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Stochastic actor-oriented modelling of the impact of COVID-19 on financial network evolution

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The coronavirus disease 2019 (COVID-19) pandemic has led to tremendous loss of human life and has severe social and economic impacts worldwide. The spread of the disease has also caused dramatic uncertainty in financial markets, especially in the early stages of the pandemic. In this paper, we adopt the stochastic actor-oriented model (SAOM) to model dynamic/longitudinal financial networks with the covariates constructed from the network statistics of COVID-19 dynamic pandemic networks. Our findings provide evidence that the transmission risk of the COVID-19, measured in the transformed pandemic risk scores, is a main explanatory factor of financial network connectedness from March to May 2020. The pandemic statistics and transformed pandemic risk scores can give early signs of the intense connectedness of the financial markets in mid-March 2020. We can make use of the SAOM approach to predict possible financial contagion using pandemic network statistics and transformed pandemic risk scores of the COVID-19 and other pandemics.

KEYWORDS
financial connectedness, longitudinal study, network analysis, pandemic networks, systemic risk

1 | INTRODUCTION

The coronavirus disease 2019 (COVID-19) pandemic has accounted for more than 150 million confirmed cases and more than 3 million deaths worldwide as of 30 April 2021 (WHO, 2021). The vaccination rollout in various nations from early 2021 onwards has not substantially reduced the number of confirmed cases, and current pandemic risk is still high according to the online dashboard at http://covid-19-dev.github.io/ based on So, Chu, Tiwari, et al. (2021). The various hygiene, social distancing and lockdown measures employed to control COVID-19 have had a significant impact on human mobility, social activities, learning mode in schools (Adnan & Anwar, 2020; Chu, Chan, et al., 2021), the world economy (Ozili & Arun, 2020; McKee & Stuckler, 2020) and financial markets (Shehzad et al., 2020). The outbreak of COVID-19 has also resulted in extraordinary uncertainty for investors and may lead to a substantial increase in financial market connectedness and systemic risk.

An important research question is how we can quantify pandemic risk and the impact of COVID-19 on financial markets statistically. A number of statistical and econometric studies have examined the latter; see, for example, Shehzad et al. (2020) for studying the effect of COVID-19 on financial markets using an asymmetric power GARCH model; Verma et al. (2021) for a statistical analysis of the impact of COVID-19 on the global economy and stock index returns using panel regression analysis and Salisu & Vo (2020) for a study looking at the predictability of stock returns using a measure of investors' awareness and emotions (called the health news index) as predictors in a time series model. Most existing research focuses on univariate or low-dimensional settings. Network analysis (Newman, 2003) is a natural approach for integrating information from multiple places or markets to assess pandemic or financial risks. So, Tiwari, et al. (2020); So, Chu, and Chan (2021) propose formulating dynamic pandemic networks to visualize and assess their connectedness, from which we can generate early warning signals of COVID-19. So, Chu, Tiwari, et al. (2021) use the topological properties of pandemic networks to construct pandemic risk measures and introduce the online dashboard to update these indicators. Chu, Liu, et al. (2021) develop a pandemic space modelling approach to visualize current pandemic status through network modelling. These network analyses of COVID-19 have prompted us to model financial networks by incorporating pandemic risk information in our modelling. So, Chu, and Chan (2021) present evidence of significant changes in financial market connectedness in the Hong Kong stock market during the early stage of COVID-19. So, Chan, and Chu (2021) study the financial connectedness and systemic risk during the COVID-19. In terms of social and financial anxiety, panic can spread faster than COVID-19, especially when people have little knowledge of the pandemic (Depoux et al., 2020). It is thus particularly meaningful to examine how COVID-19 affects, and perhaps may explain, financial market contagions.

From the findings in Shehzad et al. (2020), there is evidence that COVID-19 has a substantial impact on financial markets and the world economy. Big financial events and global public health disasters, like the COVID-19 pandemic, often trigger financial contagion and induce systemic risk in financial markets (Haldane & May, 2011; Elliott et al., 2014; Guo et al., 2021). To understand and model the impact of the COVID-19 pandemic on financial markets, it is natural to incorporate information regarding the pandemic situation in financial modelling. In this paper, we introduce the use of the pandemic network statistics in So, Chu, Tiwari, et al. (2021), who have showed that the pandemic network statistics provide early warning signals of the pandemic. Specifically, we adopt the stochastic actor-oriented model (SAOM) in Snijders (2002) to incorporate the pandemic statistics in modelling financial network evolution.

The SAOM has been applied to various fields. Boda et al. (2020) investigate how assigning fresh undergraduate cohorts into small groups two months prior to their first day at university could influence their friendship network. Cao et al. (2017) apply the SAOM to study the evolution of the macro structure of project-based collaborative networks. The SAOM regards longitudinal data as snapshots of a continuous-time Markov process, which can be represented by networks. The nodes in the networks are also known as actors. The connections among the actors are represented by edges or ties (which can be directed or undirected). We model financial networks with undirected edges using the SAOM. The actors in the SAOM are the composite market indices of major financial markets. Each composite index is associated with several pandemic network statistics and a pandemic risk score of the region to which the composite index belongs. Related network analysis of financial markets during COVID-19 can be found in the literature. Billio et al. (2021) apply a semiparametric matrix regression model to the spread of COVID-19 in financial networks. Lai & Hu (2021) study the systemic risk of global stock markets under COVID-19 based on complex financial networks. The main advantage of using the SAOM to model financial networks is that we can take their dynamic features into consideration while incorporating information from the pandemic networks explicitly to model network evolution.

The paper is structured as follows. Section 2 sets out the detailed methodology, including details of the construction of the financial networks, the SAOM modelling framework and the pandemic related variables used as our predictors in the SAOM. In Section 3, we describe the data analysis, visualization of the fitted model results and our main findings. Section 4 sets out our conclusions.

2 | METHODOLOGY

2.1 | Dynamic financial networks

A major objective of this paper is to model the impact of the COVID-19 pandemic on financial networks using the SAOM. In particular, we will incorporate pandemic network information in the prediction of financial network evolution. Specifically, we adopt the statistics of the pandemic networks as the characteristics of the financial markets in the SAOM framework, which is a useful way to predict the formation of connections within financial networks. A network is formulated by nodes and connections which link the nodes together. We denote the set of vertices at time t by $V(t)$ and the set of edges at time t by $E(t)$. We first illustrate how to construct a dynamic financial network, which is a time series of networks $G(t)=(V(t),E(t))$ constructed based on partial correlations.

Suppose that we have data from $N+G$ market indices in T days. Let P_{it} be the adjusted closing price of the ith index in day t, $i=1,2,\ldots,N+G$, where the first N indices represent the stocks or composite indices of the international financial markets. The remaining G indices are the benchmark market indices used to represent the common market factors explaining the co-movement of the first N indices (So, Chan, & Chu, 2020). The variables of interest are the continuously compounded returns, $R_{it}=\log P_{it}-\log P_{i(t-1)}$, for $t=2,\ldots,T$. We denote the vector of returns of the first N indices by $\mathbf{R}_t^{(S)}=[R_{1t}\ \ R_{2t}\ \ \ldots\ \ R_{Nt}]^T$, and the vector of returns of the last G benchmark market indices by $\mathbf{R}_t^{(M)}=\left[R_{(N+1)t}\ \ R_{(N+2)t}\ \ \ldots\ \ R_{(N+G)t}\right]^T$. In this paper, the vector $\mathbf{R}_t^{(S)}$ represents the vector of composite index returns of the international stock markets and are the vertices of the dynamic financial networks being constructed. Calculating the correlation matrix of $\mathbf{R}_t:=\left[\left(R_t^{(S)}\right)^T\ \ \left(R_t^{(M)}\right)^T\right]^T$, the covariance matrix can be expressed into the blocked matrix

