimate $\widehat{\Theta_j} = \{\widehat{\theta_1}, \widehat{\theta_2}, \widehat{\theta_3}, \widehat{w_1}, \widehat{w_2}, \widehat{w_3}\}$. The log-likelihood function has the form:

$$\widehat{\Theta_j} = \underset{\Theta_j}{\text{argmax}} \left(\sum_{k=1}^{n} ln\left(c_j\left(\widehat{F_{fr_k}}, \widehat{F_{mr_k}}; \Theta_j\right)\right) \right) \tag{A3}$$

A.3. Step 3

Define $\widehat{C_{(n)}}$ as follows:

$$\widehat{C_{(n)}}\left(\frac{x}{n}, \frac{y}{n}\right) = \frac{1}{n}\sum_{k=1}^{n} I(FRR_k \le x) \times I(MRR_k \le y) \tag{A4}$$

where $x = 0, 1, \dots, n, y = 0, 1, \dots, n$, and thus construct a grid.

Then a method known as integrated Anderson–Darling distances is used to select the optional parameters, which can be calculated as follows:

$$D_{j,\mathrm{IAD}} = \sum_{x=1}^{n} \sum_{y=1}^{n} \frac{\left(\widehat{C_{(n)}}\left(\frac{x}{n}\frac{y}{n}\right)\right) - C_j\left(\frac{x}{n}, \frac{y}{n}; \widehat{\Theta_j}\right)^2}{C_j\left(\frac{x}{n}, \frac{y}{n}; \widehat{\Theta_j}\right) \times \left(1 - C_j\left(\frac{x}{n}, \frac{y}{n}; \widehat{\Theta_j}\right)\right)} \tag{A5}$$

We choose the one with the smallest $D_{j,\mathrm{IAD}}$ from among the 4*4*4 combinations as $\Theta_i^* = \{\theta_1^*, \theta_2^*, \theta_3^*, w_1^*, w_2^*, w_3^*\}$. The indicator in which we are most interested here is $LTD^* = w_1^* \times LTD(\theta_1^*)$.

Appendix B

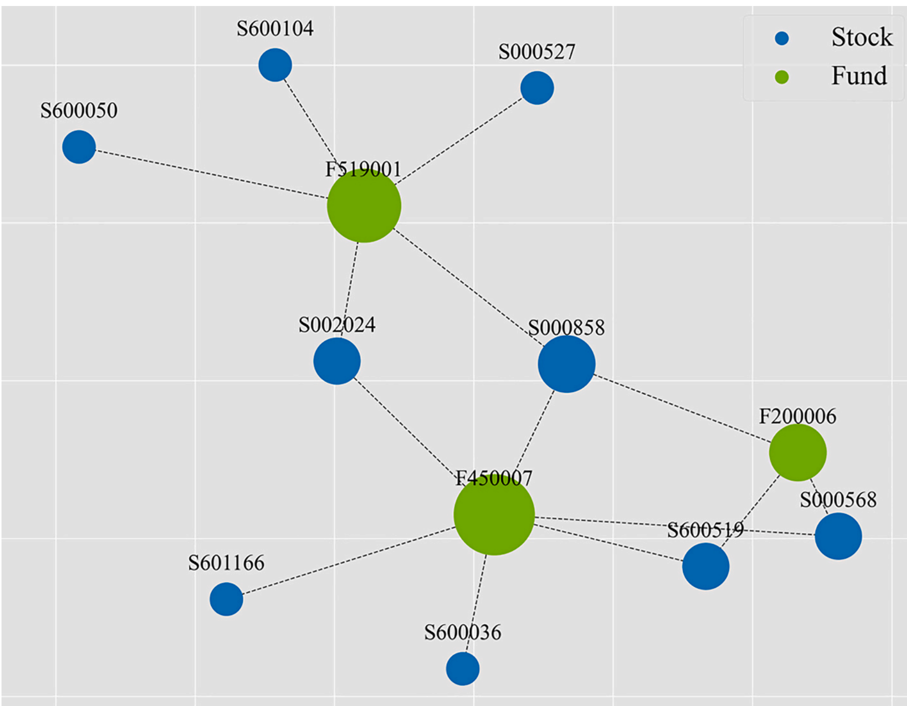

Fig. B.1. An example of a real fund's network based on stock holdings. In this picture we show a fund network, in which the larger green dots represent funds, the smaller blue dots represent stocks, and the connection between green dots and blue dots indicates that the fund holds a heavy position in the stock. These funds and stocks constitute the fund network, and we can calculate the network centrality of the funds. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table B.1
Funds' codes selected in Fig. 6a and b

Fund code			
240005	002031	630002	110029
000001	519029	630008	121006
040016	160106	002021	160610
000011	233006	002001	184689
410001	410007	110022	217013

This table shows the codes of the funds we have selected in Fig. 6a and b.

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