

Risk contagion of COVID-19 on Japanese stock market: A network approach

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Abstract

Coronavirus disease (COVID-19) is one of the worst pandemics throughout human history. From a financial perspective, our study aims to assess the contagion effect of COVID-19 on the financial markets. First, this study proposes a susceptible-infected-recovered-dead model of COVID-19 and analyzes the spread of the infection in Japan. Second, it analyzes the impact of COVID-19 on the Japanese stock market through correlation and network analyses of the Tokyo Stock Exchange Sector Indices. Finally, in financial terms, this study finds that the analyses of the interconnectedness between an infection network such as COVID-19 and financial networks can contribute to extant knowledge on pandemic risk management.

Keywords: COVID-19; financial markets; risk contagion; complex network; susceptible-infected-recovered-dead model

JEL classification: C51; G32; G10; D85; L14.

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1. Introduction

In February 2020, an outbreak of the coronavirus disease (COVID-19) occurred in the Diamond Princess, a cruise ship with 3,711 passengers and crew on board, and a total of 712 people were confirmed positive for COVID-19. After collecting the specimens at the common spaces and rooms of the ship, SARS-CoV-2 RNA was detected in a real-time polymerase chain reaction (RT-PCR) by the National Institute of Infectious Diseases, Japan (NIID, 2019).

In contrast, COVID-19 originating from Wuhan in China has spread worldwide. As of March 11, 2020, the World Health Organization (WHO) officially categorized the COVID-19 outbreak as a global pandemic (WHO, 2020). COVID-19 has already affected three correctional facilities in Osaka, Tokyo, and Hokkaido in Japan, where a total of 10 people have tested positive, placing both jail staff and inmates at risk. Authorities and rights groups believe that an exponential spread of the virus in such facilities would eventually lead to staff shortages and problems in accessing medical care.

Prime Minister Shinzo Abe declared a state of emergency for 1 month from April 7, 2020, covering Tokyo, Osaka, and five other prefectures amid the growing COVID-19 outbreak, which will empower prefectures to take restrictive measures. The others also cover the Kanagawa, Saitama, Chiba, Hyogo, and Fukuoka prefectures. However, after 1 month, the state's situation did not adequately improve.

Therefore, as of May 4, 2020, the Japanese government has encouraged residents to maintain a "new lifestyle" even after the restrictive measures over COVID-19 have been relaxed following Prime Minister Abe's extension of the nationwide state of emergency to the end of May 2020. The renewal of the state of emergency was not well received by workers in the hospitality, tourism, and other industries, and they have appealed to the government for more financial support. As a result, Japan is attempting to adapt to the new reality, with the Ministry of the Environment preparing to provide subsidies to help restaurants introduce high-performance ventilation systems to reduce COVID-19 infectious risk, regional chambers of commerce coming up with creative ways to help maintain local businesses and firms by developing contactless technology to help with the pandemic.

As of May 1, 2020, according to Johns Hopkins University data, the US is ranked the first in number of COVID-19 infections globally, with over one million patients. In contrast, Japan is ranked twenty-ninth globally, with only

14,027 infections. However, considering a small nation's land, the "three Cs" such as closed spaces, crowded spaces, and close-contact settings that must be avoided.

Using TOPIX Sector Indices¹, we analyze the interconnectedness between Japanese stock return and COVID-19.

The rest of this paper organized as follows. Section 2 reviews the literature on pandemic mathematical modeling and an application of a complex network to finance. Section 3 contains analyses on the spread of COVID-19 infection in Japan. Section 4 presents an analysis of the network structures of the Japanese stock market. Section 5 concludes.

2. Literature review

Goodell (2020) gave us the courage and motivation to study the relationship between COVID-19 and finance. Goodell (2020) considers the possible impacts of COVID-19 on financial markets and institutions, either directly or indirectly, and briefly outlined this by drawing on a variety of literature.

This study contributes to pandemic-related systemic risk literature in the financial market. Network science is a highly effective approach for examining the impact of COVID-19 on stock market investments. A complex network uses sets of "nodes" connected by "edges." In a COVID-19 network, a node represents a susceptible, infected, recovered, or dead person, and an edge represents the infectious relationship between two entities. Based on a correlation analysis, Zhang et al. (2020) investigated the systemic connections among the 12 countries using graph theory and the minimum spanning tree (MST) method, which connects all the nodes in a graph with the minimum possible total edge weight and with no loops.

Concerning an application of complex network to finance, Kanno (2015a) published one of the first articles in the systemic risk literature during the global financial crisis. The study by Kanno (2015b) is the first to apply infectious disease modeling to the financial market. This study assessed the network structure of bilateral exposures in the Japanese interbank market using modified susceptible-infected-removable (SIR) models. One of the study's relevant findings is that, after the global financial crisis, the contagious threshold for out-degree is almost unchanged, but that for in-degree has

¹They are created by dividing TOPIX constituents into the 33 industrial sectors defined by the Securities Identification Code Committee (SICC).

increased by 10%. This increase implies that contributors or contributions to the systemic risk of the Japanese interbank market have increased.

Concerning the relationship between pandemic and banking stability, Lagoarde-Segot and Leoni (2013) develop a theoretical model that shows that the likelihood of the collapse of a developing country's banking industry increases as the joint prevalence of large pandemics, such as AIDS and malaria, increases.