$$\mathrm{Cov}(\mathbf{R}_t)=\begin{bmatrix}\mathrm{Cov}(\mathbf{R}_t^{(S)}) & \Sigma_{SM,t}\\ \Sigma_{MS,t} & \mathrm{Cov}(\mathbf{R}_t^{(M)})\end{bmatrix},\ \text{where } \Sigma_{SM,t}=\begin{bmatrix}\sigma_{1(N+1),t} & \sigma_{1(N+2),t} & \cdots & \sigma_{1(N+G),t}\\ \sigma_{2(N+1),t} & \sigma_{2(N+2),t} & \cdots & \sigma_{2(N+G),t}\\ \vdots & \vdots & \ddots & \vdots\\ \sigma_{N(N+1),t} & \sigma_{N(N+2),t} & \cdots & \sigma_{N(N+G),t}\end{bmatrix},$$

and $\sigma_{ij,t} = \mathrm{Cov}(R_{it}, R_{jt})$. From the above expression, we can obtain the partial covariance matrix of $\mathbf{R}_t^{(S)}$ given $\mathbf{R}_t^{(M)}$ as $\Sigma_{S|M,t} = \mathrm{Cov}(\mathbf{R}_t^{(S)} | \mathbf{R}_t^{(M)}) = \Sigma_{SS,t} - \Sigma_{SM,t}\Sigma_{MM}^{-1}\Sigma_{MS,t}$, where $\Sigma_{SS,t} = \mathrm{Cov}(\mathbf{R}_t^{(S)})$ and $\Sigma_{MM,t} = \mathrm{Cov}(\mathbf{R}_t^{(M)})$. After standardizing $\Sigma_{S|M,t}$, we obtain the desired partial correlation matrix, $\boldsymbol{\rho}_{S|M,t}$.

To model the impact of the COVID-19 pandemic on financial network connectedness, we first construct time-varying financial networks by estimating the partial correlation matrix derived from $\Sigma_{S|M,\,t}$. The partial correlation matrix of $\mathbf{R}_t^{(S)}$, given $\mathbf{R}_t^{(M)}$, can capture the dependence between stock market index returns which cannot be explained by global market movement. The connectedness due to this type of dependence can help us to assess the systemic risk which can be attributed to unusually severe stock market co-movement. Following Xu et al. (2017) and So, Chu, and Chan (2021), we use a moving-window approach to estimate $\Sigma_{S|M,\,t}$, the partial covariance matrix at time t. Effectively, for a window of width w, we estimate the partial covariance matrix at time t for $t = w, w+1, \dots, T$ by calculating the sample covariance matrix, $\hat{\Sigma}_{SS,t}(w) = \frac{1}{w-1}\sum_{s=t-w+1}^{t}(\mathbf{R}_s^{(S)} - \hat{\boldsymbol{\mu}}_t(w))(\mathbf{R}_s^{(S)} - \hat{\boldsymbol{\mu}}_t(w))^T$, where $\hat{\boldsymbol{\mu}}_t(w)$ is the sample mean of $\mathbf{R}_s^{(S)}$, $s = t-w+1, \dots, t$. Similarly, we calculate the sample estimates $\hat{\Sigma}_{MM,t}(w)$ and $\hat{\Sigma}_{SM,t}(w)$ based on the window of w observations $\mathbf{R}_s^{(S)}$ and $\mathbf{R}_s^{(M)}$, respectively, for $s = t-w+1, \dots, t$. Then, the partial covariance and the partial correlation matrix $\boldsymbol{\rho}_{S|M,t}$ can be estimated by $\hat{\Sigma}_{S|M,t}(w) = \hat{\Sigma}_{SS,t}(w) - \hat{\Sigma}_{SM,t}(w)\hat{\Sigma}_{MM}(w)^{-1}\hat{\Sigma}_{MS,t}(w)$ and $\hat{\boldsymbol{\rho}}_{S|M,t}(w) = \mathrm{diag}\{\hat{\Sigma}_{S|M,t}(w)\}^{-\frac{1}{2}}\hat{\Sigma}_{S|M,t}(w)\,\mathrm{diag}\{\hat{\Sigma}_{S|M,t}(w)\}^{-\frac{1}{2}}$. Having computed the correlation matrices, we can define the (i,j)th entry of A_t, the adjacency matrix of $G(t)$ (i.e., the financial network at time t) as

$$A_{ij,t} = \begin{cases} 1 & \text{if}\, [\hat{\boldsymbol{\rho}}_{S|M,t}(w)]_{ij} > r, \\ 0 & \text{otherwise}, \end{cases}$$

where $[\hat{\rho}_{S|M,t}(w)]_{ij}$ is the (i,j)th element of $\hat{\rho}_{S|M,t}(w)$ and r is the threshold. We take $r = 0.5$ in this paper, and $A_{ii,\,t} \equiv 0$ for convention.

2.2 | Data source

To construct these dynamic financial networks, we collect from Bloomberg the adjusted closing prices (P_{it}, $i = 1,\dots,N$; $t = 1,\dots,T$) of $N = 41$ composite indices in 32 countries on $T = 115$ trading days from 19 December 2019 to 27 May 2020. The financial markets are relatively calm after 27 May compared to the period from March to May 2020, and thus, we do not include the subsequent data in this study. Note that $G(t)$ is the financial network and $V(t)$ is the set of composite indices on day t, $t = 1,2,\dots,T$. The set $V(t)$ generally varies over time. However, in this paper, we fix it to be constant because we have the same set of financial indices over time. Then, we calculate their continuously compounded returns (R_{it}, $i = 1,\dots,N$; $t = 1,\dots,T$). We use the MSCI World Index and MSCI Emerging Markets Index as the $G = 2$ benchmark indices to represent global market factors in financial markets. The MSCI world index captures large and mid cap across 23 developed markets with 1,583 constituents (MSCI Inc., 2021b), and the MSCI Emerging Markets Index captures large and mid cap across 27 emerging markets with 1,391 constituents (MSCI Inc., 2021a). We believe that these two MSCI indices give good proxies to explain possible co-movement among composite indices due to global market factors. Using a window width of $w = 40$ for the composite index and global amrket index data, we calculate the partial correlation matrices $\hat{\Sigma}_{S|M,t}$ for $t = w, w+1, \dots, T$, or from 12 February to 27 May 2020 ($T - w + 1 = 115 - 40 + 1 = 76$ trading days). Then, we form the edge set $E(t)$ on each day t for the pairs with correlations on day t that are greater than the threshold r.

The financial networks on every Wednesday from 19 February to 27 May 2020 (a total of 15 snapshots) are selected as our observed moments in the longitudinal analysis using the SAOM, and the data on or after 12 February 2020 are used as the lagged predictors in the model. Choosing Wednesdays allows us to focus on weekly changes in the financial networks rather than being influenced by after-the-weekend or weekend effects. Hence, we pick only the day in the middle of each week, that is, Wednesday, and use this to represent the network pattern in the corresponding week.

Using the method in Section 2.1, we construct financial networks using data from 12 February to 27 May 2020 on 41 market indices. Details of the markets including the countries and regions in which they are located are shown in Table 1. Figure 1a presents network diagrams on four selected days (for network illustration purposes), 4 March, 11 March, 15 April and 27 May 2020. Arcs indicate the connections between two financial market indices with the colours indicating the magnitudes of partial correlations. Note that the adjacency matrices do not take the magnitude of the partial correlations into account. The coloured arcs are for showing supplementary information on the strength of the partial correlations. It is not surprising to see that financial markets that are close to each other are highly connected (Asgharian et al., 2013), especially during volatile periods (Solnik et al., 1996). On 4 March 2020, at an early stage of COVID-19, we can see obvious connections in the financial network, and the network connectedness is quite high. Comparing the four selected days, the financial network connectedness is the highest on 11 March 2020, when WHO declared COVID-19 as a global pandemic. It then drops in April 2020 compared with March 2020 as shown in Figure 1a. On 15 April 2020, the financial network has sparse connections, which may be due to the partial relief of the COVID-19 pandemic. On 27 May 2020, the network connectedness increases, which may be due to the possible recurrence of the pandemic.

