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Pandemic-driven financial contagion and investor behavior: Evidence from the COVID-19[☆]

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A B S T R A C T

This paper studies the pandemic-driven financial contagion during the COVID-19 period and the impact of investor behavior on it by constructing three types of direct behavior measurements based on Google search volumes. More specifically, using a sample of 26 major stock markets around the world during the COVID-19 pandemic, we construct a non-linear financial contagion network via a dynamic mixture copula-EVT (extreme value theory) model to quantitatively detect and measure the complex nature of pandemic-driven financial contagion. Furthermore, through constructing direct investor behavior measurements including investor attention, sentiment, and fear, we find investor behavior plays an important role in explaining pandemic-driven financial contagion. We also find that the impacts of investor behavior on the pandemic-driven financial contagion are heterogeneous under several different settings, including market conditions, market development levels, regional subsets, and contagion directions.

1. Introduction

The outbreak of COVID-19 has had a great impact on investor psychology and expectation because of its unique harmfulness, wide spread, uncertainty of loss, and complexity of governance. For instance, as the COVID-19 hit the US in early March 2020, the panic index VIX soared, resulting in a significant decline in financial markets. Subsequently, affected by the government's economic stimulus policies, the financial markets experienced a historic rebound and recovery. However, despite the panic index fell, it did not fall to the pre-pandemic level. In fact, the impact of the pandemic on investor psychology will further influence or change the investor behavior such as more attention, anxiety, and even fear. This will then get reflected in investors' investment decisions and ultimately affect the performance of financial markets (Chundakkadan & Nedumparambil, 2021; Hirshleifer et al., 2020; Sun et al., 2021). On the other hand, it should be noted that under the great external shocks, the changes in investor psychology and expectations will also affect financial contagion. For instance, under the downward pressure of the global economy, the rapid spread of the pandemic combined with control measures such as economic lockdowns and home quarantine have intensified investors' pessimistic expectations on financial markets, which would result in the uncertainty of risk stacking and the complexity of cross-contagion. However, the relationship of investor behavior with pandemic-driven financial contagion has not been explored in the existing literature. These motivate us to investigate the impact of investor behavior on financial contagion driven by the pandemic.

With the development of the internet, online search volumes of search engines have been widely used to construct the direct proxy for investor behavior since the pioneering work of Da et al. (2011). Thus, instead of the indirect proxy for investor behavior, we construct the direct proxy based on Google search volumes from Google Trends to measure investor behavior and investigate the impact of investor behavior on pandemic-driven financial contagion. As the most popular search engine around the world,[1] Google is not only the dominant online search provider in the online market of its home country, but also popular in many other countries with more than 90% of search traffic in countries such as Brazil, India, Italy, Spain, and Australia.[2] To a large extent, Google search queries can reflect the attitudes of market participants and reveals information promptly. Therefore, Google Trends serve as a powerful platform to track investor behavior across countries.

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[1] Google has remained at the top of online search engine markets since its launch in 1997. For instance, in April 2020, Google accounted for 86.02 percent of the global search market, while Bing and Yahoo only accounted for 6.25 percent and 3.36 percent, respectively (data available at https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/).

[2] Data available at https://www.statista.com/statistics/220534/googles-share-of-search-market-in-selected-countries/.

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Relying on Google search behavior, we construct three types of direct measurements for investor behavior, i.e., investor attention, investor sentiment, and investor fear to test the importance of investor behavior in pandemic-driven financial contagion. The COVID-19, a unique and unprecedented pandemic event, provides a perfect testbed for studying pandemic-driven financial contagion. We begin our study by constructing a dynamic mixture copula-EVT model to examine the existence of pandemic-driven financial contagion. The constructed dynamic mixture copula-EVT model incorporates both the lower tail behavior and the complex dependence structure among different markets, which allows us to elucidate pandemic-driven financial contagion more precisely. Using the model to a sample of 26 stock markets during the COVID-19 pandemic period at a daily frequency, we find evidence of pandemic-driven financial contagion around the world. Next, we construct a pandemic-driven financial contagion network in combination with the dynamic mixture copula-EVT model in the context of non-linear and tail dependence. The proposed network provides a powerful tool to analyze the characteristics of the pandemic-driven financial contagion including contagion potential, contagion speed, contagion strength, and systemic importance of each market in the contagion network.

Finally, by constructing three types of direct measurements for investor behavior including investor attention, sentiment, and fear, we explore the impact of investor behavior on pandemic-driven financial contagion and our result shows that investor behavior plays an important role in explaining pandemic-driven financial contagion. Moreover, we further analyze the potential differences in the impacts of investor behavior on pandemic-driven financial contagion under several different settings: market conditions (melt-down and melt-up), market development levels (developed and emerging markets), regional subsets (America, Europe, and Asia), and contagion directions (contagion received from other markets and contagion transmitted to other markets). The results show heterogeneous impacts of investor behavior on the pandemic-driven financial contagion under these settings. Our results are robust to the use of weekly frequency data. These findings go further to bring some new insights on the understanding of financial contagion and have tremendous implications for portfolio selection and financial risk management.

Our paper enriches the literature that investigates the impact of investor behavior on financial contagion (Boyer et al., 2006; Jayech, 2016). First, this study fills the gap in the research on the impact of investor behavior on the pandemic-driven financial contagion, especially in the context of the contemporary global landscape--the COVID-19 pandemic. Second, unlike prior literature, which is based on the indirect proxy variable of investor behavior, we are the first to directly quantify investor behavior via Google search volumes to investigate the impact of investor behavior on pandemic-driven financial contagion. Importantly, we construct three types of direct behavior measurements, i.e., investor attention, investor sentiment, and investor fear to comprehensively study the role of investor behavior in explaining pandemic-driven financial contagion. Third, we further analyze the potential differences in the impacts of investor behavior on pandemic-driven financial contagion under several different settings, including market conditions (melt-down and melt-up), market development levels (developed and emerging markets), regional subsets (America, Europe, and Asia), and contagion directions (contagion received from other markets and contagion transmitted to other markets). This in-depth investigation has practical importance for investors and risk managers to take preventive measures to prevent the spread of crises and regulate the financial markets.

The remainder of the paper proceeds as follows. Section 2 introduces the proposed methodology. Section 3 describes data and introduces investor behavior measurement. Section 4 empirically investigates the pandemic-driven financial contagion and the impact of investor behavior on it. Finally, Section 5 concludes.

2. Literature review

Financial contagion is defined as a significant increase in the cross-market links after extreme shocks (Forbes & Rigobon, 2002). Several methods have been proposed to measure financial contagion such as the vector autoregression approach (Dungey et al., 2020), multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model (Niţoi & Pochea, 2019), quantile regression approach (Iwanicz-Drozdowska et al., 2021), and detrended cross-correlation analysis (DCCA) method (Mohti et al., 2019; Okorie & Lin, 2021). However, there are some challenges in using these methods to measure financial contagion. For instance, some methods such as the vector autoregression approach and GARCH model are based on linear assumptions and ignore the non-linear dependence that is usually observed between financial markets (Wang, Yuan, Li et al., 2021). Although some other methods such as the quantile regression approach and DCCA method could capture some non-linear dependence, they are not designed to model the entire dynamic tail dependence that is more appropriate for financial contagion (Wang, Yuan, Wang, 2021; Ye et al., 2017). To overcome these challenges, copula models have been proposed to describe the complex dynamics including non-linear and dynamic tail dependence, and have been widely used to study financial contagion (Aristeidis & Elias, 2018; Jayech, 2016; Wang, Yuan, Li et al., 2021; Wang, Yuan, Wang, 2021).

GARCH-type models have commonly been used to estimate the marginal distribution of the copula models (Jayech, 2016; Koliai, 2016; Supper et al., 2020). However, they cannot adequately approximate the tail behavior of the marginal distribution, yet the tail behavior is essential in measuring financial contagin. To address this issue, in addition to the GARCH model, Wang, Yuan, Wang (2021) model the tail behavior of the marginal distribution with EVT and construct a dynamic copula-EVT model to detect the existence of financial contagion. The dynamic copula-EVT model incorporates both the tail behavior and the complex tail dependence structure between financial markets. Therefore, it is suitable and provides a more precise way to detect and measure financial contagion.

The existing literature has systematically investigated financial contagion and its transmission mechanism during several major financial crisis events, including the 1997 Asian financial crisis, the 2008 global financial crisis, and the 2011 European debt crisis (Boyer et al., 2006; Bekaert et al., 2014; Chen et al., 2020; Samitas, Kampouris, Umar, 2020). In examining these early crises, evidence of financial contagion is found from various methods and investor behavior is found to play an important role in driving financial contagion. These works are based on constructing an indirect proxy variable of investor behavior such as relative volatility indicator (Niţoi & Pochea, 2020) and the emerging market stocks that are accessible and inaccessible to foreigners (Boyer et al., 2006). However, there is a substantial challenge in these works: Investor behavior is indirectly measured. Indirect proxies for investor behavior such as the net stock purchase (Baker & Wurgler, 2006) and dividend premium (Yang et al., 2021) are hard to timely and accurately reflect the real behavior of investors (Chundakkadan & Nedumparambil, 2021; Cookson & Niessner, 2020; Fan et al., 2021; Gu & Kurov, 2020). As an alternative behavior measurement, the direct proxy variable based on online search engines shows the information flow in financial markets more authentic and comprehensive (Hsieh et al., 2020), and it has been widely used in asset pricing and market efficiency (Da et al., 2015; Gao et al., 2020; Gu & Kurov, 2020; Hsieh et al., 2020). Despite this, these works focus solely on one type of behavior from investor attention, sentiment, and fear, and the three behavior measurements have not been considered simultaneously.