On pandemic modeling, this study investigates pandemic mathematical modeling and mentions the literature on infectious disease such as pandemic including COVID-19. Mathematical and complex network models have increasingly been used to analyze infectious disease control. The main applications of such models include predicting the impact of vaccination strategies against common infections and determining the optimal control strategies against an epidemic or pandemic.

Two books pertaining to an introduction of infectious disease modeling are mentioned. Vynnycky (2010) provides an introduction to infectious diseases toward nonspecialists to the growing field of mathematical epidemiology. In contrast, Brauer et al.(2019) provides a comprehensive, self-contained introduction to the mathematical modeling and analysis of disease transmission models, including a detailed analysis of models for important specific diseases such as tuberculosis, HIV/AIDS, influenza, Ebola virus disease, malaria, dengue fever, and the Zika virus. Kiss et al. (2018) provides the network science featuring a stronger and more methodical link of models to their mathematical origin and explains how these relate to each other with a special focus on epidemic spread on networks. In addition, the book includes the interface of graph theory, stochastic processes, and dynamical systems.

3. Impact of COVID-19 in Japan

In this section, this study explores the infectious situation of COVID-19 in Japan.

3.1. Positive rates

Testing more people for the novel COVID-19 provides more details on infection rates and enables us to grasp the scale of the COVID-19 cases in Japan. So far, Japan has conducted polymerase chain reaction (PCR) tests on more than 130,000 people for COVID-19, a much lower number than

many other countries including South Korea, which had conducted more than 520,000 tests by April 14.

Currently, the Ministry of Health, Labor, and Welfare provides data on the number of people who have tested positive divided by the number of tests conducted nationwide. However, it is emphasized that positive rates are not precise, as the number of PCR tests on the denominator relate to the dates the tests were conducted, and the number on the numerator relates to the dates the results were acquired; moreover, there is no consistency in the rate's calculation rule. The mean positive rates for the twelve prefectures ranked higher from March 11, 2020, to May 1, 2020, and are shown in the Figure 5. The average for all prefectures is 5.36%. Osaka, Chiba, and Tokyo are at an especially high level, reaching above 20%.

The state of emergency measure is conducted for all prefectures until the end of May 2020. In addition, the 13 prefectures, Tokyo, Osaka, Hokkaido, Ibaraki, Saitama, Chiba, Kanagawa, Ishikawa, Gifu, Aichi, Kyoto, Hyogo, and Fukuoka are designated as “specific alert prefectures”² since May 4, 2020. However, there are some gaps in our calculation and designated prefectures. On the rate of positive COVID-19 cases, 4 prefectures such as Ibaraki, Gifu, Nara, and Fukuoka were classified with factors (e.g., geography and closed spaces).

3.2. Susceptible-infected-recovered-dead model

SIS and SIR models are the representative infectious disease models. SIS model stands for susceptible-infected-susceptible. The idea is that a node (i.e., a person) can be in one of two states: it is infected or it is not infected but susceptible to becoming infected. This model is a variation on the seminal model in the literature, the SIR model. In the SIR model, the diffusion takes place between infected and susceptible nodes (persons). Once a person reaches the removed state, the person has either recovered and is no longer susceptible or contagious, or it has died. In contrast, in the SIS model, persons can become infected and then recover in a way that they become susceptible again, rather than being considered cured. This type of model applies to certain, nonfatal diseases with not being severe, but it is also useful as a first approximation of the models of behavior in which individuals are

²They are especially areas to be considered for the need to conduct infectious disease prevention measures.

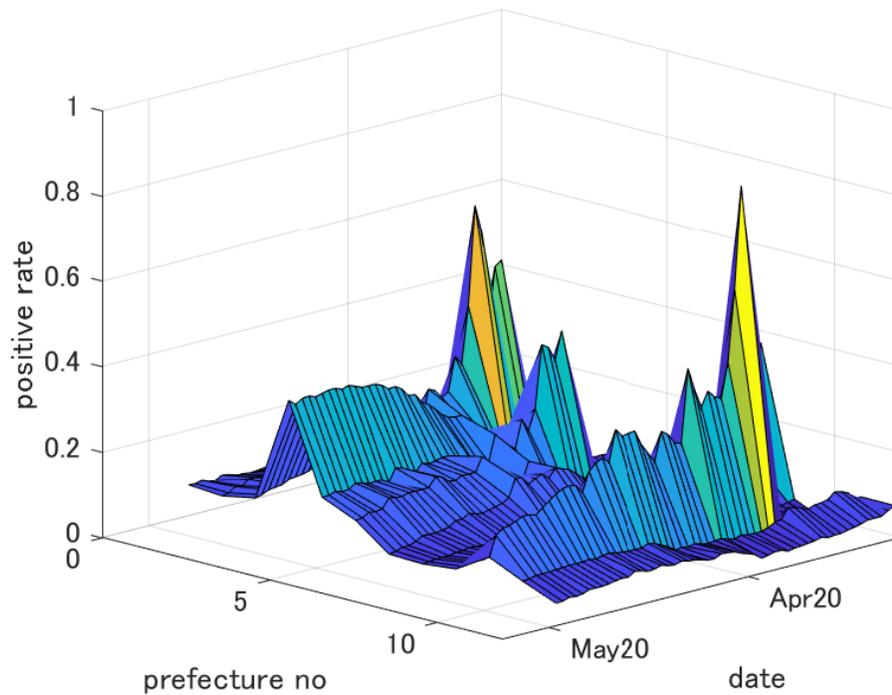


Figure 1: Positive rate curves pertaining to COVID-19 for twelve prefectures ranked higher from March 11, 2020, to May 1, 2020

Notes: Each line shows the higher ranked prefecture's positive rate. Prefecture number is designated as follows: 1: Hokkaido; 2: Saitama; 3: Chiba; 4: Tokyo; 5: Kanagawa; 6: Ishikawa; 7: Fukui; 8: Aichi; 9: Kyoto; 10: Osaka; 11: Hyogo; 12: Nara.

more likely to undertake a given action as more of their neighbors do the same, but then can also randomly stop doing the action with the possibility of performing the action again (Jackson, 2010).

