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

Amanda M.Y. Chu1 | Lupe S.H. Chan2 | Mike K.P. So2

1Department of Social Sciences, The Education University of Hong Kong, Hong Kong
2Department of Information Systems, Business Statistics and Operations Management, The Hong Kong University of Science and Technology, Hong Kong

Correspondence
Mike K.P. So, The Hong Kong University of Science and Technology, Hong Kong.
Email: immkps@ust.hk

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INTRODUCTION

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
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 $i$th 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 $R^{(S)}_t = [R_{1t}, R_{2t}, \ldots, R_{Nt}]^T$, and the vector of returns of the last $G$ benchmark market indices by $R^{(M)}_t = [R_{N+1t}, R_{N+2t}, \ldots, R_{N+Gt}]^T$. In this paper, the vector $R^{(S)}_t$ 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 $R_t = \begin{bmatrix} (R^{(S)}_t)^T & (R^{(M)}_t)^T \end{bmatrix}$, the covariance matrix can be expressed into the blocked matrix

$$
\text{Cov}(R_t) = \begin{bmatrix}
\text{Cov}(R^{(S)}_t) & \Sigma_{SM} \\
\Sigma_{MS} & \text{Cov}(R^{(M)}_t)
\end{bmatrix},
$$

where

$$
\Sigma_{SM} = \begin{bmatrix}
\sigma_{1(N+1)t} & \sigma_{1(N+2)t} & \cdots & \sigma_{1(N+G)t} \\
\sigma_{2(N+1)t} & \sigma_{2(N+2)t} & \cdots & \sigma_{2(N+G)t} \\
\vdots & \vdots & \ddots & \vdots \\
\sigma_{N(N+1)t} & \sigma_{N(N+2)t} & \cdots & \sigma_{N(N+G)t}
\end{bmatrix}.
$$
and \( \sigma_{ij} = \text{Cov}(R_t^i, R_t^j) \). From the above expression, we can obtain the partial covariance matrix of \( R_t^{(S)} \) given \( R_t^{(M)} \) as 
\[
\Sigma_{S|M,t} = \text{Cov}(R_t^{(S)} | R_t^{(M)}) = \Sigma_{S|S,t} - \Sigma_{S|M,t}\Sigma_{M|S,t}^{-1}\Sigma_{M|S,t},
\]
where \( \Sigma_{S|S,t} = \text{Cov}(R_t^{(S)}) \) and \( \Sigma_{M|M,t} = \text{Cov}(R_t^{(M)}) \). After standardizing \( \Sigma_{S|M,t} \), we obtain the desired partial correlation matrix, \( \rho_{S|M,t} \).

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 \( R_t^{(S)} \) given \( R_t^{(M)} \), 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 correlation matrix at time \( t \). Effectively, for a window of width \( w \), we estimate the partial correlation matrix at time \( t \) for \( t = w, w + 1, ..., T \) by calculating the sample covariance matrix, \( \Sigma_{S|S,w,t} = \frac{1}{T-w-w} \sum_{s=t-w}^{t}(R_s^{(S)} - \bar{\mu}_t^{(S)})(R_s^{(S)} - \bar{\mu}_t^{(S)})^\top \), where \( \bar{\mu}_t^{(S)} \) is the sample mean of \( R_s^{(S)} \), \( s = t - w + 1, ..., t \). Similarly, we calculate the sample estimates \( \Sigma_{S|M,w,t} \) and \( \Sigma_{M|M,t} \) based on the window of \( w \) observations \( R_s^{(S)} \) and \( R_s^{(M)} \), respectively, for \( s = t - w + 1, ..., t \). Then, the partial correlation and the partial correlation matrix \( \rho_{S|M,t} \) can be estimated by 
\[
\hat{\rho}_{S|M,t}(w) = \frac{\hat{\Sigma}_{S|M,w,t} - \hat{\Sigma}_{S|M,1,t}\hat{\Sigma}_{M|M,1,t}}{\hat{\Sigma}_{S|S,1,t}^{1/2}\hat{\Sigma}_{M|M,1,t}^{1/2}}.
\]
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
\[
A_{ij} = \begin{cases} 
1 & \text{if } |\hat{\rho}_{S|M,t}(w)_{ij}| > r, \\
0 & \text{otherwise},
\end{cases}
\]
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 \( A_{ij,t} \equiv 0 \) for convention.