TABLE 1 A list of the 41 stock markets included in the study grouped by country and region

Region	Country	Short name	Full name
America	Brazil	IBOV	Bovespa Index
	Canada	SPTSX	S&P/TSX Composite Index
	Mexico	MEXBOL	S&P/BMV IPC Index
	US	CCMP	NASDAQ Composite Index
	US	INDU	Dow Jones Industrial Average Index
	US	RTY	Russell 2000 Index
	US	SPX	S&P 500 Index
	US	VIX	CBOE Volatility Index
Asia	Australia	AS51	S&P/ASX 200 Index
	India	NIFTY	NIFTY 50 Index
	India	SENSEX	BSE Sensex 30 Index
	Indonesia	JCI	Jakarta Stock Exchange Composite Index
	Japan	NKY	Nikkei 225 Index
	Korea	KOSPI	Korea Composite Stock Price Index
	New Zealand	NZDOW	Dow Jones New Zealand Index
	New Zealand	NZSE50FG	NZX 50 Index
	Philippines	PCOMP	PSE Composite Index
	Singapore	STI	FTSE Straits Times Singapore Index
	Thailand	SET	SET Index
	Vietnam	HNX30	Hanoi Stock Exchange 30 Index
Eastern	Pakistan	KSE100	KSE 100 Index
Mediterranean	Saudi Arabia	SASEIDX	Tadawul All Share Index
Europe	Austria	ATX	Austrian Traded Index
	Denmark	OMXC25	OMX Copenhagen 25 Index
	France	BEL20	BEL 20 Index
	France	CAC	CAC 40 Index
	German	DAX	DAX Index
	German	SX5E	EURO STOXX 50 Index
	Hungry	BUX	Budapest SE Index
	Israel	TA-35	Tel Aviv 35 Index
	Italy	FTSEMIB	FTSE Milano Indice di Borsa Index
	Netherlands	AEX	Amsterdam Exchange Index
	Poland	WIG20	Warszawski Indeks Giełdowy 20 Index
	Portugal	PSI20	Portuguese Stock Index 20 Index
	Russia	IMOEX	MOEX Russia Index
	Russia	RTSI	Russia Trading System Index
	Spain	IBEX	Índice Bursatil Español 35 Index
	Sweden	OMXS30B	OMX Stockholm 30 Index
	Switzerland	SMI	Swiss Market Index
	Turkey	XU100	Borsa Istanbul 100 Index
	UK	UKX	Financial Times Stock Exchange 100 Index

2.3 | The SAOM: Network model construction and assumptions

In this section, we define the SAOM to model the evolution of the dynamic financial networks defined in the previous section. In particular, our 'actors' at the nodes in the SAOM are the international financial market indices. We investigate the impact of the COVID-19 on the time series

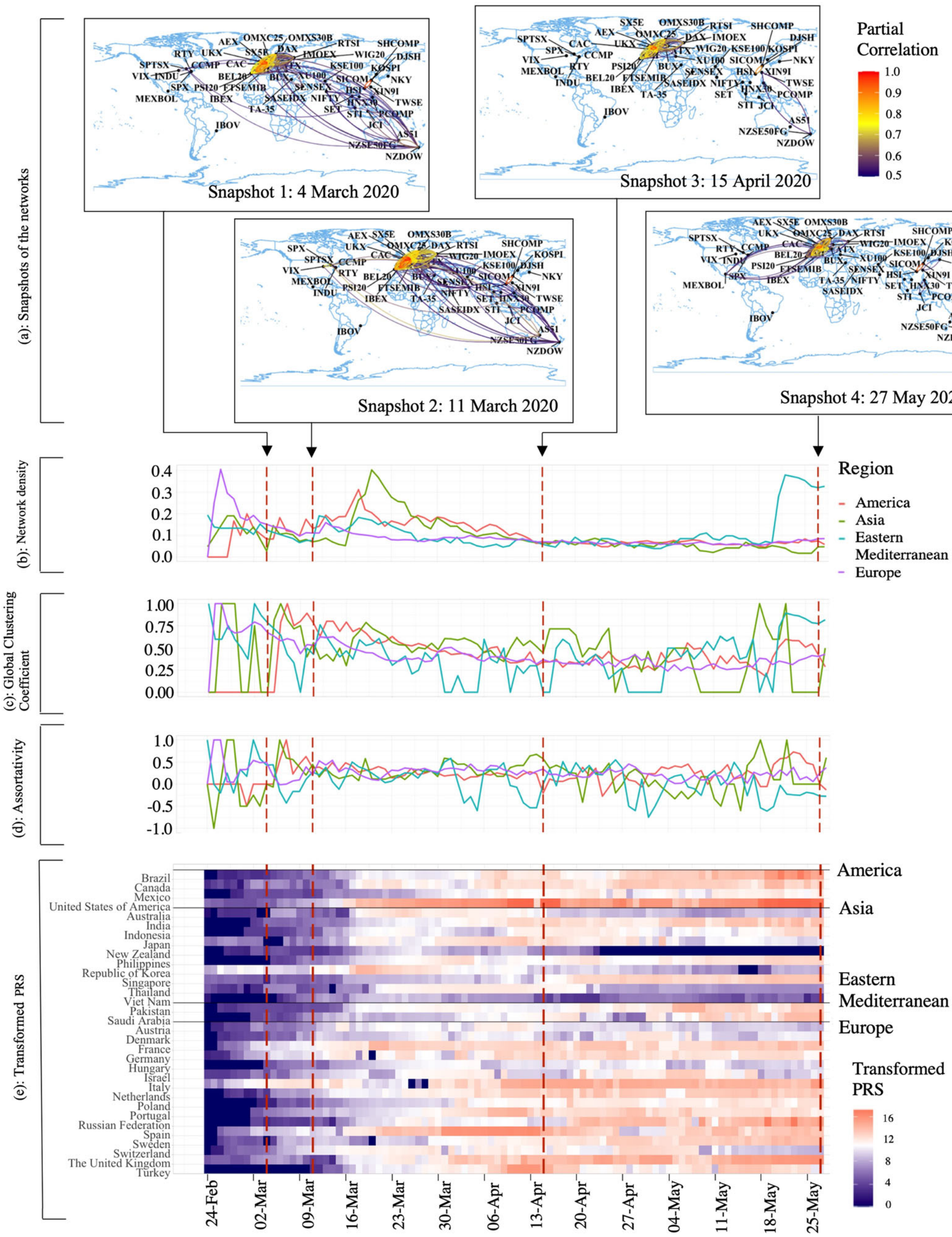


FIGURE 1 (a) Four selected snapshots of the financial networks on 4 March, 11 March, 14 April and 27 May 2020 with connections coloured by partial correlations for illustrative purposes. (b–d) Time series plots of the edge density, global clustering coefficient and assortativity of the pandemic networks from February to May 2020, coloured by four regions. (e) Heatmap of the transformed PRS for 32 countries in which stock markets were located from February to May 2020

pattern of these financial networks by using the network statistics and the risk scores from the pandemic networks as covariate inputs to the SAOM. We assign pandemic network statistics and risk scores to each financial market according to physical locations.