As the once in a 100 years catastrophic event, the COVID-19 pandemic has attracted considerable attention from scholars, policymakers, and risk managers (Cheng et al., 2022; Duan et al., 2021; Polyzos et al., 2021; Samitas, Kampouris et al., 2022; Samitas et al., 2022b, 2022c). The research related to the financial contagion driven by pandemic events (such as SARS in 2003, H1N1 in 2009, Ebola in 2014, and ZIKA in 2016) is limited until recently, when there has been a surge of interest in studying it after the outbreak of the COVID-19 (Akhtaruzzaman et al., 2021; Aslam et al., 2020; Duan et al., 2021; Guo et al., 2021; Liao et al., 2021). Wang, Yuan, Wang (2021) investigate the financial contagion between oil and stock markets during the COVID-19 and show that the magnitude of financial contagion exceeds that during the 2008 financial crisis. However, little attention is dedicated to the influence factors of the pandemic-driven financial contagion, as it is of great practical importance for risk managers to make effective policies to mitigate risk from the pandemic shock.

In this study, we first construct a dynamic mixture copula-EVT model to detect the pandemic-driven financial contagion during the COVID-19 period. Moreover, we explore whether investor behavior drives the spread of the pandemic-driven financial contagion by constructing three types of direct behavior measurements, i.e., investor attention, investor sentiment, and investor fear.

3. Methodology

3.1. Dynamic mixture copula-EVT model

There is a large amount of and still growing body of literature on the copula function due to its flexibility in describing various patterns of dependence structure such as non-linearly, asymmetry, dynamic, and tail dependence (Abakah et al., 2021; Chabi-Yo et al., 2018; Christoffersen et al., 2012; Hüttner et al., 2020; Sahamkhadam et al., 2022; Supper et al., 2020; Wang & Dyer, 2012; Wang, Yuan, Wang, 2021). A copula captures the dependence structure of a multivariate distribution and is defined as a multivariate distribution function with standard uniform margins. For any two random variables X_1 and X_2 with bivariate joint distribution function $F_{12}(X_1, X_2)$ and two continuous marginal distribution functions $F_1(X_1)$ and $F_2(X_2)$, there exists a unique copula function C, such that

$$C(u_1, u_2) = F_{12}(F_1^{-1}(u_1), F_2^{-1}(u_2)) \tag{1}$$

where $u_i = F_i(X_i)$ with i=1, 2 are uniform variables over [0, 1] and F_i^{-1} is the inverse of F_i. The copula is independent of the choice of the marginal distribution. To model the dependence, we first present the model for the marginal distribution and then the dependence structure of the copula.

3.1.1. Marginal distribution modeling

In line with the works of Koliai (2016) and Supper et al. (2020), the GARCH-EVT model is adopted to model the marginal distribution before estimating the copula. More specifically, we first use the AR(1)-GJR(1,1) model with skewed-t distribution to filter autocorrelation and heteroscedasticity and obtain the standardized residual series. We then use the peak over threshold method of EVT to describe the tail behavior of the asset returns. That is, the distribution of the standardized residuals falling or beyond the tail thresholds is set to follow a generalized Pareto distribution (GPD). In this paper, we use the 10% and 90% quantiles as the lower (upper) tail thresholds. By doing so, the standardized residuals falling (beyond) the lower (upper) tail threshold are modeled with GPD and those between the lower and upper tail thresholds are estimated using the empirical cumulative distribution function. In all, the whole marginal distribution is finally constructed through a semi-parametric approach as follows:

$$F_i(z_i) = \begin{cases} \dfrac{N_{\mu_L}}{N}(1 - \xi_L \dfrac{\hat{z}_i - \mu_L}{\beta_L})^{-1/\xi_L}, & \hat{z}_i < \mu_L, \\ \varphi(\hat{z}_i), & \mu_L \le \hat{z}_i \le \mu_U, \\ 1 - \dfrac{N_{\mu_U}}{N}(1 + \xi_U \dfrac{\hat{z}_i - \mu_U}{\beta_U})^{-1/\xi_U}, & \hat{z}_i > \mu_U, \end{cases} \tag{2}$$

where z_i is the standardized residual obtained from the AR(1)-GJR(1,1) model, u_L (u_U) is the lower (upper) tail threshold, Nu_L (Nu_U) is the number of observations falling (beyond) the lower (upper) tail threshold, ξ_L (ξ_U) and $\beta_L(\beta_U)$ are the scale parameter and shape parameter on the lower (upper) tail, respectively, T is the size of observations, and φ is the empirical cumulative distribution function about z_i.

3.1.2. Dynamic Clayton-Survival Gumbel Copula

There are a variety of copulas in the literature and each copula captures a different dependence structure and dependence degree. Therefore, an appropriate copula function should be selected depending on the nature of financial contagion, which suggests the exploration of extreme dependence (especially in the lower tail) between two markets rather than the widely used correlation in the literature (Wang, Yuan, Wang, 2021; Ye et al., 2017). Therefore, we are merely interested in the lower tail dependence and looking for the copula that captures the lower tail dependence feature. The lower tail dependence is defined as the conditional probability of two variables jointly suffering extreme downward movements and can be expressed as:

$$\lambda_L = \lim_{u \to 0} P(X_1 < F_1^{-1}(u) | X_2 < F_2^{-1}(u)) = \lim_{u \to 0} \frac{C(u, u)}{u}, \tag{3}$$

where $\lambda_L \in [0, 1]$. λ_L being zero or positive implies that X_1 and X_2 are asymptotically independent or dependent in the lower tail, respectively. Larger λ_L shows stronger lower tail dependence.

The Clayton copula and Gumbel copula as well as the mixture of the two copulas, with or without time variation, have received much recent attention and have been popularly used in modeling tail dependence (Okimoto, 2008; Wang & Dyer, 2012; Wang, Yuan, Wang, 2021). As the mixture copula is more flexible and performs better than the single copula (Wang, Yuan, Li et al., 2021), we construct a dynamic mixture Clayton-survival Gumbel copula to measure the dynamic lower tail dependence as follows:

$$C^{DCSG}(u_1, u_2; \theta) = \omega C^{DC}(u_1, u_2; k_t^C) + (1 - \omega) C^{DSG}(u_1, u_2; k_t^{SG}) \tag{4}$$

where $\omega \in [0, 1]$ is the weight parameter, and C^{DC} and C^{DSG} are the dynamic Clayton copula and dynamic survival Gumbel copula, respectively. The dynamic Clayton copula function and dynamic survival Gumbel copula function are expressed as

$$C^{DC}(u_1, u_2; k_t^C) = (u_1{}^{-k_t^C} + u_2{}^{-k_t^C} - 1)^{\frac{-1}{k_t^C}} \tag{5}$$

$$C^{DSG}(u_1, u_2; k_t^{SG}) = u + v - 1 + \exp\left\{ -\left[(-ln(u_1))^{k_t^G} + (-ln(u_2))^{k_t^G} \right]^{\frac{1}{k_t^G}} \right\} \tag{6}$$

with the time variation in the dependence parameters are given by

$$k_t^C = \left(w_1 + \beta_1 k_{t-1}^C + \alpha_1 \cdot \frac{1}{10} \sum_{i=1}^{10} |u_{1,t-i} - u_{2,t-i}| \right)^2, \tag{7}$$

$$k_t^{SG} = 1 + \left(w_2 + \beta_2 k_{t-1}^C + \alpha_2 \cdot \frac{1}{10} \sum_{i=1}^{10} |u_{1,t-i} - u_{2,t-i}| \right)^2, \tag{8}$$

where $k_t^C \in [0, +\infty)$ and $k_t^{GS} \in [1, +\infty)$. The lower tail dependence on day t for C^{DC} and C^{DSG} are accordingly expressed as: $\lambda_L^C = 2^{-1/k_t^C}$, $\lambda_L^{SG} = 2\text{-}2^{-1/k_t^G}$. Therefore, the lower tail dependence estimated by the dynamic mixture Clayton-survival Gumbel copula on day t is expressed as: $\lambda_L^{DCSG} = \omega \cdot 2^{-1/k_t^C} + (1\text{-}\omega) \cdot (2 - 2^{1/k_t^G})$.