Both models are, however, unsuitable for modeling COVID-19 as infected patients who have preexisting diseases, which tend to become severe, can result in patients' sudden death in a shorter time. Thus, the susceptible-infected-recovered-dead (SIRD) model is adapted in our study (Vynnycky, 2010). This model was also adopted in our study of systemic risk pertaining to the Japanese interbank market (Kanno, 2015b). The SIRD model has four compartments³ model, which has four states of susceptible (S), infected (I), recovered (R), and dead (D) (Figure 2).

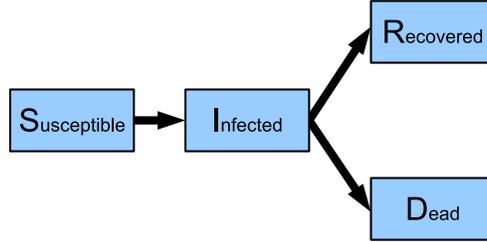


Figure 2: Illustration of SIRD model

As an assumption, the total of the referenced population is constant (e.g., $N = 124$ million in Japan and $N = 13.3$ million in Tokyo) for each state for the period considering both birth and death rates pertaining to COVID-19 in the compartment. It is especially applicable for low fatality diseases with so large outbreak. In addition, we assume that the recovered person cannot be reinfected.

The dynamics of the SIRD model's compartments is then modeled by ordinary differential equations as follows:

$$\frac{dS_t}{dt} = -\beta_t \frac{I_t}{N} S_t, \quad \frac{dI_t}{dt} = \beta_t \frac{I_t}{N} S_t - \gamma_t I_t - \delta_t I_t, \quad \frac{dR_t}{dt} = \gamma_t I_t, \quad \frac{dD_t}{dt} = \delta_t I_t, \quad (1)$$

³The term of "compartment" comes from the fact that the model population is stratified into broad subgroups (compartments) such as those who are susceptible and infectious. The model describes transmission of the infection using the total number of individuals in these categories.

where initial values at time $t = 0$, i.e., S_0 , I_0 , R_0 , and D_0 satisfy the following equation. $S_0 + I_0 + R_0 + D_0 = N$ ($N = \text{population}$). S_0 , I_0 , R_0 , D_0 , and N are obtained from the data published by each prefecture and the Ministry of Health, Labor and Welfare in Japan.

3.3. Parameter modeling

The modeling parameters in equation (1) need to be modeled for the calibration (i.e., optimization) described in Subsection 3.4 (Caccavo, 2020).

Infection parameters: β . The propagation rate β is used as a fitting parameter to describe infectious data. The number of infections per person per unit of time can decrease during the COVID-19 pandemic and is described by the following equation:

$$\beta_t = \beta_0 \exp\left(-\frac{t}{\tau_\beta}\right) + \beta_1, \quad (2)$$

where β_0 is the initial infection that decreases exponentially owing to some measures. β_1 is the infection at the infinite time which can be set to zero. τ_β is the characteristic decrease of time.

Recovery parameters: γ . The recovery rate γ may be time dependent, but whether it has linearity or not is unknown. In terms of doctors and drugs, as the resources treating COVID-19 are inadequate, recovery time is quite difficult to predict. Therefore, γ is modeled using a logistic function as

$$\gamma_t = \gamma_0 + \frac{\gamma_1}{1 + \exp(-t + \tau_\gamma)}. \quad (3)$$

Death parameters: δ . Considering the deaths caused by COVID-19, the number of deaths is currently increasing and its function time dependent, but this will decrease with time when new treatment methods are developed. Hence, the exponential decay function is adopted as follows:

$$\delta_t = \delta_0 \exp\left(-\frac{t}{\tau_\delta}\right) + \delta_1. \quad (4)$$

γ_1 and τ_γ can be decreased to reduce the number of parameters if the recovery function is a monotonic increasing function without a regime. This decision is explained in Subsection 3.4 of the optimization later.

Basic reproduction number: \mathcal{R}_0 . In epidemiology, the basic reproduction number is heuristically defined to be the average number of new infections caused by individuals that are infected shortly after disease introduction in a completely susceptible population (Anderson and May, 1992; Kiss et al., 2018). In case of $\mathcal{R}_0 > 1$, the infection results in the spreading, but not in case $\mathcal{R}_0 < 1$.

The reproduction number is obtained setting $i := I/N$ in equation (1) as follows:

$$\frac{di_t}{dt} = \beta_t \frac{i_t}{N} S_t - (\gamma_t + \delta_t) i_t. \quad (5)$$

As the number of infected persons increases, $di_t/dt > 0$, $\forall t > 0$ then needs to be satisfied as

$$\mathcal{R} := \frac{\beta_t}{\gamma_t + \delta_t} \frac{S_t}{N} > 1. \quad (6)$$

Hence, because $S_0/N \approx 1$ at $t = 0$ is true for a large population with relatively low cases of infections, \mathcal{R}_0 is approximated as

$$\mathcal{R}_0 := \frac{\beta_t}{\gamma_t + \delta_t} \frac{S_0}{N} \approx \frac{\beta_0}{\gamma_0 + \delta_0} > 1. \quad (7)$$

3.4. Optimization

Using MATLAB 2019a software, the programming of the SIRD model and the calibration (i.e., optimization) of the model parameters have been conducted. The optimization is based on the minimization of the residuals between the model's objective function and officially published epidemiological data. After several trials, γ_1 and τ_γ in equation (3) are set to zero.