The SAOM is a class of network models which mimics network evolution as individual actors/nodes creating, maintaining or terminating ties/edges to other actors, which can be characterized by covariates or behaviours. We adopt the non-directed network setting to model the financial networks. Following Snijders (2017), we need to focus on the 'opportunity' and 'decision rule' about changing a tie/edge/connection, where the formation of edges can be described in two microsteps. For simplicity, we select the one-sided initiative; that is, one actor or financial market is selected and has a multinomial choice about changing one of the edges. The selected actor/node has the right to change an edge. We first state some of the underlying model assumptions (following Snijders, 2017) before proceeding to describe the SAOM construction. In the SAOM setting, we define a continuous time network characterized by the adjacency matrix at time t, $A_t = [A_{ij,t}]_{i,j=1}^{N_t}$. The network is a continuous time stochastic process defined on the time domain $\mathcal{T} := [t_0, t_M]$ with the discrete states in the edges represented by $A_t \in \{0,1\}^{N_t \times N_t}$ at each time $t \in \mathcal{T}$, where N_t is the number of actors/nodes (financial market indices) in the network at time t. In our case, $N_t = N$ since we have a constant number of financial market indices in the network over time. At any given time point $t \in \mathcal{T}$, only one edge variable $A_{ij,t}$ can change. Assume that $\{A_t\}$, $t \in [t_0, t_M]$ is a continuous time Markov chain, observed at $t = t_0, \ldots, t_M$. The Markov property implies that A_t is conditionally independent of A_s and $s < t_{m-1}$ given $A_{t_{m-1}}$.

From now on, we use the terms actor and node interchangeably to represent financial market indices. The SAOM takes a micro-step mechanism. At each time t, only one selected actor has the opportunity to make a change. The selected actor can decide whether to make a change in his/her edges. The network change process can be decomposed into two sub-processes: the opportunity to change and the actor's decision. The Markov assumption implies that the waiting time between consecutive changes for an actor is exponentially distributed. Let $\lambda_i(x; \rho_m)$ be the rate of change of the network at time point t with network x, that is, the mean parameter of the exponential distribution, where $t \in \mathcal{T}_m := [t_m, t_{m+1})$ and ρ_m is a parameter. We set $\mathcal{T}_m$ to be the mth period. In general, $\lambda_i(x; \rho_m)$ takes the form (Snijders et al., 2007)

$$\lambda_i(x; \rho_m) = \rho_m \exp\left(\sum_{k=1}^{K} \alpha_k a_{ki}(x)\right),$$

where $a_{ki}(x)$ denotes the kth statistics of actor i determining the characteristics of the ith actor in network x and α_k is the coefficient indicating dependence on the statistics $a_{ki}(A_t)$, $i = 1, 2, \ldots, N_t$. In the first microstep, actor i in network x is selected to have an opportunity to make changes in his/her edge with the probability (Snijders, 2017)

$$P(\text{actor } i \text{ is selected}) = \frac{\lambda_i(x; \rho_m)}{\lambda_+(x; \rho_m)},$$

where $\lambda_+(x; \rho_m) = \sum_{i=1}^{N_t} \lambda_i(x; \rho_m)$. In this paper, we take $\lambda_i(x; \rho_m) = \rho_m$, meaning that the transition rates of all actors are the same in the interval $[t_m, t_{m+1})$ for $m = 0, 1, \ldots, M-1$. Then, the probability of actor i being selected at time $t \in [t_m, t_{m+1})$ is

$$P(\text{actor} i \text{is selected}) = \frac{\lambda_i(x; \rho_m)}{\lambda_+(x; \rho_m)} = \frac{\rho_m}{\sum_{i=1}^{N_t} \rho_m} = \frac{1}{N_t};$$

that is, all actors have the same probability of being chosen. The change that takes place in the SAOM in a microstep is regarded as an actor's choice and so the model is 'actor-oriented'.

In the second microstep, the selected actor may create or drop one edge, or make no change. Let $x^{(\pm ij)} \in \{0,1\}^{N_t \times N_t}$ be the candidate network which is identical to x except for the edge $A_{ij,t}$. The decision of actor i to make a change from x to $x^{(\pm ij)}$ is based on utility theories suggesting that the action will be decided by maximizing the following utility function

$$U_i(x^{(\pm ij)}, v; \boldsymbol{\beta}) = f_i(x^{(\pm ij)}, v; \boldsymbol{\beta}) + \varepsilon_i,$$

where $f_i(x^{(\pm ij)}, v; \boldsymbol{\beta})$ is an objective function capturing all related information from the current network and covariates v and ε_i is a random component. A common assumption in utility theories is to set $\varepsilon_j \sim \text{Gumbel}(0,1)$, i.e., the pdf of ε_j is $e^{-(\varepsilon_j + e^{-\varepsilon_j})}$, to be identical and independent for $j = 1, 2, \ldots, N_t$. Then, it can be shown that $U_i(x^{(\pm ij)}, v; \boldsymbol{\beta})$ is maximized with the transition probability to change from x to $x^{(\pm ij)}$ given by (Snijders, 2017)

$$p_{ij} = \frac{\exp(f_i(x^{(\pm ij)}, v; \boldsymbol{\beta}))}{\sum_{h=1}^{N_t} \exp(f_i(x^{(\pm ih)}, v; \boldsymbol{\beta}))}, \tag{1}$$

where $x^{(\pm ii)} = x$ when there is no change being made. In the SAOM adopted in this paper, $f_i(x^{(\pm ij)}; \boldsymbol{\beta})$ takes a linear form

$$f_i(x^{(\pm ij)}, v; \boldsymbol{\beta}) = \sum_{k=1}^{K} \beta_k s_{ki}(x^{(\pm ij)}, v),$$

where $s_{ki}(x^{(\pm ij)}, v)$'s are the K effects of the networks, which depend on the candidate network $x^{(\pm ij)}$ and the covariates v only,[1] and $\boldsymbol{\beta} \in \mathbb{R}^K$ is a vector of parameters. We specify below various choices for the effects based on the data.

[1] In general, the effects could be dependent on the current network x.

2.4 | Network effects

To estimate the unknown parameters in the SAOM, we apply SIENA (Simulation Investigation of Empirical Network Analysis) using R for our financial network modelling. More details of SIENA can be found in Ripley et al. (2021) and Snijders (2019). To study the temporal properties of the dynamic financial networks, we consider two different kinds of effects $s_{ki}(x^{(\pm ij)}, v)$. The following effects depend only on the network configurations, which are (1) density effect (degree in RSiena, the SIENA in R), defined as $s_{1i}(A_t,v) = A_{i+,t}$, where $A_{i+,t} = \sum_j A_{ij,t}$; (2) transitive triads effect (transTriads in RSiena), defined as $s_{2i}(A_t,v) = \sum_{k<h} A_{ik,t}A_{kh,t}A_{hi,t}$; (3) out-isolation (outIsoin RSiena), defined as $s_{3i}(A_t,v) = I\{A_{i+,t} = 0\}$, and (4) out degree related activity effect (outAct in RSiena), defined as $s_{4i}(A_t,v) = A_{i+,t}^2$. To understand the implications of these effects, we can re-write (1) by dividing both the numerator and the denominator by $\exp(f_i(x,v;\boldsymbol{\beta}))$:

$$p_{ij} = \frac{\exp\{f_i(x^{(\pm ij)},v;\boldsymbol{\beta}) - f_i(x,v;\boldsymbol{\beta})\}}{\sum_{h=1}^{N_t}\exp\{f_i(x^{(\pm ih)},v;\boldsymbol{\beta}) - f_i(x,v;\boldsymbol{\beta})\}} = \frac{\exp\left\{\sum_{k=1}^{K}\beta_k(s_{ki}(x^{(\pm ij)}) - s_{ki}(x))\right\}}{\sum_{h=1}^{N_t}\exp\left\{\sum_{k=1}^{K}\beta_k(s_{ki}(x^{(\pm ih)}) - s_{ki}(x))\right\}}.$$

In particular, if $i = j$, it corresponds to the case that no action has been taken, and $p_{ii} = \left[\sum_{h=1}^{N_t}\exp\{\sum_{k=1}^{K}\beta_k(s_{ki}(x^{(\pm ih)}) - s_{ki}(x))\}\right]^{-1}$. Hence, the probability that the network x changes to the network $x^{(\pm ij)}$ depends only on the difference in the effects evaluated at x and $x^{(\pm ij)}$. Inputting $x = A_t$, let $A_t^{(\pm ij)}$ be the network identical to A_t except $A_{ij,t}$. For notation simplicity, we write $s_{ki}(A_t)$ for $s_{ki}(A_t, v)$. A useful measure to compare the two networks A_t and $A_t^{(\pm ij)}$ is the log-odds defined by

$$LO(A_t, A_t^{(\pm ij)}) = \log\left(\frac{p_{ij}}{p_{ii}}\right) = \sum_{k=1}^{K}\beta_k(s_{ki}(A_t^{(\pm ij)}) - s_{ki}(A_t)),$$

implying that the difference, $\Delta s_{ki} = s_{ki}(A_t^{(\pm ij)}) - s_{ki}(A_t)$, contributes linearly to the log-odds ratio. We now examine how the four Δs_{ki}, $k = 1, \ldots, 4$, affect the log-odds ratio.