3.2. Pandemic-driven contagion network

3.2.1. Pandemic-driven contagion network construction

A complex network is a collection of nodes linked by edges, and it is always employed to show the complex links between financial markets (Cheng et al., 2022; Demange, 2018; Gençay et al., 2020; Hurn et al., 2022; Samitas, Kampouris, Kenourgios, 2020; Schuldenzucker et al., 2020). In this study, we propose a new pandemic-driven financial contagion network based on the dynamic mixture copula-EVT model to investigate the characteristics of pandemic-driven financial contagion. In our pandemic-driven financial contagion network, the nodes are considered as 26 stock markets, and the edges between nodes represent the existence of pandemic-driven financial contagion between the corresponding stock markets. The network structure of the edges can also be expressed as an asymmetrical binary matrix E:

$$E = \begin{pmatrix} e_{1,1} & e_{1,2} & \cdots & a_{1,n} \\ e_{2,1} & e_{2,2} & \cdots & e_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{n,1} & e_{n,2} & \cdots & e_{n,n} \end{pmatrix} \tag{9}$$

where n is the number of the stock markets and $e_{i,j} \in \{0,1\}$. If there is pandemic-driven financial contagion between market i and market j, then $e_{i,j} = 1$; otherwise, $e_{i,j} = 0$. To test the existence of pandemic-driven financial contagion and construct the asymmetrical binary matrix E, the dynamic mixture copula-EVT model is estimated and lower tail dependence is used as the measurements of pandemic-driven financial contagion. Specifically, we formulate a hypothesis to examine the existence of pandemic-driven financial contagion as follows:

$$\begin{cases} H_0 : \bar{\lambda}_{crisis} \leq \bar{\lambda}_{pre-crisis} \\ H_1 : \bar{\lambda}_{crisis} > \bar{\lambda}_{pre-crisis} \end{cases} \tag{10}$$

where $\bar{\lambda}_{crisis}$ and $\bar{\lambda}_{pre-crisis}$ are the mean dependence coefficients in the lower-tail for crisis and pre-crisis periods, respectively. The Fisher's z-transformation is used to test the hypothesis.

3.2.2. Network metrics

Measuring and analyzing structural metrics in the complex network is important for a deep understanding of financial contagion characteristics and systemic importance. We investigate five structural metrics of the constructed non-linear pandemic-driven financial contagion network as below.

(1) Node degree. The degree of a node is defined as the number of all edges connected to the nodes. In terms of the adjacency matrix E with elements, the node degree indexed i can be formalized as: $D_i = \sum_{j=1,j\neq i}^{n} e_{i,j}$. The financial market with a higher degree is more likely to exhibit financial contagion.

(2) Clustering coefficient. The clustering coefficient is a key indicator reflecting the connectivity of the node's neighborhood. It is defined as the ratio of the number of edges connecting the node's neighbors to the maximum number of edges between all of its neighbor nodes. For a node i with k_i neighbor nodes and E_i edges between the neighbor nodes, the clustering coefficient of a node i is formalized as $CC_i = \frac{2E_i}{k_i(k_i-1)}$. The financial market with a higher clustering coefficient means that its neighbors are easier to exhibit financial contagion.

(3) Closeness centrality. Closeness centrality measures the speed of the information flow from a given node to other nodes. It is defined as the normalized inverse of the sum of the topological distances. For a node i with the shortest path between nodes i and j, the closeness centrality of node i is formalized as $CC(i) = \frac{N-1}{\sum_{i\neq j} d(i,j)}$. The financial market with larger closeness centrality is faster to exhibit financial contagion in the network.

(4) Eigenvector centrality. Eigenvector centrality assesses a node's systemic importance in the network. In terms of the adjacency matrix E with the largest eigenvalue λ, a node's eigenvector centrality indexed i is defined as the sum of neighboring node j's eigenvector centralities and can be formalized as: $EC(i) = \frac{1}{\lambda} \sum_j e_{ij} EC(j)$. The financial market with higher eigenvector centrality implies a greater contagion strength in the network.

(5) Betweenness centrality. Betweenness centrality provides a way to detect the influence degree of a node on the information flow. In the case of betweenness centrality, a node is well connected if it is located on many of the shortest directed paths between other nodes. The betweenness centrality of node i is formulated as $BC_i = \sum_{j,k} g_{jk}(i)/g_{jk}$, where $i \neq j \neq k$, g_{jk} is the number of shortest paths connecting nodes j and k, and $g_{jk}(i)$ is the number of shortest paths connecting nodes j and k and node i is on. The financial market with higher betweenness centrality is more important in the network because it can control the information flow.

4. Data description and behavior measurement

4.1. Stock return

In this study, we focus on the financial contagion of the COVID-19 pandemic on the international stock markets and the impact of investor behavior on the pandemic-driven contagion effect. Considering the stock market capitalization and the availability of Google search volumes on the stock index symbol, we choose 26 major stock markets from 26 countries as our empirical sample. Detailed information for all stock markets is summarized as Table A.1 in Appendix. These stock markets account for the vast majority of the world's capitalization in the stock market and include major emerging and developed markets from America, Asia, and Europe. To explore the financial contagion driven by the COVID-19 pandemic, the daily data of our sample are selected spanning from January 1, 2019 to March 27, 2022. Considering the increasing Google search volumes on the words relating to COVID-19 and the date January 12, 2020 used to name the 2019 novel coronavirus by the World Health Organization, the date January 12, 2020 is used to divide the sample into the pre-crisis period and crisis period.

All daily closing price data are obtained from the Wind database. Any observations without actual trading due to holidays or other reasons are equal to the previous day's trading price. The returns for all stock indices are defined as the rolling average of two-day logarithmic returns and the logarithmic return is computed as: $r_t = \ln(P_t/P_{t-1})$, where P_t is the closing price of the stock index on day t. The summary statistics of daily stock returns are summarized in Table A.2 in Appendix. All return series are stationary as indicated by the augmented Dickey–Fuller (ADF) test. Moreover, the mean for each return series is smaller than its standard deviation, indicating high risks in stock markets. The skewness and kurtosis show that the probability distributions of all returns are asymmetric and leptokurtic, and the normality assumption is strongly rejected as indicated by the Jarque–Bera test. Lastly, Ljung–Box Q and ARCH tests provide clear evidence of autocorrelation and heteroscedasticity for each stock market.

4.2. Investor behavior measurement

Google Trends (https://www.google.com/trends/), provides a search volume index (SVI) for each search item. Three types of Google search items are considered to construct direct proxies of investor behavior including investor attention, investor sentiment, and investor fear. More concretely, following Hsieh et al. (2020), the daily search volume of each stock symbol, presented in Table A.1 in Appendix, is taken as the proxy of investor attention. To quantify the investor sentiment, we follow Soo (2018) and select the widely used negative word lists and positive word lists as the proxy of investor sentiment. Moreover, as negative investor sentiment (panic behavior) may play a significant role in a low economic state, we also select several fear words relating to COVID-19 during the pandemic period to construct the proxy of investor fear behavior.

We use the words representing investor sentiment and fear in English (as of January 2020, English was the most popular language online, representing 25.9 percent of worldwide internet users).[3] These

[3] Data available at https://www.statista.com/statistics/262946/share-of-the-most-common-languages-on-the-internet/.

words are listed in Table A.3 in Appendix. The SVIs for investor attention, sentiment, and fear are all downloaded by selecting the area filter "World" and category filter "Finance" from Google Trends. As SVIs vary according to the time range set by the user, we set the time range at 6 months when downloading SVI data from Google Trends. We also examine the time range of three months for robustness. To study the impact of investor behavior on daily pandemic-driven financial contagion, the daily SVI data are matched with the daily stock price. Moreover, we also conduct our check for the impact of investor behavior on pandemic-driven financial contagion using weekly Google search volume data. To match the two datasets, we average the daily contagion index data into weekly observations. All of these settings yield similar results.

According to Bijl et al. (2016), the attention index for country i at time t is calculated as:

$$Attention_{i,t} = \frac{SVI_{i,t} - \frac{1}{n}\sum_{j=1}^{n} SVI_{i,j}}{\delta_{i,SVI}} \tag{11}$$

where n is the number of SVI observations and $\delta_{i,SVI}$ is the full-sample standard deviation of SVI observations. The Eq. (11) is also the process normalizing the SVI. Following Da et al. (2015) and Dzieliński et al. (2018), we also construct the country-level attention index as: $Attention_{i,t} = (SVI_{i,t} - SVI_{i,t-1})/(SVI_{i,t-1}+1)$ or $Attention_{i,t} = \log(SVI_{i,t}+1) - \log(SVI_{i,t-1}+1)$. In each case, the empirical results remain robust. Inspired by Baker et al. (2012)'s idea of global and local sentiment, Huang et al. (2016)'s idea of local and nonlocal attention, and Yang et al. (2021)'s idea of foreign investors' trading behavior and domestic investors' trading behavior, we also construct global attention index and local attention index. The global attention index at time t is constructed by averaging the attention indices of the 26 countries (Gao et al., 2020). Then we decompose the country-level attention into the global attention component and the local attention component, i.e.,

$$Attention_{i,t} = \alpha_i Attention_{G,t} + Attention_{iL,t} \tag{12}$$

where $Attention_{G,t}$ and $Attention_{iL,t}$ refer to the global attention at time t and local attention of country i at time t, respectively.