The calibration results of model parameters and the basic reproduction numbers are shown in Table 1. As shown in Table 1, the basic reproduction numbers in Japan nationwide and Tokyo are higher than that announced by the Japanese government.⁴

⁴According to a suggestion in the “Novel Coronavirus Expert Meeting” of the government, the nationwide basic reproduction number is 2 as of March 25, 2020, but has been reduced to 0.7 as of April 10, 2020, after the declaration of a state of emergency. In contrast, as of March 14, 2020, when Tokyo's infected persons increased, the number became 2.6 and thereafter reduced to 0.5 as of April 10, 2020.

Table 1: SIRD model parameters and basic reproduction number \mathcal{R}_0 , obtained from an optimization

parameter	β_0	β_1	τ_β	δ_0	δ_1	τ_δ	γ_0	\mathcal{R}_0
Japan	0.126	0	20	0.01	0.007	25	0.0015	4.091
Tokyo	0.143	0	20	1.63×10^{-14}	0.011	16.2	0.0015	5.882

Figures 3–4 indicate the results estimated using the SIRD model in Japan nationwide and Tokyo from March 18, 2020, to May 7, 2020. The lower-right panel in both figures indicates the time decay of infection, death, and daily recovery rate. In the panel of Figure 4, the death rate is constant as well as the initial recovery rate.

4. Impact of COVID-19 on Japanese stock market

This section describes the analyses pertaining to the correlation and network structures of the Japanese stock market. The analyses are conducted using the data of TSE Sector Indices⁵ returns in the Japanese stock market.

4.1. Correlation analysis

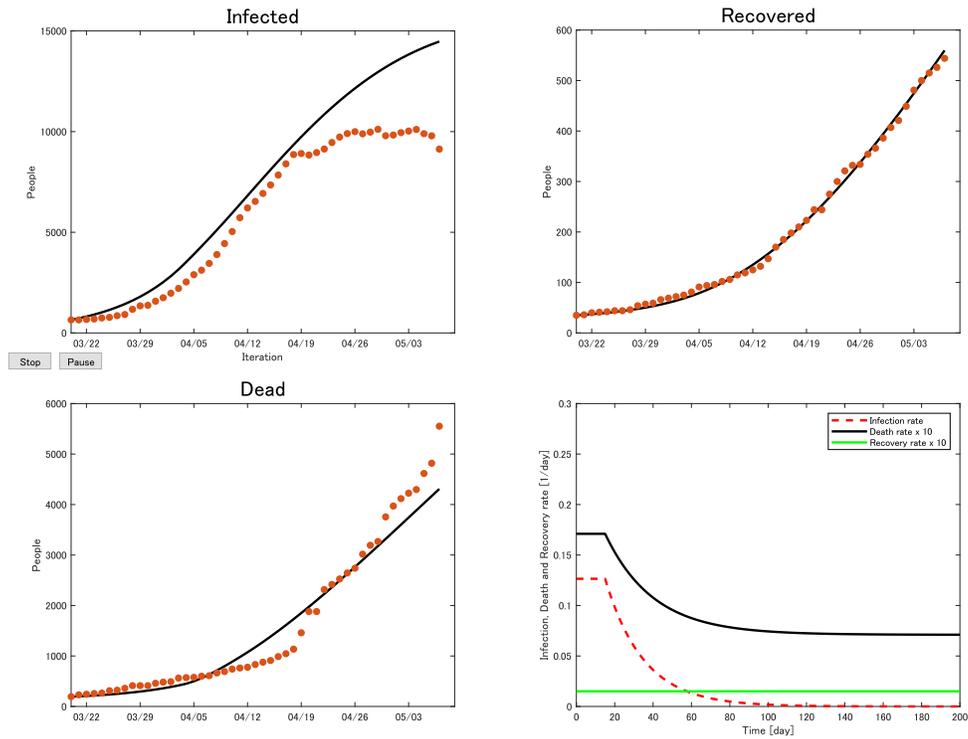
One of the best ways to understand the relationships among firms is to consider how their stock sector index prices are correlated. It is common that firms operating in the same sector show similar price fluctuations.

Connecting the pairwise TSE-listed firms according to the correlation between their prices, a correlation structure of their stocks can be defined. The correlation $\rho_{ij}(\Delta t)$ between these returns, i.e., i and j , over time Δt (e.g., 1 day) is computed as follows:

$$\rho_{ij}(\Delta t) = \frac{E[p_i p_j] - E[p_i]E[p_j]}{\sqrt{(E[p_i^2] - E[p_i]^2)(E[p_j^2] - E[p_j]^2)}}, \quad (8)$$