(1) The term in $LO(A_t, A_t^{(\pm ij)})$ relating to the difference in the density is $\beta_1\Delta s_{1i}$, where $\Delta s_{1i} = A_{i+,t}^{(\pm ij)} - A_{i+,t}$. If $\beta_1 > 0$, then creating an additional link in the graph $A_t^{(\pm ij)}$ increases the log-odds, while deleting a link decreases it. The effect of Δs_{1i} is similar to the effect of a categorical variable in linear regressions.
(2) The term in $LO(A_t, A_t^{(\pm ij)})$ relating to the difference in the transitive triads is $\beta_2\Delta s_{2i}$, where Δs_{2i} is the number of additional closed triplets created in $A_t^{(\pm ij)}$. If $\beta_2 > 0$, creating a link that forms additional triangles in the graph $A_t^{(\pm ij)}$ increases the log-odds and encourages the small-world property.
(3) The term in $LO(A_t, A_t^{(\pm ij)})$ relating to the difference in the out-isolation is $\beta_3\Delta s_{3i}$, where $\Delta s_{3i} = I\{A_{i+,t}^{(\pm ij)} = 0\} - I\{A_{i+,t} = 0\}$, the number of additional isolated nodes when the graph is changed from A_t to $A_t^{(\pm ij)}$. This effect is included because we want to test whether isolated nodes have different behavior than connected nodes on link formation.
(4) The term in $LO(A_t, A_t^{(\pm ij)})$ relating to the difference in the out degree related activity is $\beta_4\Delta s_{4i}$, where $\Delta s_{4i} = \left(A_{i+,t}^{(\pm ij)}\right)^2 - A_{i+,t}^2$. The purpose of including this effect is to see if the degree of node i itself, $A_{i+,t}$, affects the log-odds rather than their difference. To understand this effect, consider the change from $A_{ij,t} = 0$ in A_t to $A_{ij,t}^{(\pm ij)} = 1$ in $A_t^{(\pm ij)}$. Then, we have

$$\Delta s_{4i} = \left(A_{i+,t}^{(\pm ij)}\right)^2 - A_{i+,t}^2 = (A_{i+,t} + 1)^2 - A_{i+,t}^2 = 2A_{i+,t} + 1.$$

Similarly if $A_{ij,t} = 1$ and $A_{ij,t}^{(\pm ij)} = 0$, then $\Delta s_{4i} = -2A_{i+,t} + 1$. This effect is a good proxy for including the degree of nodes in the log-odds.

2.5 | Using pandemic networks to define covariates

A main objective of this paper is to investigate the impact of the COVID-19 on financial network evolution. Specifically, we test whether the pandemic information set out in So, Chu, Tiwari, et al. (2021) is useful in explaining changes in the financial network dynamic under the SAOM. In So, Chu, Tiwari, et al. (2021), the dynamic pandemic networks based on changes in the number of COVID-19 confirmed cases are constructed, from which we can calculate the time series of network statistics (including network density, clustering coefficient and assortativity) and a pandemic risk score called the preparedness risk score (PRS) and use these as covariates in the SAOM. The PRS accounts for the risk of asymptomatic or presymptomatic transmission. We adopt it as a measure of the transmission risk, which potentially influences the financial networks.

The following details for the construction of the pandemic networks and the pandemic network statistics can be found in So, Chu, Tiwari, et al. (2021). Let $X_{i,t}$ be the number of confirmed COVID-19 cases of country i in day t, $i = 1,2,\ldots,32$ countries. We calculate the daily changes for each country as $Y_{i,t} = \sqrt{X_{i,t}} - \sqrt{X_{i,t-1}}$. The sample correlation between country i and country j's daily changes in day t, $\hat{\rho}_{ij,t}$, is calculated using $(Y_{i,t-k}, Y_{j,t-k})$, for $k = 0,\ldots,13$. We build the pandemic network at time t by defining $A^p_{ij,t}$, the (i,j)th element of the adjacency matrix (A^p_t) of the pandemic network at time t:

$$A^p_{ij,t} = \begin{cases} 1 & \text{if} \hat{\rho}_{ij,t} > r_p, \\ 0 & \text{otherwise}, \end{cases} \tag{2}$$

where $r_p = 0.5$. Let E^p_t and V^p_t be the number of edges and the number of nodes (countries) in the pandemic network, respectively. The network density of the pandemic network at time t is defined as

$$D^p_t = \frac{2E^p_t}{V^p_t(V^p_t - 1)},$$

which measures how dense the pandemic network is at time t. The global clustering coefficient of the pandemic network is defined as

$$C^p_t = \frac{\sum_{i=1}^{V_t} \binom{k_{it}}{2} c_{it}}{\sum_{i=1}^{V_t} \binom{k_{it}}{2}},$$

where k_{it} is the number of neighbours (or degree) of node i, and $c_{it} = (\text{number of triangles formed by node i}) / \binom{k_{it}}{2}$. C^p_t measures how strong nodes, or countries in the pandemic network, at time t are clustered together. The assortativity of the pandemic network at time t is defined as

$$AS^p_t = \frac{\sum_{i=1}^{V^p_t} \sum_{j=1}^{V^p_t} \frac{k_{it}k_{jt}}{V^p_t} I(A^p_{ij,t} = 1) - \left[\sum_{i=1}^{V^p_t} \sum_{j=1}^{V^p_t} \frac{(k_{it} + k_{jt})}{2V^p_t} I(A^p_{ij,t} = 1)\right]^2}{\sum_{i=1}^{V^p_t} \sum_{j=1}^{V^p_t} \frac{(k^2_{it} + k^2_{jt})}{2V^p_t} I(A^p_{ij,t} = 1) - \left[\sum_{i=1}^{V^p_t} \sum_{j=1}^{V^p_t} \frac{(k_{it} + k_{jt})}{2V^p_t} I(A^p_{ij,t} = 1)\right]^2},$$

which measures the correlation of the degree of the nodes in the pandemic networks. The PRS of country i at time t is defined as

$$S_t = \omega_t^T A^P_t \omega_t,$$

where ω_t is the vector of the population size of each country subtracted by the total number of confirmed cases in each country up to time t. The PRS counts the total number of possible interactions of susceptible population contributed from all pairs of countries which are linked together at time t.

As in the COVID-19 case reporting in WHO and So, Chu, Tiwari, et al. (2021), we classify financial markets according to their geographical locations into four regions: Asia, America, Europe and Eastern Mediterranean. Based on this classification, we use pandemic network statistics in the four regions to define the SAOM covariates for the financial networks. For example, we take pandemic network statistics in Europe as covariates for the market index in the United Kingdom. The network statistics are helpful in accounting for the different stages of COVID-19 between regions, as shown in the time series plots in Figure 1b–d. For each network statistic, their lag-1 to lag-5 values are used as predictors in the SAOM.