Following Baker and Wurgler (2006), we adopt the principal component approach to extract the first principal component from the SVIs of sentient (fear) words and normalize the first principal component data to obtain the sentiment (fear) index. Moreover, to verify the empirical results, we also follow Soo (2018) to construct the sentiment index as the difference between the total number of positive SVIs and the total number of negative SVIs divided by the total number of positive and negative SVIs. In each case, empirical results remain consistent.

5. Empirical analysis

5.1. Network analysis of pandemic-driven contagion

As previously discussed, we use the AR-GJR-EVT model to estimate the marginal distribution, and employ the dynamic mixture copula function to estimate the lower tail dependence for the 325 ($(n^2 - n)/2, n = 26$) pairs of stock markets. The 10% significance level is used to verify the existence of pandemic-driven financial contagion and then we construct the pandemic-driven financial contagion network as shown in Fig. A.1 of Appendix, which provides a visual expression of pandemic-driven financial contagion between any two stock markets. The topological placement within pandemic-driven contagion network is helpful to analyze the pandemic-driven financial contagion in a better fashion and is crucial for investors to adjust their risk hedging strategies. For instance, there is financial contagion between the Spain market and Russian market. According to this, investors should decrease the percentage of investments in the Spain market and Russian market.

Table 1 gives the values of network metrics and their rankings to explore the characteristics of the pandemic-driven financial contagion for each stock market. The values and rankings under different metrics are varying for different finance markets, indicating that different financial markets show different contagion characteristics. For example, the Indian market and Australian market have the largest degree, betweenness centrality, closeness centrality, and eigenvector centrality, but have a lower clustering coefficient ranked by 23 and 21 respectively. This indicates that the Indian market and Australian market are significantly affected by the COVID-19 pandemic. Under the influence of the pandemic, the two markets are easier and faster to spread financial contagion with other markets, they also play a crucial role in the pandemic-driven financial contagion network. Risk managers should put special focus and supervision on the financial markets with higher network metrics to reduce the risk of spreading COVID-19. On the other hand, the five metrics in the Chinese market are the lowest and their values are all equal to 0, revealing no financial contagion between the Chinese market and other markets. That is to say, the Chinese market is least affected by the COVID-19. This finding is in line with the fact that at the beginning of the COVID-19 outbreak, China had shut down the city immediately and temporarily sacrificing economic development to ensure that the pandemic was controlled as soon as possible. As it turned out, China not only controlled the pandemic in a short time, but also became the only country with positive GDP growth in the context of the global downturn in 2020. Although the Chinese market shows a stable development trend and strong resilience at this stage, it is necessary to maintain a cautiously optimistic attitude. The Chinese market will still face the impact of financial risks as the pandemic in other countries is still spreading and China is experiencing a new round of pandemic in 2022. These findings are helpful for risk managers to identify the international risk management system to reduce the negative outcomes of the pandemic on the financial markets.

Table 1
The values of network metrics and their rankings.

Label	Node degree	Clustering coefficient	Closeness centrality	Eigenvector centrality	Betweenness centrality
Argentina	9 (10)	0.417 (22)	0.615 (11)	0.450 (14)	6.851 (9)
Australia	15 (2)	0.438 (21)	0.727 (2)	0.782 (2)	18.696 (2)
Austria	9 (10)	0.750 (3)	0.615 (11)	0.581 (11)	1.213 (18)
Brazil	3 (22)	0.667 (7)	0.522 (24)	0.208 (23)	0.125 (24)
China	0 (26)	0.000 (26)	0.000 (26)	0.000 (26)	0.000 (25)
France	9 (10)	0.806 (2)	0.615 (11)	0.603 (10)	1.064 (19)
Germany	6 (16)	0.667 (7)	0.571 (16)	0.379 (17)	1.924 (15)
Hungary	13 (4)	0.474 (18)	0.686 (4)	0.688 (6)	17.633 (3)
India	22 (1)	0.333 (23)	0.923 (1)	1.000 (1)	68.630 (1)
Indonesia	4 (21)	0.167 (25)	0.545 (19)	0.182 (24)	3.072 (13)
Ireland	13 (4)	0.603 (12)	0.686 (4)	0.756 (3)	7.376 (8)
Italy	11 (9)	0.691 (6)	0.649 (8)	0.677 (7)	3.560 (12)
Japan	5 (19)	0.700 (5)	0.545 (19)	0.324 (19)	0.421 (22)
Malaysia	3 (22)	0.667 (7)	0.533 (22)	0.210 (22)	0.188 (23)
Mexico	12 (7)	0.470 (20)	0.667 (7)	0.635 (9)	16.291 (4)
Netherlands	6 (16)	0.733 (4)	0.571 (16)	0.401 (16)	0.597 (21)
Norway	7 (15)	0.619 (11)	0.585 (15)	0.409 (15)	2.225 (14)
Portugal	3 (22)	1.000 (1)	0.533 (22)	0.222 (21)	0.000 (25)
Russia	14 (3)	0.495 (16)	0.706 (3)	0.755 (4)	11.295 (5)
South Korea	9 (10)	0.472 (19)	0.615 (11)	0.487 (13)	5.388 (11)
Spain	10 (10)	0.489 (17)	0.632 (10)	0.542 (12)	6.366 (10)
Sweden	6 (16)	0.667 (7)	0.558 (18)	0.364 (18)	1.292 (16)
Thailand	12 (8)	0.530 (14)	0.649 (8)	0.658 (8)	8.799 (7)
Turkey	5 (19)	0.500 (15)	0.545 (19)	0.282 (20)	1.242 (17)
United Kingdom	13 (4)	0.538 (13)	0.686 (4)	0.734 (5)	9.088 (6)
United States	3 (22)	0.333 (23)	0.480 (25)	0.139 (25)	0.667 (20)

Notes: The five common network metrics (degree, clustering coefficient, closeness centrality, eigenvector centrality, and betweenness centrality) are used to depict and reveal the characteristics of the pandemic-driven financial contagion during the COVID-19 period. The rankings for all markets are provided in the parenthesis, the higher the ranking is, the more influence has the market in the disaster-driven financial contagion network.

5.2. Investor behavior on pandemic-driven financial contagion

In this subsection, we examine whether pandemic-driven financial contagion can be explained by investor behavior in the following

Table 2
Stationarity test results.

Variable	LLC test		ADF test	
	t statistic	p	chi-square statistic	p
Contagion	−25.515	0.000	288.967	0.000
Country attention	−28.076	0.000	609.888	0.000
Local attention	27.466	0.000	975.367	0.000
Global attention	−140.000	0.000	71.479	0.038
Sentiment	−140.000	0.000	198.105	0.000
Fear	−120.000	0.000	343.867	0.000

Notes: This table reports the stationarity test results of the data used in the regression analysis for the full sample during the whole COVID-19 period. The regression equation is expressed as: $Contagion_{i,t} = Constant + \beta Contagion_{i,t-1} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t}$, where $Contagion_{i,t}$ refers the pandemic-driven contagion of country i at time t and is defined as the sum of the tail dependence between country i and its contagious countries. $Behavior_{i,t}$ corresponds to the proxy variables of investor behavior including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively. LLC and ADF refer to Levin–Lin–Chu unit-root test and Fisher-type unit-root test based on augmented Dickey–Fuller, respectively.

regression:

$$Contagion_{i,t} = Constant + \beta Contagion_{i,t-1} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t} \quad (13)$$

where $Contagion_{i,t}$ refers the pandemic-driven contagion of country i at time t and is defined as the sum of the tail dependence between country i and its contagious countries (Fan et al., 2021). $Behavior_{i,t}$ corresponds to the proxy variables of investor behavior including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively.

To avoid the spurious regression, we use the Levin–Lin–Chu (LLC) unit-root test and Fisher-type unit-root test based on ADF to test the stationarity of each variable. Table 2 summarizes the test results, which show that all variables reject the null hypothesis that there is a unit root at the 1% significance level. Therefore, all variables are stationary.[4]

Table 3 reports the regression results of the effects of investor behavior including country attention, local attention, global attention, investor sentiment, and investor fear on the pandemic-driven financial contagion. As shown in Table 3, all regression coefficients in model (1) to model (5) are negative and significant at the 1% level. This indicates that investor attention and investor sentiment as well as investor fear are significantly and negatively related to the pandemic-driven financial contagion. These results suggest that investor behavior plays a significant role in explaining pandemic-driven financial contagion.

Although the ongoing Russia-Ukraine war has attracted global attention, the fact that the COVID-19 pandemic is still raging on a global scale cannot be ignored. Recently, the COVID-19 in Asia has rebounded significantly and the number of newly confirmed COVID-19 cases in the world in recent weeks has once again shown an increasing trend and a new round of pandemic has broken out. The continued rise of pandemic risks will exacerbate the vulnerability of the financial markets and destroy the stability of the pandemic-driven financial contagion network. Therefore, emotional factors and investor behavior should be considered for risk managers to reduce the spread of the pandemic-driven financial contagion. Specifically, risk managers can adjust investor psychology to reduce the influence of investor behavior on financial contagion from the following two aspects. On the one hand, they can timely publish information such as prices of necessary materials, real-time disaster relief, and transportation and logistics to effectively reduce uncertainty and reduce the degree of overreaction to the COVID-19 among residents, enterprises, and financial sectors. On the other hand, they can improve the information transparency and enhance the early information accuracy to effectively reduce the availability bias on individual beliefs and decision-making.