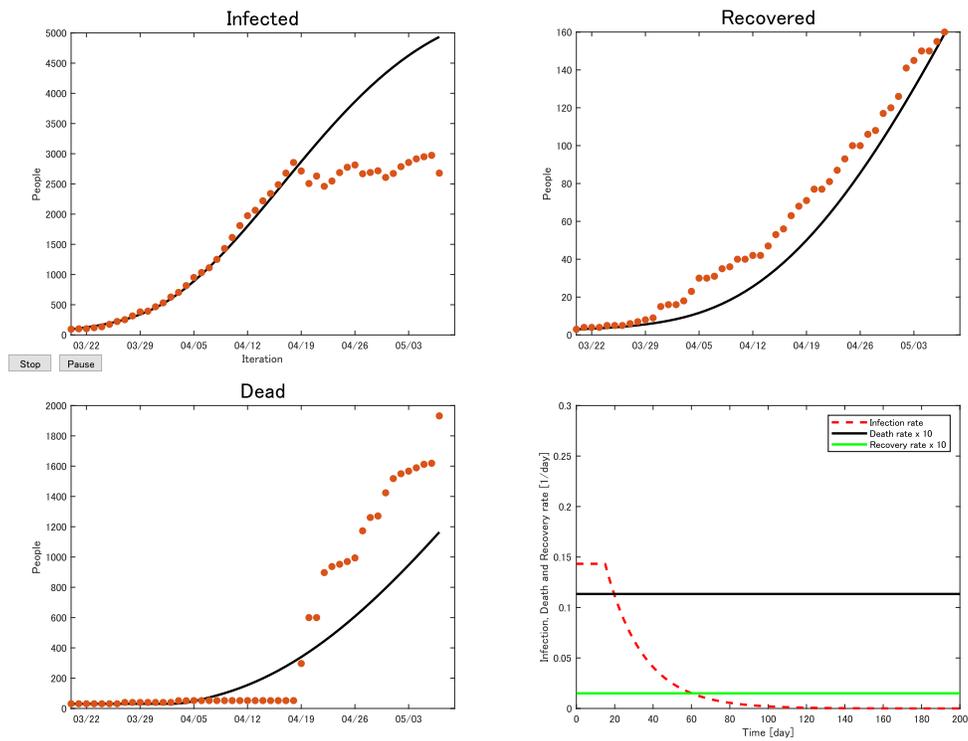
⁵The TOPIX Sector Indices consists of indexes created by dividing the constituents of TOPIX into 33 categories according to the industrial sectors defined by the Securities Identification Code Committee (SICC).

Figure 3: Japan's COVID-19 curves estimated by SIRD model



Notes: The four panels present compartment graphs for infected persons and recovered persons from the upper-left panel to the upper-right panel and deaths and time decay from the lower-left panel to the lower-right panel for the period from March 18, 2020, to May 7, 2020.

Figure 4: Tokyo's COVID-19 curves estimated by the SIRD model



Notes: The four panels present compartment graphs for infected persons and recovered persons from the upper-left panel to the upper-right panel and deaths and time decay from the lower-left panel to the lower-right panel for the period from March 18, 2020, to May 7, 2020.

where the entry can be associated with a metric distance through the following relation (Caldarelli, 2013):

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}. \quad (9)$$

This distance takes a value between 0 and 2, and, for example, if $\rho_{ij} = 0.5$, then $d_{ij} = 1$.

Figure 5 indicates that the TSE index returns from January 1, 2020, to May 1, 2020. Apparently, there is the structural break among the stock index return fluctuations owing to WHO's global pandemic declaration as of March 11, 2020. As shown in the upper panel of Table 2, the linear correlation before WHO's global pandemic declaration is 81% high, whereas, as shown in the lower panel of Table 2, the correlation after the declaration is slightly lower at 75%. In addition, the number of correlation coefficients over 0.9 significantly changes from 96 to 65. These facts indicate the existence of the sudden variation of Japanese stock market owing to the spread of the COVID-19 infection.

Table 3 denotes the ranking of sector indexes in terms of mean, standard deviation, and the Sharpe ratio for the period since January 1, 2020. The Sharpe ratio is the expected return earned in excess of the risk-free rate per unit of volatility or total risk. Volatility measures the price fluctuations of an asset or portfolio. In our study, a newly issued 10-year Japanese government bond yield is used as a risk-free rate. However, as its yield is recently negative, the zero rate or a little positive rate is applied as the risk-free rate. In terms of mean and standard deviation, Air Transportation, Marine Transportation, Textiles and Apparels, Wholesale Trade, and Real Estate, as well as Iron and Steel and Rubber Products industries are in the top 10. The former industries relate to dense human contacts resulting in the infection of COVID-19, whereas the latter is related to the low demand of the automobile industry.⁶

In contrast, in terms of the Sharpe ratio's decrease, Pharmaceutical, Information & Communication, Precision Instruments, and Electric Appliances are ranked in the top ten. Particularly, pharmaceutical firms are rethinking

⁶On May 12, 2020, Toyota Motor Corporation released its earnings for financial year 2020 ending March 31, 2021 and predicted that the annual profit for 2021 would drop by 80%.

their business plans to handle COVID-19. As the remaining industries are typical manufacturing industries, they are largely affected by the activities of other industries and social environment.

The following time-series correlation matrix, $\rho_{ij}(\Delta t)$, represents the relationships between the stock return of i and j :

4.2. Network analysis

This subsection analyzes the change of the network structure of Japanese stock market around WHO's global pandemic declaration on March 11, 2020. This analysis is based on a two-correlation matrix calculated in the correlation analysis of Subsection 4.1.