For the pandemic risk score, we can use the country-wise time-varying PRS in Figure 1 to form the SAOM covariates for the financial markets by mapping financial market indices to their respective countries. For example, we use the PRS of the United States as a covariate for SP500. A problem in using the PRS data is that the distribution of the PRS is highly right skewed and the magnitude of the scores is extremely small, which leads to unstable estimation of the SAOM using `RSiena`. To address this, we define the transformed PRS as $\log(1 + 10^9 \times PRS)$, which has a more symmetrical distribution and is of similar magnitude to the network statistics. Note that the PRS plotted in the heat maps shown in Figure 1e are not standardized. For better convergence of the algorithm (Ripley et al., 2021), we standardize all covariates before inputting them into the SAOM. Most of the covariates fall between -2 to 2 after standardization.

The fifth and sixth effects included in the SAOM are defined by v_{it}, the covariates defined by pandemic network statistics and their lagged values. The pandemic network statistics we consider are the network density, D^P_t; the global clustering coefficient, C^P_t; the assortativity, AS^P_t, and the PRS, S_t. These two effects are known as (5) covariate-ego (egoX in RSiena), defined as $s_{i5}(A_t) = v_{it}A_{i+,t}$, and (6) covariate-ego $\times$ alter (egoXaltX in RSiena), defined as $s_{i6}(A_t) = \sum_k A_{ik,t}v_{it}v_{kt}$, where v_{it} is a covariate of market index i at time t. Similar to the first four effects, the corresponding log-odds are given as follows:

(5) The term in $LO(A_t, A_t^{(\pm ij)})$ relating to the difference of covariate-ego is $\beta_5\Delta s_{5i}$, where $\Delta s_{5i} = v_{it}(A_{i+,t}^{(\pm ij)} - A_{i+,t}) = v_{it}(A_{ij,t}^{(\pm ij)} - A_{ij,t})$. (This is because all the edges are the same in graph A_t and $A_t^{(\pm ij)}$ except for the edge between actor i and j.) In this case, the log-odds is proportional to the pandemic covariate v_i, and thus, the SAOM can test whether pandemic network statistics and the PRS for COVID-19 have any effect on financial network evolution.
(6) The term in $LO(A_t, A_t^{(\pm ij)})$ relating to the difference of covariate-ego $\times$ alter is $\beta_6\Delta s_{6i}$, where $\Delta s_{6i} = v_{it}\sum_k v_{kt}(A_{ik,t}^{(\pm ij)} - A_{ik,t}) = v_{it}v_{jt}(A_{ij,t}^{(\pm ij)} - A_{ij,t})$. In this case, the log-odds will be affected by the product of both covariates v_{it} and v_{jt}.

2.6 | Estimation

The detailed estimation procedure, which is based on the method of moments, was described in Amati et al. (2015) and Ripley et al. (2021). Briefly speaking, moment equations are established based on the sufficient statistics of the transition rates and the parameters of the effects discussed in Amati et al. (2015), with Robbins-Monro stochastic approximation being used to solve the system of moment equations. The RSiena package in R provides necessary functions for the estimation.

3 | SAOM ANALYSIS OF FINANCIAL NETWORKS DURING THE COVID-19

3.1 | Pandemic data description

To further explore the detailed changes in the financial networks during the COVID-19, Figure 2 shows a summary. The networks were stable from mid-February 2020 until 24 February 2020, when many connections were added. The growth trend reached its peak in mid-March 2020. After that, a substantial number of old edges tended to be dropped in April 2020. The network evolution became active again in May 2020.

Following the rationale in So, Chu, and Chan (2021) which identified abnormal financial network connectedness during the COVID-19, we plot the time series of pandemic network statistics in Figure 1b–d. We observe quite different network characteristics in the pandemic networks in early March, April and May 2020. Similarly, the heatmap of the transformed PRS in Figure 1e also shows distinct patterns in early March, April and May 2020. These changes in the pattern of the network statistics and the PRS may explain the different financial connectedness in Figure 1a. For example, a higher PRS seems to be associated with higher financial network connectedness. Therefore, we adopt pandemic network covariates in the SOAM, that is, v_{it} as defined in Section 2.5, to investigate whether or not the severity of the pandemic (using statistics from the pandemic networks, as well as the risk scores as proxies) can predict financial connectedness.

3.2 | Model fitting

The full SAOM considered in this paper contains 14 rate of change parameters and four network effects (density, transitive triads, out-isolation and out degree related activity). To specify the two covariate effects, that is, covariate-ego and covariate-ego $\times$ alter as set out in Section 2.5, for each of the four pandemic network statistics (network density, global clustering coefficient, assortativity and transformed PRS), we include their five lagged values separately as v_{it} to define multiple effects five and six. Thus, we have a total of 14 (for the rate parameters) $+$ 4 (for effects one to four) $+ 4 \times 5 \times 2$ (for effects five and six) $=$ 58 parameters in the full model. We then conduct variable elimination to remove insignificant effects from the full model using F tests and eventually retain the 23 variables listed in Table 2. All 14 rate parameters are kept and restricted to be positive in the estimation (Ripley et al., 2021). The out-isolation and out degree effects defined in Section 2.4 are removed, implying that the isolation and the degree of nodes are not useful for predicting financial network connectedness and evolution. Seven pandemic covariates effects are retained. These represent the lagged effects of pandemic network density, global clustering coefficient, assortativity and the transformed PRS. From the seven significant pandemic covariate effects, we obtain strong statistical evidence that pandemic network properties and the related pandemic risk scores can help explain financial network evolution during the COVID-19. The impact may not be spontaneous and may take up to 5 days to become apparent. We will see how the propagation of pandemic risk can potentially lead to changes in financial market connectedness.

In the SAOM modelling, an essential objective is to investigate how pandemic networks possibly influence the formation of financial networks over time. To examine this, we focus on the two effects in Section 2.5 in the log-odds:

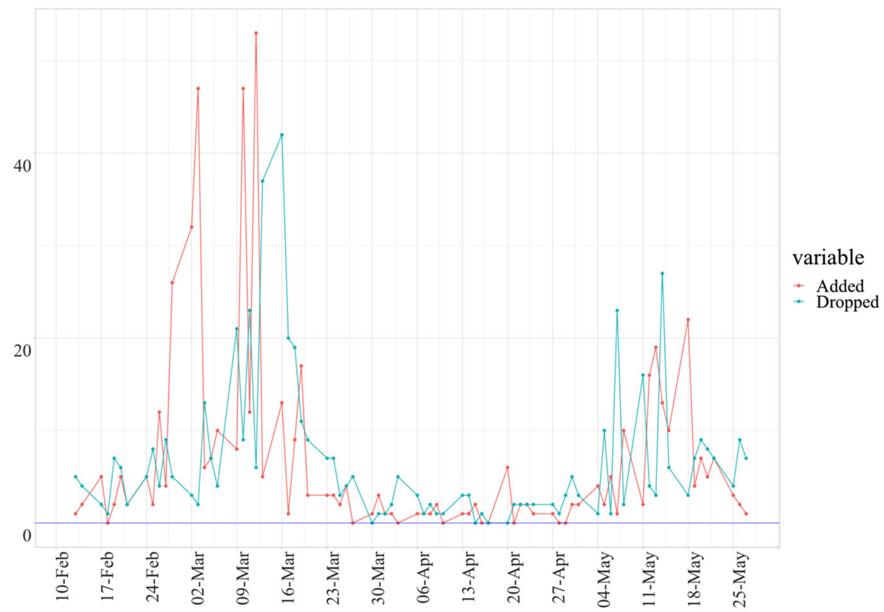


FIGURE 2 The number of network connections added or dropped compared to the previous trading day, from February to May 2020