Table 3
The influence of investor behavior on pandemic-driven contagion.

Dep. Variable	$Contagion_t$				
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Constant	0.221***	0.215***	0.288***	0.218***	0.862***
	(29.29)	(28.86)	(34.02)	(29.16)	(44.45)
$Contagion_{t-1}$	0.920***	0.922***	0.895***	0.921***	0.738***
	(334.76)	(338.34)	(289.16)	(337.02)	(129.12)
Country $attention_t$	−0.011***				
	(−5.35)				
Local $attention_t$		−0.005**			
		(−1.99)			
Global $attention_t$			−0.018***		
			(−17.78)		
$Sentiment_t$				−0.005***	
				(−5.02)	
$Fear_t$					−0.001***
					(−8.61)
Obs.	20 280	20 280	20 280	20 280	
Adj R-squared	0.850	0.850	0.852	0.850	0.559

Notes: This table reports the results of the following regression for the full sample: $Contagion_{i,t} = Constant + \beta Contagion_{i,t-1} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t}$, where $Contagion_{i,t}$ refers the pandemic-driven contagion of country i at time t and is defined as the sum of the tail dependence between country i and its contagious countries. $Behavior_{i,t}$ corresponds to the proxy variables of investor behavior including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively. t-statistic is reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively. Country and daily fixed effects are included in the regression. The sample period for investor attention and sentiment is from January 1, 2019, to March 27, 2022, while for investor fear is from January 13, 2020 to March 27, 2022.

5.3. Further analysis of investor behavior on pandemic-driven contagion

5.3.1. Impacts during market melt-down and melt-up periods

The stock markets around the world dropped in an unprecedented way after the outbreak of the COVID-19 pandemic, and then quickly bounced back due to swift policy responses from governments and central banks around the world. As displayed in Fig. 1, the S&P 500 index bottomed out on March 23, 2020, dropping around 34% from its peak on February 19, 2020, and quickly bounced back. The dynamic evolution trend of the closing prices for the S&P 500 index is very similar to those for the other stock indices. As a result, major stock markets exhibit melt-down and melt-up periods (V-shape) during the COVID-19 pandemic period. Most extant literature on financial contagion focused on the whole crisis sample period (Bekaert et al., 2014; Borri & Giorgio, 2021; Calabrese & Crook, 2020). However, there are obvious differences in investor behavior and financial contagion under different market states (Forbes & Warnock, 2021; Fry-McKibbin et al., 2021; Gao et al., 2020; Reyes, 2019; Soo, 2018). Therefore, the relationship of investor behavior with financial contagion during the market melt-up is likely to be different from that during the market melt-down. This motivates us to compare the potential difference in the impacts of investor behavior on the pandemic-driven financial contagion during the stock market melt-down and melt-up periods. The date March 23, 2020 is used to split the COVID-19 period into the market melt-down period (January 12, 2020 to March 23, 2020) and the market melt-up period (March 24, 2020 to March 27, 2022).

After identifying the existence of pandemic-driven financial contagion between any two paired markets during both market melt-down and market melt-up periods, we further investigate the impacts of investor behavior on pandemic-driven financial contagion in the two periods through Eq. (13). Table 4 reports the regression results of the effects of investor behavior including country attention, local attention,

[4] We also test the stationarity of the data used in the regression analyses in Section 5.3 and find that those data are stationary in all cases. Due to space limitations, the stationarity test results are not listed but are available upon request.

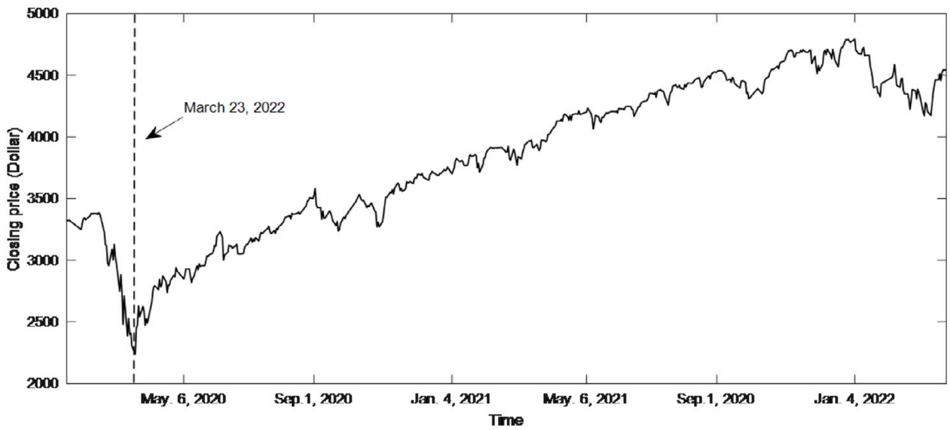

Fig. 1. Daily closing prices of S&P index during the COVID-19 period. This figure plots the daily closing prices of S&P index from January 12, 2020 to March 27, 2022.

Table 4
Investor behavior on financial contagion under different market conditions.

Dep. Variable	$Contagion_t$				
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Panel A. In the market melt-down period					
Constant	0.177***	0.444***	0.233***	2.026***	2.026***
	(15.93)	(15.56)	(19.36)	(19.09)	(16.16)
$Contagion_{t-1}$	0.935***	0.937***	0.910***	0.910***	0.652***
	(225.33)	(227.41)	(199.86)	(195.17)	(30.45)
Country $attention_t$	−0.029***				
	(−4.44)				
Local $attention_t$		−0.020***			
		(−3.01)			
Global $attention_t$			−0.078***		
			(−13.54)		
$Sentiment_t$				−0.037***	
				(−12.26)	
$Fear_t$					−0.003***
					(−7.97)
Obs.	7566	7566	7566	7566	1092
Adj R-squared	0.874	0.874	0.877	0.877	0.592
Panel B. In the market melt-up period					
Constant	0.222***	0.219***	0.302***	0.220***	1.367***
	(34.14)	(33.85)	(40.43)	(33.91)	(69.91)
$Contagion_{t-1}$	0.886***	0.888***	0.844***	0.887***	0.402***
	(265.15)	(267.41)	(218.46)	(266.31)	(49.36)
Country $attention_t$	−0.009***				
	(−4.44)				
Local $attention_t$		−0.002			
		(−1.06)			
Global $attention_t$			−0.020***		
			(−21.50)		
$Sentiment_t$				−0.004***	
				(−2.28)	
$Fear_t$					−0.0005***
					(−6.41)
Obs.	19110	19110	19110	19110	12636
Adj R-squared	0.789	0.789	0.794	0.789	0.167

Notes: This table reports the results of the following regression during the market melt-down and melt-up periods: $Contagion_{i,t} = Constant + \beta Contagion_{i,t-1} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t}$, where $Contagion_{i,t}$ refers the pandemic-driven contagion of country i at time t and is defined as the sum of the tail dependence between country i and its contagious countries. $Behavior_{i,t}$ corresponds to the proxy variables of investor behavior including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively. t-statistic is reported in parentheses. *** indicates significance at the 1% level. Country and daily fixed effects are included in the regression. The sample period for investor attention and sentiment is from January 1, 2019 to March 27, 2022, while for investor fear is from January 13, 2020 to March 27, 2022.

global attention, investor sentiment, and investor fear on pandemic-driven financial contagion. All regression coefficients are negative and significant at the 1% level. This indicates that investor behavior in all cases can significantly and negatively explain pandemic-driven financial contagion in both market melt-down and market melt-up periods. Moreover, these significant relationship coefficients related to the investor behavior in Panel A are smaller than those in Panel B. The result implies that investor behavior is easier to influence the spread of pandemic-driven financial contagion during the market melt-down period than during the market melt-up period, which is consistent with the notion that compared to positive events, negative events can produce more intense consequences (Baumeister et al., 2001). One possible explanation for this is that compared to good news in the market melt-up condition, investors would put more weight on bad news in the market melt-down condition, and tend to wonder what the market is going on, and thus submit more online search queries (Reyes, 2019; Tantaopas et al., 2016). Therefore, it is necessary to pay attention to the rise of risk aversion under pessimism to prevent it affects normal economic activities, such as the excessive increase in cash reserves by entrepreneurs and the excessive increase in insurance investment by investors.

5.3.2. *Impacts within emerging and developed markets*

Existing studies demonstrate obvious differences between developed markets and emerging markets in the relationship of investor behavior on market returns (Gao et al., 2020) and the cross dependence between markets (Christoffersen et al., 2012; Niţoi & Pochea, 2019), while there is a paucity of studies that the two types of markets with different development level and economic structure differ in the impact of investor behavior on pandemic-driven financial contagion. This motivates us to group the big sample markets into developed and emerging markets and investigates the difference in the relationship of investor behavior with pandemic-driven financial contagion within these two types of markets.