Because a correlation coefficient has no direction, its analysis results in an undirected graph. In addition, all the edges count the same in degree definitions, but the extension of the degree is conducted by adding the weights of the edges rather than their number. The weighted degree counting weights of edges a_{ij}^w between two nodes i and j is then defined as

$$k_i^w = \sum_{j=1}^n a_{ij}^w, \quad (10)$$

where, in an undirected graph, a_{ij}^w equals to a_{ji}^w .

Table 4 and Figure 6 indicate weighted degrees and the undirected graphs of the TSE sector network around WHO's global pandemic declaration as of March 11, 2020, respectively. The upper panel of Figure 6 is an undirected graph before the declaration and the lower panel of Figure 6 is one after the declaration. Different from degree-based network graphs, the edges correspond to correlation coefficients not holding exposures. Because the mean of weighted degrees between the correlations increased and their standard deviation decreased after the declaration, the connections (i.e., correlations) among specified industries have become stronger than after its declaration. In addition, the weighted-degree reduced in only in real estate industry.

Minimum spanning tree. Figure 6 draws all edges between nodes, and hence it is not easy to understand the correlation relationship between nodes. By contrast, a spanning tree of that graph is a subgraph that is a tree and connects all the nodes together. A single graph can have many different spanning trees. A minimum spanning tree (MST) for a weighted, connected, and undirected graph is a spanning tree with weight less than or equal to

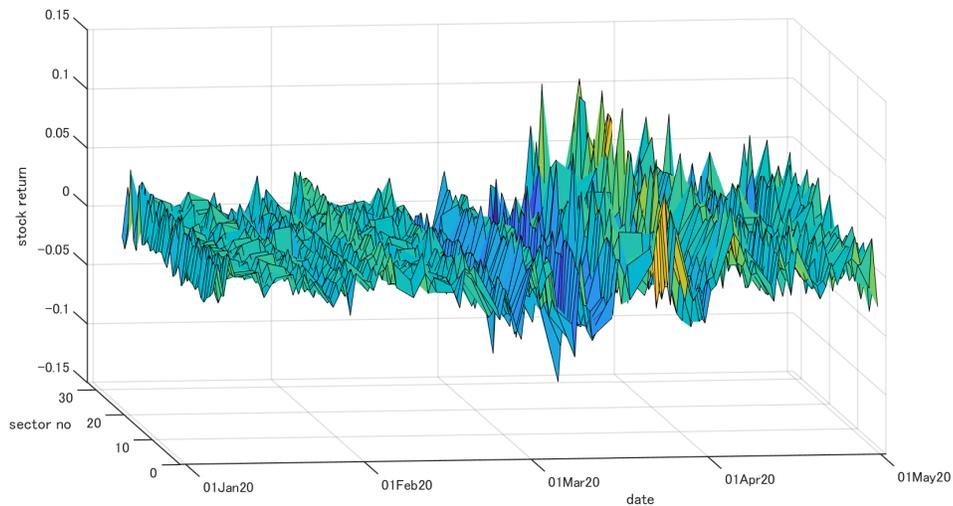


Figure 5: TSE index returns from January 1, 2020, to May 1, 2020

Notes: Each line shows TOPIX Sector Index return. The “sector no” is as follows: 1: Electric Appliances, 2: Information & Com., 3: Chemicals, 4: Transport Equipment, 5: Pharmaceutical, 6: Services, 7: Banks, 8: Machinery, 9: Retail Trade, 10: Wholesale Trade, 11: Land Transport, 12: Foods, 13: Construction, 14: Precision Instruments, 15: Other Products, 16: Real Estate, 17: Insurance, 18: Electric Power and Gas, 19: Other Financing Business, 20: Securities and Commodities Futures, 21: Glass and Ceramics Products, 22: Nonferrous Metals, 23: Rubber Products, 24: Iron and Steel, 25: Metal Products, 26: Textiles and Apparels, 27: Oil and Coal Products, 28: Air Transport, 29: Pulp and Paper, 30: Mining, 31: Warehousing and Harbor Transport, 32: Marine Transport, 33: Fishery, Agriculture & Forestry.

Table 3: TSE Sector Indices ranking in terms of worsening condition: mean, standard deviation, and Sharpe ratio

R	mean			standard deviation			Sharpe ratio		
	Period-1	Period-2	Total period	Period-1	Period-2	Total period	Period-1	Period-2	Total period
1	24:Iron and Steel 32:Marine Transp.	28:Air Transp. 24:Iron and Steel	24:Iron and Steel 28:Air Transp.	32:Marine Transp. 23:Rubber P.	28:Air Transp. 32:Marine Transp.	32:Marine Transp. 28:Air Transp.	2:Info. & Com. 14:Precision Instr.	15:Other P. 29:Pulp and Pa-	5:Pharmaceutical 2:Info. & Com.
2	30:Mining	19:Other Financ- ing Business	30:Mining	16:Real Estate	26:Textiles and Apparels	16:Real Estate	5:Pharmaceutical	33:Fishery, Agri. & Forestry	29:Pulp and Pa- per
3	22:Nonferrous Metals	16:Real Estate	32:Marine Transp.	28:Air Transp.	10:Wholesale Trade	26:Textiles and Apparels	19:Other Financ- ing Business	18:Electric Power and Gas	18:Electric Power and Gas
4	7:Banks	30:Mining	22:Nonferrous Metals	10:Wholesale Trade	16:Real Estate	10:Wholesale Trade	16:Real Estate	5:Pharmaceutical	14:Precision Instr.
5	28:Air Transp.	26:Textiles and Apparels	26:Textiles and Apparels	25:Metal P.	17:Insurance	23:Rubber P.	1:Electric Appli- ances	9:Retail Trade	12:Foods
6	27:Oil and Coal P.	10:Wholesale Trade	7:Banks	15:Other P.	23:Rubber P.	17:Insurance	20:Sec. and Com- modities Futures	8:Machinery	15:Other P.
7	26:Textiles and Apparels	4:Transp. Equip- ment	21:Glass and Ce- ramics P.	14:Precision Instr.	27:Oil and Coal P.	27:Oil and Coal P.	6:Services	12:Foods	1:Electric Appli- ances
8	21:Glass and Ce- ramics P.	32:Marine Transp.	25:Metal P.	2:Info. & Com.	29:Pulp and Pa- per	25:Metal P.	12:Foods	2:Info. & Com.	3:Chemicals
9	33:Fishery, & Forestry	17:Insurance	16:Real Estate	17:Insurance	30:Mining	30:Mining	3:Chemicals	11:Land Transp.	9:Retail Trade