### 2.2 Data source

To construct these dynamic financial networks, we collect from Bloomberg the adjusted closing prices \( P_t^i, i = 1,...,N; t = 1,...,T \) 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 \( t \), \( t = 1,2,...,T \). 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 \( (R_t, i = 1,...,N; t = 1,...,T) \). 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 \( \Sigma_{S|M,t} \) for \( t = w, w + 1, ..., T \), 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 (Agharian 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.
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

### 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                                 |
|              | 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       | FTSEMI     | FTSE Milano Indice di Borsa Index              |
|              | Netherlands | AEX        | Amsterdam Exchange Index                       |
|              | Poland      | WIG20      | Warszawski Indeks Gieldowy 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       |
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 $t$, $A_t = [A_{ij}^t]_{N \times N}$. The network is a continuous time stochastic...
process defined on the time domain $T := [t_0, t_m]$ with the discrete states in the edges represented by $A_t \in \{0, 1\}^{N_t \times N_t}$ at each time $t \in T$, 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 $t \in T$, only one edge variable $A_k, t$ can change. Assume that $[A_k, t] \in [t_0, t_m]$ 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 $\lambda_1$ be 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 $t \in T$, only one edge variable $A_k, t$ can change. Assume that $[A_k, t] \in [t_0, t_m]$ 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 $A_{t_{m-1}}$.

In the second microstep, the selected actor may create or drop one edge, or make no change. Let $A_{\mathcal{I}}$ be the candidate network $A_{\mathcal{I}}$ given by

\[
\lambda_i(x; \rho_m) = \rho_m \exp \left( \frac{\sum_{k=1}^K a_k(\alpha(x))}{\lambda_i(x; \rho_m)} \right),
\]

where $a_k(x)$ denotes the $k$th statistics of actor $i$ determining the characteristics of the $i$th actor in network $x$ and $a_k$ is the coefficient indicating dependence on the statistics $a_k(x_i)$, $i = 1, \ldots, N_t$. 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 et al., 2007)

\[
P(\text{actor } i \text{ is selected}) = \lambda_i(x; \rho_m),
\]

where $\lambda_i(x; \rho_m) = \sum_{k=1}^N \lambda_i(x; \rho_m)$. 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

\[
P(\text{actor } i \text{ is selected}) = \frac{\lambda_i(x; \rho_m)}{\lambda_i(x; \rho_m)} = \frac{\rho_m}{\sum_{i=1}^N \rho_m} = \frac{1}{N_t},
\]

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 $x^{\#} \in \{0, 1\}^{N_t \times N_t}$ be the candidate network which is identical to $x$ except for the edge $A_{\mathcal{I}}$. The decision of actor $i$ to make a change from $x$ to $x^{\#}$ is based on utility theories suggesting that the action will be decided by maximizing the following utility function

\[
U_i(x^{\#}, v; \beta) = f_i(x^{\#}, v; \beta) + \epsilon_i,
\]

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

\[
p_0 = \frac{\exp(f_i(x^{\#}, v; \beta))}{\sum_{x} \exp(f_i(x^{\#}, v; \beta))},
\]

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

\[
f_i(x^{\#}, v; \beta) = \sum_{k=1}^K \beta_k s_k(x^{\#}, v),
\]

where $s_k(x^{\#}, v)$’s are the $K$ effects of the networks, which depend on the candidate network $x^{\#}$ and the covariates $v$ only, and $\beta \in \mathbb{R}^K$ is a vector of parameters. We specify below various choices for the effects based on the data.

\footnote{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 $s_t(x^{\text{it}}, v)$. The following effects depend only on the network configurations, which are (1) density effect (degree in RSiena, the SIENA in R), defined as $s_1(A_t, v) = A_{t+1}^i$, where $A_{t+1} = \sum A_{t+1i}$; (2) transitive triads effect (transTriads in SIENA), defined as $s_2(A_t, v) = \sum_{k,t} A_{t+1i} A_{t+1j} A_{t+1k}$; (3) out-isolation (outAct in RSiena), defined as $s_3(A_t, v) = I(A_{t+1} - 0)$, and (4) out degree related activity effect (outAct in RSiena), defined as $s_4(A_t, v) = A_{t+1}^2$. To understand the implications of these effects, we can re-write (1) by dividing both the numerator and the denominator by $\exp\{f_t(x^{\text{it}}, v; \beta)\}$:

$$p_i = \frac{\exp\{f_t(x^{\text{it}}, v; \beta)\} - f_t(x^{\text{it}}, v; \beta)}{\sum_{x} \exp\{f_t(x^{\text{it}}, v; \beta)\} - f_t(x^{\text{it}}, v; \beta)} = \frac{\exp\left\{\sum_{k=t-1}^{K} \beta_k (s_k(x^{\text{it}}, v) - s_k(A_t))\right\}}{\sum_{x} \exp\left\{\sum_{k=t-1}^{K} \beta_k (s_k(x^{\text{it}}, v) - s_k(A_t))\right\}}.$$

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

$$\text{LO}(A_t, A_{t+1}^{(\pm)}) = \text{log} \left( \frac{p_i}{1-p_i} \right) = \sum_{k=t}^{K} \beta_k (s_k(A_{t+1}^{(\pm)}) - s_k(A_t)),$$

implying that the difference, $\Delta s_i = s_k(A_{t+1}^{(\pm)}) - s_k(A_t)$, contributes linearly to the log-odds ratio. We now examine how the four $\Delta s_i$, $k = 1, ..., 4$, affect the log-odds ratio.