Table 5 summarizes the results of regressing the investor behavior (including country attention, local attention, global attention, investor sentiment, and investor fear) on pandemic-driven financial contagion according to Eq. (13) within emerging markets and developed markets, respectively. All investor behavior variables except the country attention and local attention in Panel A and the local attention in Panel B, have a significantly negative relationship with pandemic-driven financial contagion. This indicates that investor behavior, in general, explains pandemic-driven financial contagion within both emerging and developed markets. Moreover, these significant relationship coefficients related to the investor behavior within emerging markets are bigger than those within developed markets. As is evident, pandemic-driven financial contagion within developed markets is more subject to investor behavior, which is similar to the conclusion by Tantaopas et al. (2016) who demonstrate that the impacts of investor behavior on trading volume, return predictability, and volatility in the developed markets

Table 5
Investor behavior on financial contagion under different market development levels.

Dep. Variable	$Contagion_t$				
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Panel A. Within emerging markets					
Constant	0.236***	0.236***	0.236***	0.242***	0.301***
	(46.49)	(46.49)	(46.57)	(47.12)	(34.45)
$Contagion_{t-1}$	0.657***	0.657***	0.657***	0.649***	0.596***
	(89.44)	(89.44)	(89.34)	(87.31)	(62.38)
Country attention$_t$	−0.002				
	(−1.31)				
Local attention$_t$		−0.002			
		(−1.27)			
Global attention$_t$			−0.002***		
			(−2.91)		
Sentiment$_t$				−0.006***	
				(−7.10)	
Fear$_t$					−0.0002**
					(−2.63)
Obs.	10 140	10 140	10 140	10 140	6903
Adj R-squared	0.441	0.441	0.441	0.444	0.363
Panel B. Within developed markets					
Constant	0.288***	0.288***	0.290***	0.295***	0.500***
	(50.82)	(50.77)	(51.15)	(51.55)	(45.52)
$Contagion_{t-1}$	0.596***	0.596***	0.592***	0.587***	0.373***
	(74.91)	(75.00)	(74.36)	(73.20)	(33.58)
Country attention$_t$	−0.005**				
	(−2.56)				
Local attention$_t$		−0.004			
		(−1.51)			
Global attention$_t$			−0.005***		
			(−5.88)		
Sentiment$_t$				−0.009***	
				(−8.11)	
Fear$_t$					−0.0004***
					(−4.59)
Obs.	10 140	10 140	10 140	10 140	6903

Notes: This table reports the results of the following regression within emerging markets and developed markets: $Contagion_{i,t} = Constant + \beta Contagion_{i,t-1} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t}$, where $Contagion_{i,t}$ refers the pandemic-driven contagion of country i at time t and is defined as the sum of the tail dependence between country i and its contagious countries. $Behavior_{i,t}$ corresponds to the proxy variables of investor behavior including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively. t-statistic is reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively. Country and daily fixed effects are included in the regression. The sample period for investor attention and sentiment is from January 1, 2019, to March 27, 2022, while for investor fear is from January 13, 2020 to March 27, 2022.

Table 6
Investor behavior on financial contagion within different regions.

Dep. Variable	$Contagion_t$				
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Panel A. Within Asia					
Constant	0.108***	0.107***	0.112***	0.109***	0.157***
	(31.79)	(31.57)	(32.41)	(31.81)	(20.81)
$Contagion_{t-1}$	0.749***	0.751***	0.738***	0.747***	0.649***
	(95.23)	(95.81)	(91.77)	(94.41)	(59.65)
Country attention$_t$	−0.0066***				
	(−3.80)				
Local attention$_t$		−0.003			
		(−1.32)			
Global attention$_t$			−0.005***		
			(−7.00)		
Sentiment$_t$				−0.003***	
				(−3.94)	
Fear$_t$					−0.0002***
					(−3.02)
Obs.	7020	7020	7020	7020	4779
Adj R-squared	0.567	0.567	0.570	0.567	0.432
Panel B. Within America					
Constant	0.059***	0.058***	0.060***	0.058***	0.121***
	(34.35)	(33.83)	(34.88)	(34.01)	(23.42)
$Contagion_{t-1}$	0.476***	0.483***	0.465***	0.477***	0.209***
	(31.44)	(31.92)	(30.52)	(31.33)	(9.92)
Country attention$_t$	−0.0069***				
	(−5.46)				
Local attention$_t$		−0.002			
		(−1.12)			
Global attention$_t$			−0.004***		
			(−7.38)		
Sentiment$_t$				−0.002***	
				(−3.10)	
Fear$_t$					−0.0003***
					(−4.98)
Obs.	3120	3120	3120	3120	2124
Adj R-squared	0.252	0.245	0.258	0.247	0.059
Panel C. Within Europe					
Constant	0.529***	0.529***	0.540***	0.544***	0.879***
	(63.42)	(63.36)	(64.47)	(64.63)	(61.52)
$Contagion_{t-1}$	0.440***	0.441***	0.429***	0.425***	0.178***
	(49.94)	(50.01)	(48.42)	(47.89)	(15.17)
Country attention$_t$	−0.009***				
	(−3.81)				
Local attention$_t$		−0.007***			
		(−2.85)			
Global attention$_t$			−0.011***		
			(−10.53)		
Sentiment$_t$				−0.013***	
				(−11.12)	
Fear$_t$					−0.0007***
					(−8.05)
Obs.	10 140	10 140	10 140	10 140	6903
Adj R-squared	0.199	0.198	0.206	0.207	0.043

Notes: This table reports the results of the following regression within Asia, America, and Europe: $Contagion_{i,t} = Constant + \beta Contagion_{i,t-1} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t}$, where $Contagion_{i,t}$ refers the pandemic-driven contagion of country i at time t and is defined as the sum of the tail dependence between country i and its contagious countries. $Behavior_{i,t}$ corresponds to the proxy variables of investor behavior including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively. t-statistic is reported in parentheses. *** indicates significance at the 1% level. Country and daily fixed effects are included in the regression. The sample period for investor attention and sentiment is from January 1, 2019, to March 27, 2022, while for investor fear is from January 13, 2020 to March 27, 2022.

are more pronounced than those in the developing markets. This may be because there is better information transmission, a higher shareholder right, and better fairness of the law rule protecting investors in developed markets, and where, the investors are well integrated, the market performance and co-movement thus are more likely to be influenced by investor behavior (Fang et al., 2020). Therefore, it is a good way to prevent the spread of pandemic-driven financial contagion for market participants to gather information frequently and improve information transparency to obtain a better efficient market.

5.3.3. Impacts within different regions

The co-movement and systemic risk in financial markets are different in different regional subsets. For instance, Paltalidis et al. (2015) document the dramatic variation in systemic risk and contagion speed between different areas, Christoffersen et al. (2012) and Niţoi and Pochea (2019) show that the dependence between markets differs across regional subsets. These potential differences motivate us to analyze the difference in the relationship between pandemic-driven financial contagion and investor behavior at the regional level. Therefore, we divide our empirical sample into three different regions including America, Asia, and Europe. The regression results for the impacts of the investor behavior including country attention, global attention, investor sentiment, and investor fear on pandemic-driven financial contagion within Asia, America, and Europe are reported in Table 6.

The results of Table 6 show that most of the investor behavior variables are negatively and significantly related to the pandemic-driven financial contagion, except for the local attention in model (2) in Panel A and Panel B. This reveals that pandemic-driven financial contagion is affected by most of the investor behavior variables except the local attention in the Asian and American groups. Furthermore, these significant relationship coefficients related to the investor behavior in Panel C are smaller than those in Panel A and Panel B, showing that the impact of investor behavior on pandemic-driven financial contagion is the strongest within European markets. To summarize, our results generally support that investor behavior explains pandemic-driven financial contagion within three different regions, and the impacts of investor behavior on the pandemic-driven financial contagion within the three different regions are heterogeneous. That is to say, investor psychology has strong regional characteristics, which forms heterogeneous beliefs in investment decisions. Therefore, investor psychology under different regional subsets should be considered for risk managers to make effective policies to prevent pandemic-driven financial contagion.

5.3.4. Impacts with different contagion directions

There are obvious differences in risk spillovers and financial contagion between those received from other markets and that transmitted to other markets (Carvalho & Gupta, 2018; Fan et al., 2021). This implies that the impacts of investor behavior on financial contagion received from other markets or that transmitted to other markets may be different. Therefore, we conduct a comparative analysis on the relationship of investor behavior with pandemic-driven financial contagion in different directions. According to the work of Wang, Yuan, Wang (2021), we construct a time-delay copula function to investigate the causal dependence between markets and then identify the direction of pandemic-driven financial contagion. The time-delay copula is expressed as:

$$C(u_1, u_{2,\tau}) = F(F_1^{-1}(u_1), F_2^{-1}(u_{2,\tau})), \tag{14}$$

where $\tau \in Z^+$ is the time-delay, its value is determined by the minimum Bayesian information criterion and Akaike information criterion, and $C(u_1, u_{2,\tau})$ is the copula function for variables u_1 and u_2 with delay τ day(s). Not surprisingly, we also construct a dynamic time-delay Clayton-survival Gumbel copula to describe the non-contemporaneous and non-linear lower tail dependence. Similar to the dynamic Clayton-survival Gumbel copula introduced in Section 3.1.2, the dynamic time-delay Clayton-survival Gumbel copula and its lower tail dependence are expressed as:

$$C^{DCSG}(u_1, u_{2,\tau}; k_{t+\tau}^{C}, k_{t+\tau}^{SG}) = \omega C^{C}(u_1, u_{2,\tau}; k_{t+\tau}^{C}) + (1-\omega) C^{SG}(u_1, u_{2,\tau}; k_{t+\tau}^{SG}), \tag{15}$$

$$\lambda_{t+\tau}^{DCSG} = \omega \cdot 2^{-1/k_{t+\tau}^{C}} + (1\text{-}\omega) \cdot (2 - 2^{1/k_{t+\tau}^{SG}}) \tag{16}$$

where $\omega \in [0,1]$ is the weight parameter, $k_{t+\tau}^{C}$ and $k_{t+\tau}^{SG}$ are the dependence parameters of time-delay Clayton copula and time-delay survival Gumbel copula at time $t+\tau$, respectively.