Notes: Abbreviations: R: Ranking; P.: Products; Agri.: Agriculture; Instr.: Instruments; Sec.: Securities; Transp.: Transportation. Period-1 indicates the period from January 1, 2020, to March 10, 2020. Period-2 indicates the period from the date of the WHO's declaration of the pandemic, March 11, 2020, to May 1, 2020. Total period indicates Period-1 plus Period-2.

the weight of every other spanning tree. The weight of a spanning tree is the sum of weights given to each edge of the spanning tree (Caldarelli, 2007).

Figure 7 indicates that the number of subgraphs reduced from 5 to 4 around WHO’s declaration; specifically, the centered subgraph has become larger and explicitly represents systematic returns variation characteristics. In addition, small subgraphs indicate that the clustering of stocks correspond to related industries (i.e., sets of (Fishery, Agriculture & Forestry, Marine Transport, Oil and Coal Products) and (Iron and Steel, Nonferrous Metals, Securities and Commodities Futures, Electric Power and Gas)).

Table 4: Weighted-degrees around WHO’s declaration

	before	after
Mean	23.5	25.7
Standard deviation	2.4	1.9

5. Conclusions

Our study contributes to the literature by assessing a contagion effect of COVID-19 on the Japanese stock market. First, we proposed a SIRD model of COVID-19 and analyzed the infectious expansion pertaining to Japan nationwide and Tokyo locally.

Second, we analyzed the impact of COVID-19 on the Japanese stock market through the infection network and TSE Sector Indices’ correlation analysis. On the decreasing Sharpe ratio, we ranked the Pharmaceutical, Information & Communication, Precision Instruments, and Electric Appliances. In particular, pharmaceutical firms face the development and clinical trial of new drugs to handle COVID-19. In network analysis, the connections (correlations) among specified industries have become stronger after declaration.

Finally, this study’s analyses of contagion risk from the interconnectedness between the COVID-19 infectious network and Japanese stock network contributes to the existing knowledge on the risk management of a global pandemic risk, which is one of the most severe systemic risks throughout human history.

In conclusion, we believe that unless effective vaccines are developed, the spread of the COVID-19 infection will still continue worldwide. Moreover, as

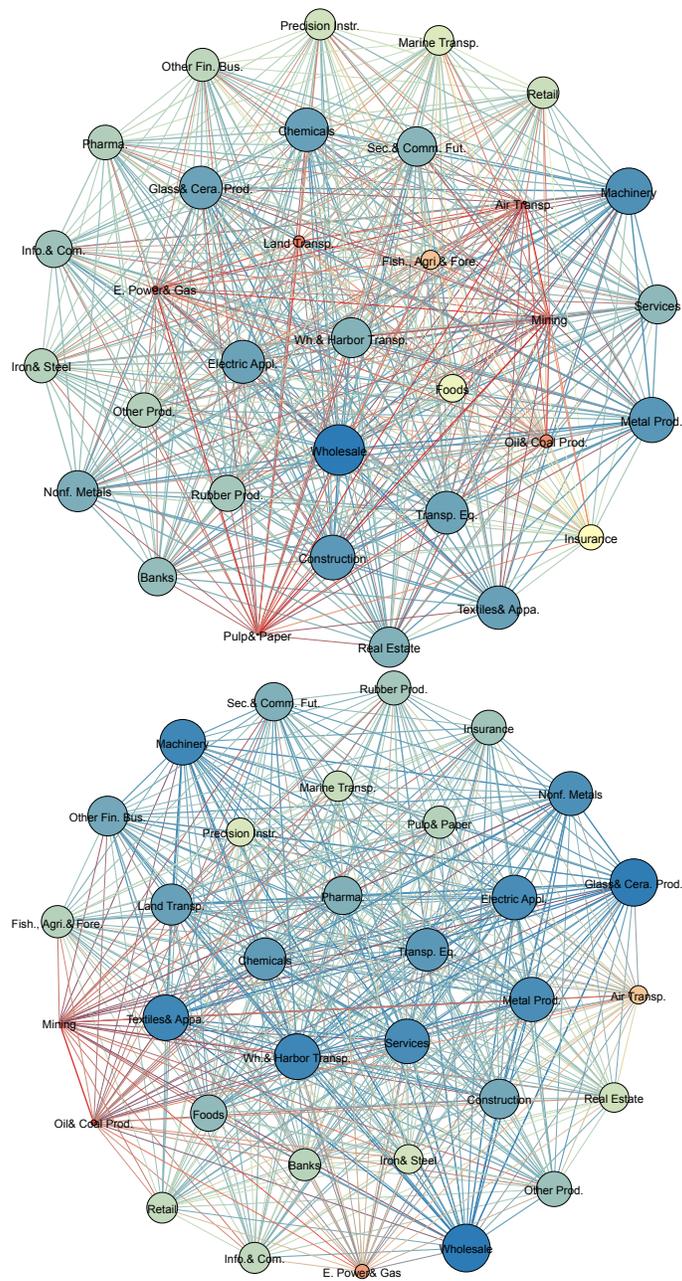


Figure 6: Undirected graphs of the TSE sector network around WHO's global pandemic declaration