1. The term in $\text{LO}(A_t, A_{t+1}^{(\pm)})$ relating to the difference in the density is $\beta_1 \Delta s_1$, where $\Delta s_1 = A_{t+1} - A_{t+1}$. If $\beta_1 > 0$, then creating an additional link in the graph $A_{t+1}^{(\pm)}$ increases the log-odds, while deleting a link decreases it. The effect of $\Delta s_1$ is similar to the effect of a categorical variable in linear regressions.

2. The term in $\text{LO}(A_t, A_{t+1}^{(\pm)})$ relating to the difference in the transitive triads is $\beta_2 \Delta s_2$, where $\Delta s_2$ is the number of additional closed triplets created in $A_{t+1}^{(\pm)}$. If $\beta_2 > 0$, creating a link that forms additional triangles in the graph $A_{t+1}^{(\pm)}$ increases the log-odds and encourages the small-world property.

3. The term in $\text{LO}(A_t, A_{t+1}^{(\pm)})$ relating to the difference in the out-isolation is $\beta_3 \Delta s_3$, where $\Delta s_3 = I(A_{t+1}^{(\pm)} - 0) - I(A_{t+1} - 0)$, the number of additional isolated nodes when the graph is changed from $A_t$ to $A_{t+1}^{(\pm)}$. 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 $\text{LO}(A_t, A_{t+1}^{(\pm)})$ relating to the difference in the out degree related activity is $\beta_4 \Delta s_4$, where $\Delta s_4 = (A_{t+1}^{(\pm)})^2 - A_{t+1}$. The purpose of including this effect is to see if the degree of node $i$ itself, $A_{t+1}^{(\pm)}$, affects the log-odds rather than their difference. To understand this effect, consider the change from $A_{t+1} = 0$ in $A_t$ to $A_{t+1}^{(\pm)} = 1$ in $A_{t+1}^{(\pm)}$. Then, we have

$$\Delta s_4 = (A_{t+1}^{(\pm)})^2 - A_{t+1}^2 = (A_{t+1} + 1)^2 - A_{t+1}^2 = 2A_{t+1} + 1.$$

Similarly if $A_{t+1} = 1$ and $A_{t+1}^{(\pm)} = 0$, then $\Delta s_4 = -2A_{t+1} + 1$. 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 $X_{it}$ be the number of confirmed COVID-19 cases of country $i$ in day $t$, $i = 1, 2, ..., 32$ countries. We calculate the daily changes for each country as $Y_{it} = \sqrt{X_{it}} - \sqrt{X_{i,t-1}}$. The sample correlation between country $i$ and country $j$’s daily changes in day $t$, $\hat{\rho}_{ij}$, is calculated using $(Y_{i,t-k}, Y_{j,t-k})$, for $k = 0, ..., 13$. We build the pandemic network at time $t$ by defining $A_{ij}^p$, the $(i,j)$th element of the adjacency matrix ($A_t^p$) of the pandemic network at time $t$:

$$A_{ij}^p = \begin{cases} 1 & \text{if } \hat{\rho}_{ij} > r_p, \\ 0 & \text{otherwise,} \end{cases}$$

where $r_p = 0.5$. Let $E_t^p$ and $V_t^p$ 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

$$D_t^p = \frac{2E_t^p}{V_t^p(V_t^p-1)},$$

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

$$C_t^p = \frac{\sum_{i=1}^{V_t^p} {\binom{k_i}{2}} c_t}{\sum_{i=1}^{V_t^p} k_i(k_i-1)},$$

where $k_i$ is the number of neighbours (or degree) of node $i$, and $c_t = (\text{number of triangles formed by node } i)/{\binom{V_t^p}{3}}$. $C_t^p$ 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

$$AS_t^p = \frac{\sum_{i=1}^{V_t^p} \sum_{j=1}^{V_t^p} \frac{k_i k_j l(A_{ij}^p = 1)}{2V_t^p} - \left[ \sum_{i=1}^{V_t^p} \sum_{j=1}^{V_t^p} \frac{\binom{k_i}{2} k_j l(A_{ij}^p = 1)}{2V_t^p} \right]^2}{\sum_{i=1}^{V_t^p} \sum_{j=1}^{V_t^p} \frac{\binom{k_i}{2} k_j l(A_{ij}^p = 1)}{2V_t^p} - \left[ \sum_{i=1}^{V_t^p} \sum_{j=1}^{V_t^p} \frac{\binom{k_i}{2} k_j l(A_{ij}^p = 1)}{2V_t^p} \right]^2}.$$