Then we can construct a directional network of pandemic-driven financial contagion based on the tail dependence obtained from the dynamic time-delay Clayton-survival Gumbel copula. For any two countries i and j, we draw a directed edge from i to j if there is pandemic-driven financial contagion between i and lagged j. Fig. A.2 in Appendix gives a visual expression of the directed pandemic-driven financial contagion network among the 26 stock markets.

We next examine how a country's pandemic-driven financial contagion received from (or transmitted to) other markets is explained by the investor behavior according to the following regressions:

$$Contagion_{i,t}^{in} = Constant + \beta Contagion_{i,t-1}^{in} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t} \tag{17}$$

$$Contagion_{i,t}^{out} = Constant + \beta Contagion_{i,t-1}^{out} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t} \tag{18}$$

where $Contagion_{i,t}^{in}$ ($Contagion_{i,t}^{out}$) refers to the pandemic-driven financial contagion received (transmitted) by country i from (to) country i's contagious countries at time t and is defined as the sum of the lower tail dependence between country i and its lagged contagious countries (between the lagged country i and its contagious countries). $Behavior_{i,t}$ refers to the proxy variables of investor behavior for country i at time t including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively.

Table 7
Investor behavior on financial contagion with different directions.

Dep. Variable	$Contagion_t$				
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Panel A. Financial contagion received from other countries					
Constant	0.027***	0.027***	0.031***	0.027***	0.081***
	(49.24)	(49.17)	(52.57)	(49.28)	(41.35)
$Contagion_{t-1}^{in}$	0.787***	0.788***	0.762***	0.787***	0.545***
	(181.97)	(182.25)	(168.09)	(181.67)	(79.86)
Country $attention_t$	−0.002***				
	(−2.96)				
Local $attention_t$		−0.0010*			
		(−1.73)			
Global $attention_t$			−0.004***		
			(−17.67)		
$Sentiment_t$				−0.002***	
				(−3.55)	
$Fear_t$					−0.00008***
					(−4.39)
Obs.	20 228	20 228	20 228	20 228	13 780
Adj R-squared	0.622	0.622	0.628	0.622	0.320
Panel B. Financial contagion transmitted to other markets					
Constant	0.020***	0.020***	0.021***	0.020***	0.089***
	(41.66)	(41.17)	(42.74)	(41.19)	(40.73)
$Contagion_{t-1}^{out}$	0.843***	0.846***	0.836***	0.846***	0.500***
	(223.06)	(226.25)	(217.33)	(226.13)	(70.26)
Country $attention_t$	−0.004***				
	(−6.37)				
Local $attention_t$		−0.0012*			
		(−1.86)			
Global $attention_t$			−0.003***		
			(−11.20)		
$Sentiment_t$				−0.001**	
				(−2.23)	
$Fear_t$					−0.0001***
					(−4.25)
Obs.	20 228	20 228	20 228	20 228	13 780
Adj R-squared	0.718	0.717	0.719	0.717	0.266

Notes: This table reports the results of the following regression: $Contagion_{i,t}^{in/out} = Constant + \beta Contagion_{i,t-1}^{in/out} + \gamma Behavior_{i,t} + \mu_i + \mu_t + \varepsilon_{i,t}$, where $Contagion_{i,t}^{in}$ ($Contagion_{i,t}^{out}$) refers to the pandemic-driven financial contagion received (transmitted) by country i from (to) country i's contagious countries at time t and is defined as the sum of the lower tail dependence between country i and its lagged contagious countries (between the lagged country i and its contagious countries). $Behavior_{i,t}$ refers to the proxy variables of investor behavior for country i at time t including investor attention (country attention, local attention, and global attention), investor sentiment, and investor fear. μ_i and μ_t are country and daily fixed effects, respectively. t-statistic is reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Country and daily fixed effects are included in the regression. The sample period for investor attention and sentiment is from January 1, 2019, to March 27, 2022, while for investor fear is from January 13, 2020 to March 27, 2022.

Table 7 reports the regression results of Eqs. (17) and (18). Based on the regression coefficients of the investor behavior indices, investor behavior is significantly related to the pandemic-driven financial contagion in all cases. This finding demonstrates that investor behavior can explain financial contagion for both the contagion received from other markets and that transmitted to other markets. Moreover, these significant relationship coefficients related to the investor behavior in Panel A are greater than those in Panel B except for the global attention and investor sentiment in model (2) and model (3). This shows that except for the global attention and investor sentiment, investor behavior has a more pronounced impact on financial contagion transmitted to other markets compared to that received from other markets. Therefore, the financial contagion with different directions should be distinguished when policymakers design effective policies to manage financial risk.

6. Conclusions

COVID-19 provides an ideal testbed for studying pandemic-driven financial contagion, which is helpful for researchers, investors, and risk managers to better grasp financial contagion. In this study, we analyze pandemic-driven financial contagion during the COVID-19 period and the impact of investor behavior on it based on the investors' Google search volumes.

We first construct a non-linear financial contagion network via a dynamic mixture copula-EVT model to quantitatively measure pandemic-driven financial contagion and the contagion characteristics. The constructed dynamic mixture copula-EVT model provides a precise way to measure financial contagion and help international investors and policy makers better understand financial contagion. As a result, our empirical findings would provide important insights and guidance for international investors and policy makers to design corresponding risk-hedging strategies and develop effective policies for mitigating risk, respectively. The empirical results confirm the existence of pandemic-driven financial contagion and show that the Indian market and the Australian market are significantly affected by the COVID-19 pandemic, they are easy to spread financial contagion with other markets and important in the pandemic-driven financial contagion network. This suggests that risk managers should closely monitor the change in the level of extreme tail dependence between financial markets and would help investors to make appropriate investment strategies to enhance investors' portfolio performance as contagion weaken the benefits of portfolio diversification. For instance, investors should refrain from holding a portfolio including the assets with a higher degree such as the Indian and Australian markets, while the Chinese market with degree 0 is a safe haven during the COVID-19 pandemic and forms an impeccable hedging tool for the other market investors.

Moreover, three direct measurements for investor behavior using the Google search volume index are constructed to explore the impact of investor behavior on the pandemic-driven financial contagion. We find that investor behavior explains pandemic-driven financial contagion and provide conclusive evidence of the heterogeneous impact of investor behavior on pandemic-driven financial contagion under several settings including market conditions, market development levels, regional subsets, and contagion directions. This result would help financial risk managers and policymakers to design effective risk management policies to forestall and defuse financial risks. With the obvious rebound of the COVID-19 pandemic in Asia and the outbreak of a new round of pandemic in China recently, risk managers should intensify macro-control efforts and adjust the investor psychology to prevent and control the cross-transmission of financial risks. However, policies that only consider macroeconomic factors and ignore investor behavior factors are likely to be sub-optimal to prevent the spread of pandemic-driven financial risk, because investor behavior plays an important role in explaining pandemic-driven financial contagion. Importantly, compared to adjust the investor psychology, macro-control efforts will carry a significant cost, while many economies cannot bear to further increase their deficits at such a critical time (Polyzos et al., 2021). In addition, factors including the market states, market development levels, regional subsets, and contagion directions should also be considered to reduce the spread of the pandemic-driven financial contagion.

The investor behavior measurements based on online search volume, a significant improvement of widely used indirect measurements, may yield many other potential applications. On the one hand, beyond constructing online search behavior measurements to investigate the impact of investor behavior on pandemic-driven financial contagion, online search behavior constitutes one potential application in testing other economic models and theories. On the other hand, using the online search measurements instead of traditional indirect behavior measurements like trading volume and volatility, to empirically investigate a variety of financial issues in behavioral finance such as investors' trading behavior and its impact on stock returns. These applications could improve our understanding of financial markets from a behavioral perspective.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

See Tables A.1–A.3 and Figs. A.1 and A.2.

Table A.1
Country and the stock market.