$$\beta_5 \Delta s_{5i} + \beta_6 \Delta s_{6i} = \beta_5 v_{it}(A_{ij,t}^{(\pm ij)} - A_{ij,t}) + \beta_6 v_{it} v_{jt}(A_{ij,t}^{(\pm ij)} - A_{ij,t}) = (\beta_5 v_{it} + \beta_6 v_{it} v_{jt})(A_{ij,t}^{(\pm ij)} - A_{ij,t}), \tag{3}$$

where β_5 and β_6 are unknown parameters corresponding to the covariate effects and v_{it} is a pandemic network covariate of node i at time t in Section 2.5. To visualize the effects efficiently, consider specifically the effect of adding one edge between node i and j in A_t to form $A_t^{(\pm ij)}$, in this case, $A_{ij,t}^{(\pm ij)} - A_{ij,t} = 1$. Since we standardize all v_i before inputting them to the SAOM for model fitting, the log-odds in (3) due to the pandemic covariates v_{it} and v_{jt} can be written as a two-dimensional function of v_{it} and v_{jt},

$$F(v_{it}, v_{jt}) = \beta_5 \left(\frac{v_{it} - \bar{v}}{\sigma_v}\right) + \beta_6 \left(\frac{v_{it} - \bar{v}}{\sigma_v}\right)\left(\frac{v_{jt} - \bar{v}}{\sigma_v}\right), \tag{4}$$

where $\bar{v}$ and σ_v are, respectively, the sample mean and standard deviation of the covariates v_{it}. We call $F(v_{it}, v_{jt})$ in Equation 4 the composite effect. Table 3 shows six heat maps of $F(v_{it}, v_{jt})$ to visualize the composite effect of different pandemic network covariates v_{it} and v_{jt} on the evolution of the financial network. Note that we have seven significant effects in Table 2 but only six heat maps in Table 3 because we combine the two lag-five global clustering coefficient effects together to form a composite effect. In the heat maps in Table 3, the x axis corresponds to the covariate (we call it v_{it}) of node i which is given an opportunity to make a change, and the y axis refers to the covariate (we call it v_{jt}) of node j that may be connected or disconnected by node i. From the covariates constructed from the pandemic network statistics, only network density shows a significant effect at lag one. When both v_{it} and v_{jt} are large/small, the chance of network link formulation in the financial networks tends to be higher. This observation is consistent with the result from Table 2 that the significant covariate-ego $\times$ alter effects described in Section 2.5 are all positive. Similarly, in the global clustering coefficient of the pandemic networks, simultaneously large or small v_{it} and v_{jt} may trigger financial network edge formation but the effect appears in lag-2. High lag-three pandemic network assortativity also encourages financial link formulation. Regarding the effect of the PRS, it takes three to 4 days to show a significant impact on financial network connectedness. Again, when the lag-3 PRS in node i and node j simultaneously increase or decrease, the financial network will tend to be denser. In short, when pandemic network connectedness or the PRS (reflecting the pandemic severity) in the two locations corresponding to nodes i and $j$move in the same direction in the past few days, the financial networks tend to be more connected during the COVID-19. In terms of financial risk management, we can keep track of the pandemic severity at different locations to foresee how the financial networks will evolve.

To study the actual longitudinal impact of the pandemic covariates on financial market connectedness, we calculate $F(v_{it}, v_{jt})$ for significant effects v_{it} and all possible pairs of i and j (there are $N(N-1)/2$ pairs, $N = 41$ in our case), to obtain the distribution of $F(v_{it}, v_{jt})$ on day t. Figure 3a–f presents these distributions using boxplots for all six covariates listed in Table 3 on each trading day. From Figure 3a–d, we

TABLE 2 Summary statistics of the final model

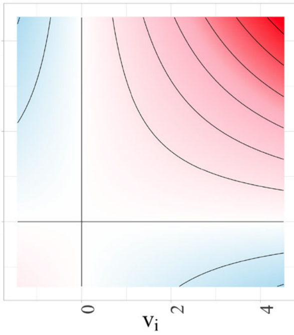
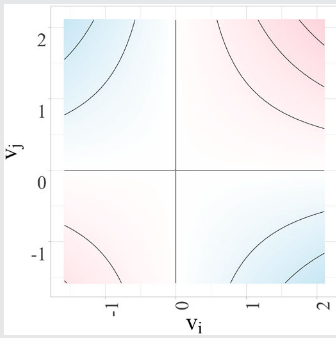
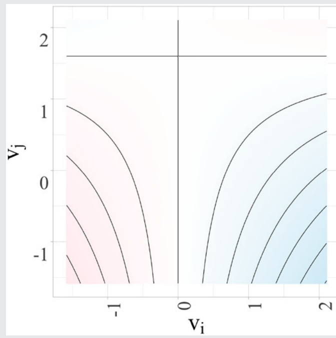
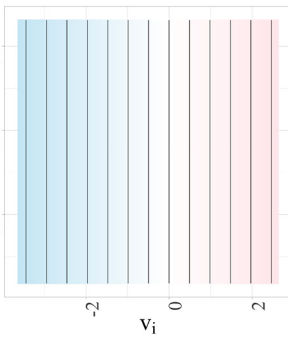
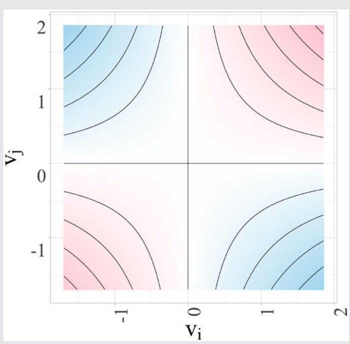
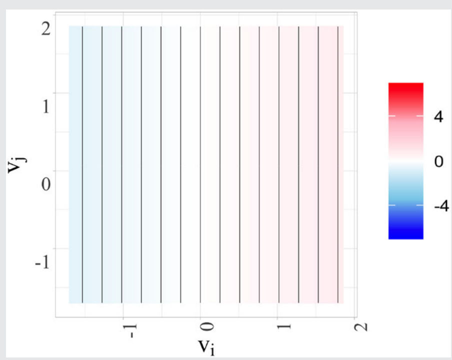
Effects	Estimate	Standard error	*t* ratio	*p* value
Rate of change of period 1	0.5750	0.1463	3.9305	1e-04*
Rate of change of period 2	3.8998	0.4783	8.1541	0*
Rate of change of period 3	2.7093	0.6367	4.2553	0*
Rate of change of period 4	16.0101	17.5514	0.9122	0.3617
Rate of change of period 5	1.1982	0.2649	4.5236	0*
Rate of change of period 6	0.3542	0.1183	2.9946	0.0027*
Rate of change of period 7	0.3620	0.1239	2.9216	0.0035*
Rate of change of period 8	0.1294	0.0688	1.8807	0.06*
Rate of change of period 9	0.0916	0.0574	1.5956	0.1106
Rate of change of period 10	0.3079	0.1132	2.7198	0.0065*
Rate of change of period 11	0.5344	0.1613	3.3127	9e-04*
Rate of change of period 12	2.6265	0.6447	4.0738	0*
Rate of change of period 13	7.5786	5.2842	1.4342	0.1515
Rate of change of period 14	1.0487	0.2751	3.8127	1e-04*
Financial network effects				
Density	−3.9538	0.2676	−14.7724	0*
Transitive triads	0.4880	0.0293	16.6524	0*
Pandemic covariates				
Covariate-ego × alter of lag-3 transformed PRS	0.7757	0.1280	6.0592	0*
Covariate-ego of lag-4 transformed PRS	0.3920	0.1190	3.2949	0.001*
Covariate-ego × alter of lag-1 pandemic network density	0.3199	0.1136	2.8155	0.0049*
Covariate-ego × alter of lag-2 global clustering coefficient	0.4082	0.1068	3.8214	1e-04*
Covariate-ego of lag-5 global clustering coefficient	−0.2900	0.0922	−3.1466	0.0017*
Covariate-ego × alter of lag-5 global clustering coefficient	0.1814	0.0552	3.2847	0.001*
Covariate-ego of lag-3 degree assortativity	0.4065	0.0819	4.9644	0*