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

$$S_{ti} = \alpha_i A_t^p \alpha_t,$$

where $\alpha_i$ 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 networks 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 $\log(1 + 10^9 \times \text{PRS})$, 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 $V_{ib}$, the covariates defined by pandemic network statistics and their lagged values. The pandemic network statistics we consider are the network density, $D_t^p$, the global clustering coefficient, $C_t^p$; the assortativity, $AS_t^p$; and...
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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, \( v_t \), 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 \( v_{t-5} \) 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:

\[
\text{(5) The term in } \text{LO}(A_i, A_j^{(i)}) \text{ relating to the difference of covariate-ego is } \beta_5 \Delta s_{5i}, \text{ where } \Delta s_{5i} = v_{t-5}(A_i^{(i+1)}) - v_{t-5}(A_i^{(i-1)}) - v_{t-5}(A_{i,t}^{(i)}) - v_{t-5}(A_{i,t}^{(i+1)}).
\]

\[
\text{(6) The term in } \text{LO}(A_i, A_j^{(i)}) \text{ relating to the difference of covariate-ego } \times \text{ alter is } \beta_6 \Delta s_{6i}, \text{ where } \Delta s_{6i} = v_{t-5} \sum_i A_{i,t}^{(i)} - v_{t-5} A_{i,t}^{(i)} - v_{t-5} A_{i,t}^{(i+1)} - v_{t-5} A_{i,t}^{(i+2)}.
\]
The number of network connections added or dropped compared to the previous trading day, from February to May 2020

\[ \beta_5 \Delta s_{5t} + \beta_6 \Delta s_{6t} = \beta_5 v_6 (A_{ij}^{[2]} - A_{ij}^{[3]}) + \beta_6 v_6 (A_{ij}^{[4]} - A_{ij}^{[5]}) = (\beta_5 v_6 + \beta_6 v_6 v_6) (A_{ij}^{[4]} - A_{ij}^{[5]}), \]  

(3)

where \( \beta_5 \) and \( \beta_6 \) are unknown parameters corresponding to the covariate effects and \( v_6 \) 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 \( A_{ij}^{[4]} \), in this case, \( A_{ij}^{[4]} - A_{ij}^{[5]} = 1 \). Since we standardize all \( v_6 \) before inputting them to the SAOM for model fitting, the log-odds in (3) due to the pandemic covariates \( v_6 \) and \( v_6 \) can be written as a two-dimensional function of \( v_6 \) and \( v_6 \),

\[ F(v_6, v_6) = \beta_5 \left( \frac{v_6 - \bar{v}_6}{\sigma_v} \right) + \beta_6 \left( \frac{v_6 - \bar{v}_6}{\sigma_v} \right) \left( \frac{v_6 - \bar{v}_6}{\sigma_v} \right), \]  

(4)

where \( \bar{v}_6 \) and \( \sigma_v \) are, respectively, the sample mean and standard deviation of the covariates \( v_6 \). We call \( F(v_6, v_6) \) in Equation 4 the composite effect. Table 3 shows six heat maps of \( F(v_6, v_6) \) to visualize the composite effect of different pandemic network covariates \( v_6 \) and \( v_6 \) 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 \( v_6 \)) of node \( i \) which is given an opportunity to make a change, and the \( y \) axis refers to the covariate (we call it \( v_6 \)) 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 \( v_6 \) and \( v_6 \) 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 \( x \) alter effects described in Section 2.5 are all positive. Similarly, in the global clustering coefficient of the pandemic networks, simultaneously large or small \( v_6 \) and \( v_6 \) 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 \( F(v_6, v_6) \) for significant effects \( v_6 \) 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 \( F(v_6, v_6) \) 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
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 $v_i$ (the network density) in panel (a), $F(v_i, v_j)$ 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, $F(v_i, v_j)$ 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 $F(v_i, v_j)$ 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.

| 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.
| Covariate                      | Lagged effect (I)                                                                 | Lagged effect (II)                                                                 |
|--------------------------------|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Network density                | $F(v_i, v_j)$, where the subscript $t$ is omitted for brevity                     |                                                                                  |
| Global clustering coefficient  | $F(v_i, v_j)$, where the subscript $t$ is omitted for brevity                     |                                                                                  |
| Assortativity                  | $F(v_i, v_j)$, where the subscript $t$ is omitted for brevity                     |                                                                                  |
| Transformed PRS                | $F(v_i, v_j)$, where the subscript $t$ is omitted for brevity                     |                                                                                  |

Note: All heatmaps use the same colour scale.
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 modeling 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.

ORCID
Amanda M.Y. Chu https://orcid.org/0000-0002-9543-747X
Mike K.P. So https://orcid.org/0000-0003-0781-8166

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