Country	Region	Stock symbol	Country	Region	Stock symbol
Panel A. Emerging markets			Panel B. Developed markets		
Argentina	America	MERV	Australia	Asia	AORD
Brazil	America	IBOVESPA	Austria	Europe	ATX
China	Asia	CSI300	France	Europe	CAC40
Hungary	Europe	BUX	Germany	Europe	DAX
India	Asia	SENSEX	Ireland	Europe	ISEQ
Indonesia	Asia	JKSE	Italy	Europe	FTSEMIB
Malaysia	Asia	KLSE	Japan	Asia	N225
Mexico	America	MXX	Netherlands	Europe	AEX
Portugal	Europe	PSI20	Norway	Europe	OBX
Russia	Europe	RTS	Spain	Europe	IBEX35
Korea	Asia	KS11	Sweden	Europe	OMXSPI
Thailand	Asia	SETI	United Kingdom	Europe	FTSE100
Turkey	Asia	XU100	United States	America	SPX

Notes: This table reports the 26 major stock markets from 26 countries chosen as our empirical sample. The stock symbols are also used as the Google search queries for constructing investor attention measurement.

Table A.2
Descriptive statistics on the daily return.

Country	Mean (%)	S.D.	Skew.	Kurt.	J–B	LBQ	ARCH	ADF
Argentina	0.140	0.022	−2.072	21.015	11 148.934***	161.497***	296.016***	−17.316***
Brazil	0.034	0.012	−1.529	23.839	14 472.615***	154.685***	147.595***	−17.704***
China	0.043	0.009	−0.415	6.323	382.675***	201.955***	77.445***	−16.000***
Hungary	0.013	0.011	−1.921	16.165	6135.755***	230.709***	205.048***	−16.733***
India	0.061	0.010	−0.350	10.341	1774.144***	184.063***	320.093***	−16.777***
Indonesia	0.016	0.008	−0.023	15.740	5295.272***	225.226***	202.976***	−16.084***
Malaysia	−0.005	0.006	−1.103	13.476	3739.450***	241.839***	347.794***	−15.461***
Mexico	0.035	0.008	−0.403	6.067	328.001***	187.766***	170.765***	−16.435***
Portugal	0.027	0.009	−1.156	11.935	2778.894***	262.552***	283.569***	−14.918***
Russia	−0.033	0.018	−4.344	59.919	108 161.458***	160.075***	94.246***	−18.476***
Korea	0.040	0.009	−0.512	13.006	3300.931***	259.261***	239.182***	−14.911***
Thailand	0.009	0.008	−1.511	15.477	5376.313***	233.785***	293.578***	−16.293***
Turkey	0.115	0.011	−1.277	7.828	973.238***	273.434***	176.146***	−14.590***
Australia	0.039	0.008	−1.297	14.813	4772.040***	200.509***	222.092***	−17.178***
Austria	0.021	0.012	−1.068	13.105	3480.429***	368.805***	361.660***	−13.783***
France	0.044	0.010	−0.889	12.482	3036.167***	240.882***	299.363***	−15.520***
Germany	0.040	0.010	−0.689	11.568	2456.819***	232.136***	279.222***	−15.664***
Ireland	0.034	0.011	−0.724	7.736	800.181***	273.298***	309.980***	−14.818***
Italy	0.038	0.011	−1.991	17.896	7755.983***	272.432***	250.437***	−15.483***
Japan	0.043	0.009	0.105	11.399	2303.021***	236.617***	160.613***	−15.231***
Netherlands	0.052	0.009	−1.023	13.065	3441.510***	241.334***	282.458***	−15.504***
Norway	0.055	0.009	−1.323	12.578	3221.385***	185.175***	227.072***	−16.779***
Spain	−0.003	0.010	−0.949	13.142	3473.249***	256.553***	225.690***	−15.163***
Sweden	0.065	0.009	−0.995	11.932	2731.812***	230.958***	167.465***	−15.917***
United Kingdom	0.014	0.009	−0.780	15.079	4839.644***	193.769***	195.145***	−16.304***
United States	0.077	0.009	−1.068	15.202	5006.599***	167.993***	142.546***	−17.087***

Notes: S.D., Skew., and Kurt. refer to the standard deviation, skewness, and Kurtosis, respectively. J–B is the Jarque–Bera test for the normality of the time series. LBQ refers to the Ljung–Box Q test of autocorrelation at order five. The ARCH test is used to test heteroscedasticity at order five. ADF is the augmented Dickey–Fuller test for the stationarity of time series. *** indicates significance at the 1% level.

Table A.3
Google search query on investor sentiment and fear.

Panel A. Investor sentiment query							
Positive sentiment list				Negative sentiment list			
Up	Most	Record	Gain	Downs	Foreclosing	Dips	Reduction
Highs	Biggest	Strengthen	Very	Low	Slow	Concerning	Cool
Increasing	Fastest	Good		Falling	Contract	Flattening	Crisis
Rise	Best	Booming		Declining	Recession	Worrying	Weaken
Great	Pushing	Well		Dropping	Bubble	Stopping	
Panel B. Investor fear query							
Corona	Virus	Sars	Mers	Epidemic	Infected		

Notes: This table reports the Google search queries for constructing investor sentiment and investor fear measurements.

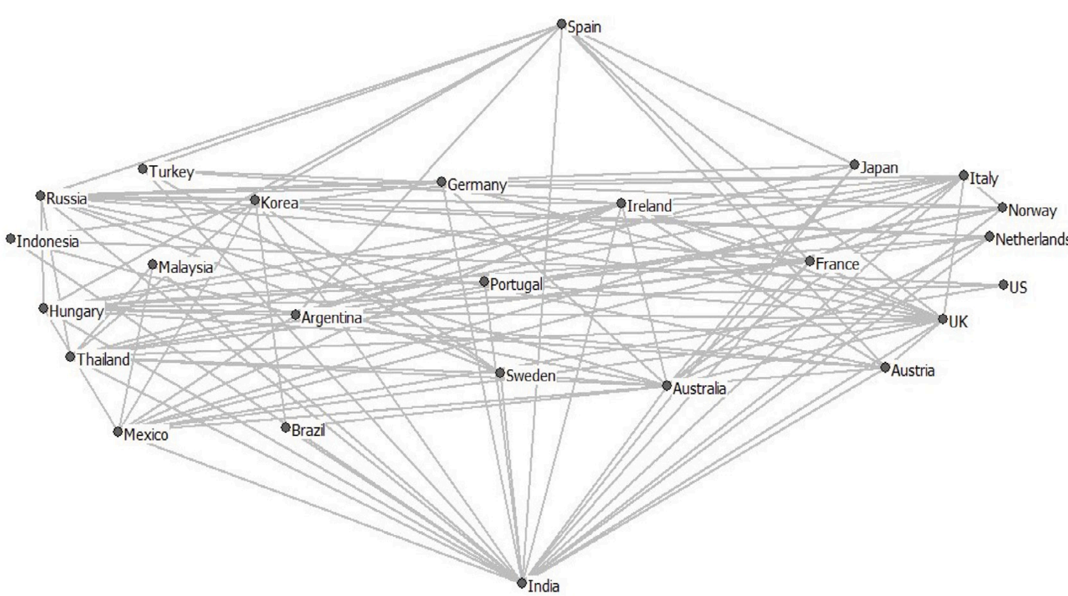

Fig. A.1. Pandemic-driven financial contagion network without direction. This figure plots the financial contagion network during the COVID-19 period. The edges between nodes represent the existence of pandemic-driven financial contagion between the corresponding stock markets.

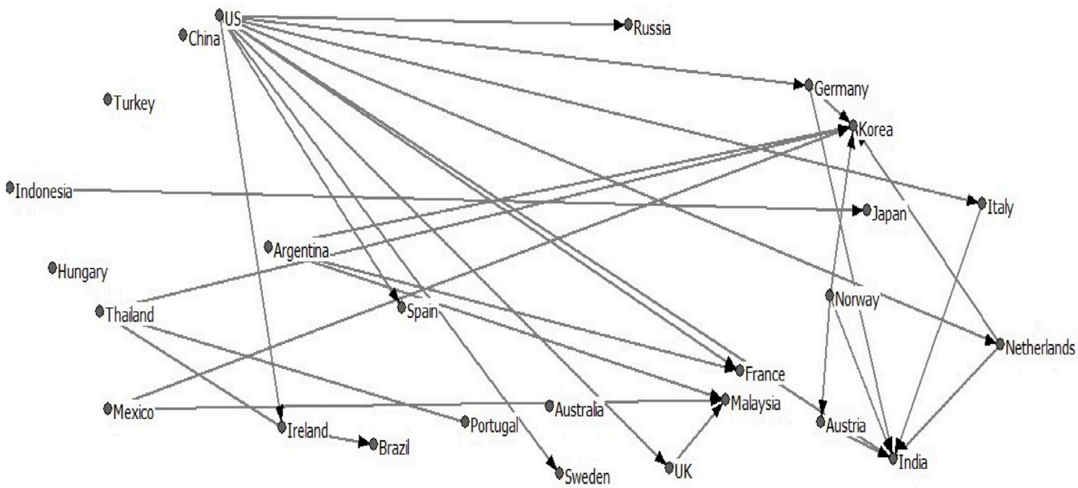

Fig. A.2. Pandemic-driven financial contagion network with directions. This figure plots the directed network of financial contagion during the COVID-19 period. The base of the edge indicates the source of financial contagion, and the head of the edge shows the recipient of financial contagion.

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