*Significant at the 0.1 level.

observe that the boxplots of the four network statistics in mid- to late-February 2020 are wider than that after March 2020, meaning that they may have made a substantial contribution to the formation of financial network connections over that period in February. For example, for v_{it} (the network density) in panel (a), $F(v_{it}, v_{jt})$ is highly volatile in late-February and mid-March, with a strongly positive effect in many of the pairs (i, j) in terms of edge formulation in the financial networks. Similarly, we also observe high variability in the clustering coefficients and assortativity in panels (b) and (c) in late-February and early-March. On the other hand, from Figure 3e, $F(v_{it}, v_{jt})$ corresponding to the transformed PRS are predominately positive and large in late-February and early-March and quite highly volatile throughout the investigation period of February to May 2020. From the above findings, we can categorize the effect of the pandemic network statistics and the pandemic risk scores as short- and long-term effects, respectively, because the network statistics only affect the financial networks in the earlier stages but the transformed PRS affects them across all periods. In particular, the transmission risk of the COVID-19, measured using the transformed PRS, is a main explanatory factor of financial network connectedness for the period March to May 2020. More severe transmission risk may lead to further lockdown of businesses and cities which may harm the economy, thus affecting the financial markets. We can keep track of lagged pandemic network statistics and transformed PRS to evaluate financial risk through financial market connectedness.

We observe from Figure 3a–e that the implied $F(v_{it}, v_{jt})$ from the pandemic networks is volatile in mid-February 2020, whereas the financial networks from Figure 2 are quite stable in mid-February 2020. The pandemic statistics and transformed PRS can give early signals of the intense connectedness of the financial markets in March 2020. This is useful for financial management since we can use lagged pandemic network statistics and transformed PRS to infer future financial connectedness and, thus, to monitor systemic risk in financial markets more effectively. Furthermore, we can use the SAOM approach to predict possible financial contagion using pandemic network statistics and transformed PRS of the COVID-19 and other pandemics.

TABLE 3 Two-dimensional plots of the composite effects $F(v_i, v_j)$, where the subscript t is omitted for brevity

<table>
<tr><th>Covariate</th><th>Lagged effect (I)</th><th>Lagged effect (II)</th></tr>
<tr><td>Network density</td><td>(a) lag 1: $0.3199(v_i-\bar{v})(v_j-\bar{v})/\sigma_v^2$

</td><td></td></tr>
<tr><td>Global clustering coefficient</td><td>(b) lag 2: $0.4082(v_i-\bar{v})(v_j-\bar{v})/\sigma_v^2$

</td><td>(c) lag 5: $-0.2900(v_i-\bar{v})/\sigma_v+0.1814(v_i-\bar{v})(v_j-\bar{v})/\sigma_v^2$

</td></tr>
<tr><td>Assortativity</td><td>(d) lag 3: $0.4065(v_i-\bar{v})/\sigma_v$

</td><td></td></tr>
<tr><td>Transformed PRS</td><td>(e) lag 3: $0.7757(v_i-\bar{v})(v_j-\bar{v})/\sigma_v^2$

</td><td>(f) lag 4: $0.3920(v_i-\bar{v})/\sigma_v$

</td></tr>
</table>

Note: All heatmaps use the same colour scale.

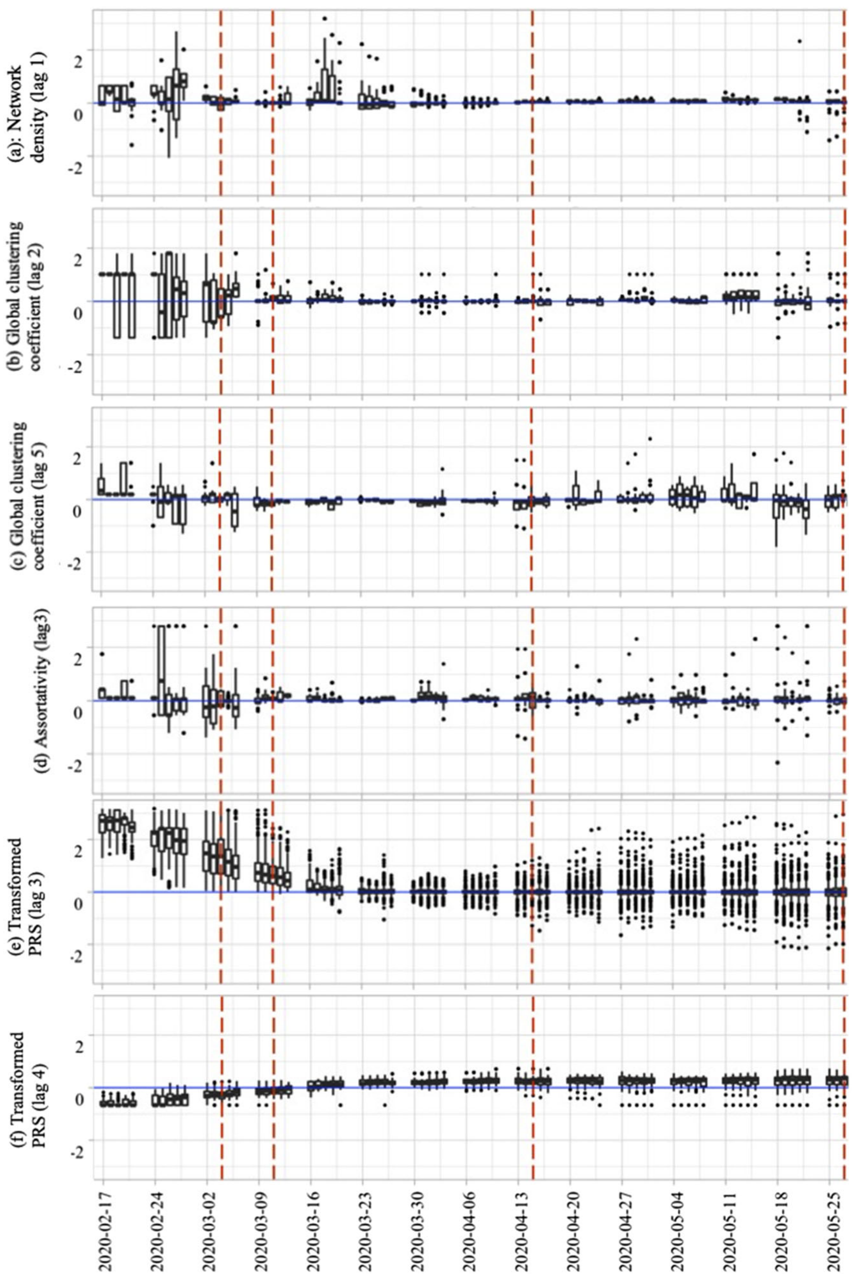


FIGURE 3 Boxplots of $F(v_{it}, v_{jt})$ for the significant covariates from February to May 2020. The four vertical lines represent the four days specified in Section 3: 4 March, 11 March, 15 April and 27 May 2020

4 | CONCLUSIONS

Using the SAOM with longitudinal financial and pandemic datasets, we investigate how financial networks evolve by applying pandemic network statistics and transformed PRS as predictors. The results provide evidence that financial markets where the pandemic statistics and prevalence of the COVID-19 co-move in the same direction tend to be more connected. Moreover, pandemic network statistics contribute to financial network connectedness in the short term in the early stages of the pandemic, while the long-term connectedness is driven by the pandemic risk. The results also show that we can detect the early signs of financial contagion by observing the lagged pandemic networks. Future research on modelling longitudinal pandemic and financial networks simultaneously is worthy of study.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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