Notes: These graphs are drawn in accordance with the Fruchterman–Reingold algorithm. The size of a node (a circle) is proportional to the total number of links in the correlation network. The upper panel shows the undirected graph for the period from January 1, 2020, to March 10, 2020, before WHO's declaration and the lower panel shows the graph for the period from March 11, 2020, to May 1, 2020, after WHO's declaration.

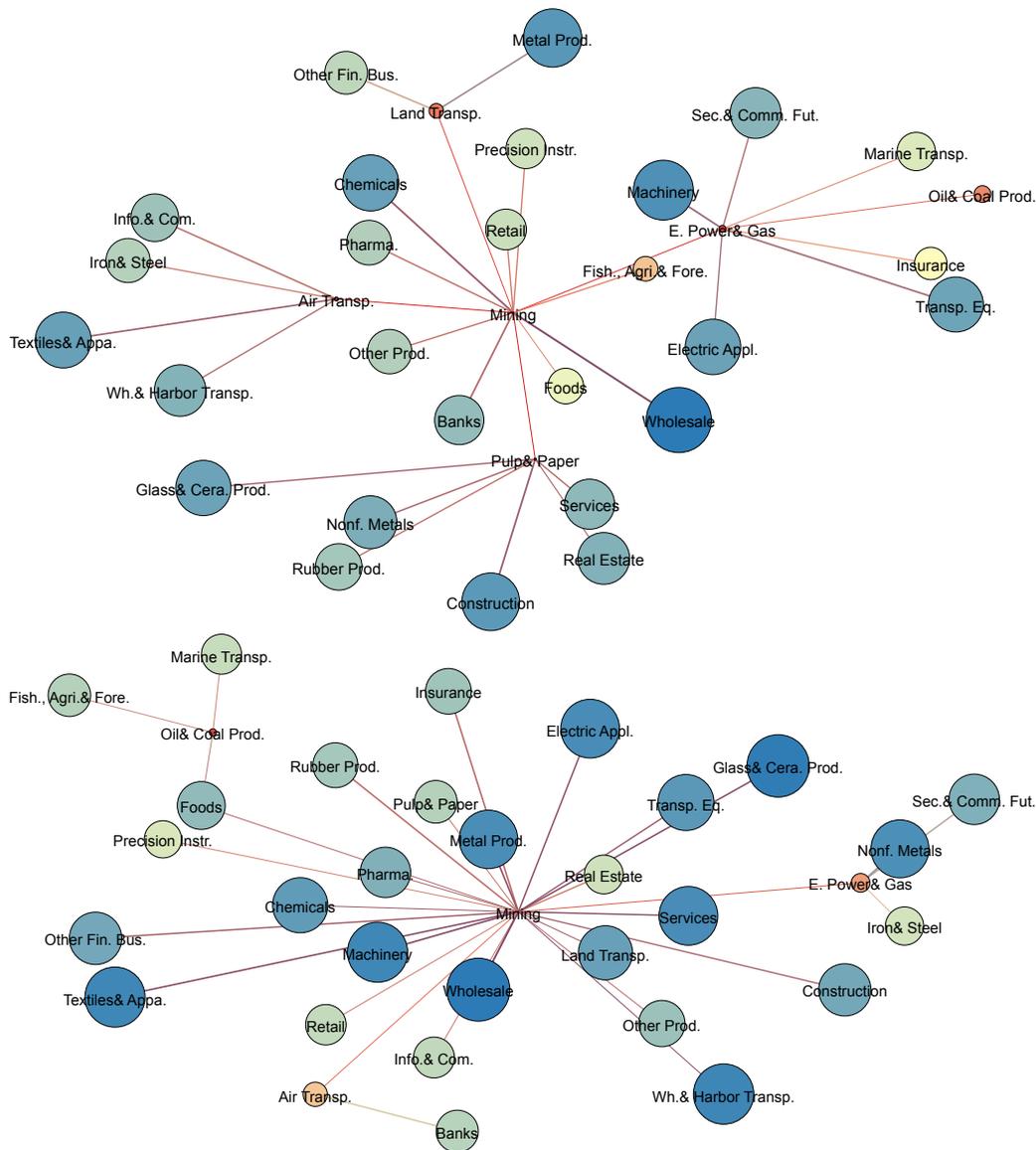


Figure 7: Correlation-based minimum spanning tree graphs of the TSE sector indexes returns network around WHO's global pandemic declaration

Notes: These graphs are drawn in accordance with the Kruskal's minimum spanning tree algorithm. The size of a node (a circle) is proportional to the total number of links in the correlation network. The upper panel shows the undirected graph for the period from January 1, 2020 to March 10, 2020 before WHO's declaration and the lower panel shows the graph for the period from March 11, 2020 to May 1, 2020 after WHO's declaration.

financial markets are affected through the complex networks, understanding network structures in conducting the financial measures for pandemic risks is necessary.

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