(調査研究報告書)

An impact analysis of COVID-19 on life insurers' securities investments☆

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1. Introduction

There has been growing interest in the risk contagion effect of the novel coronavirus disease (COVID–19) on firms' financial health. Hence, lack of both theoretical and empirical studies on the impact of COVID–19 on firms and the industry network has become a major issue worldwide.

COVID–19, originating from Wuhan, China, has spread worldwide. In February 2020, in Japan, an outbreak of COVID–19 occurred onboard the Diamond Princess, a cruise ship with 3,711 passengers and crew on board; 712 people among these tested positive for COVID–19. Severe acute respiratory syndrome coronavirus 2 (SARS–CoV–2) RNA was detected in samples drawn from the ship's common spaces and rooms through a real-time polymerase chain reaction (RT–PCR) test conducted by the National Institute of Infectious Diseases, Japan (NIID, 2019).

On March 11, 2020, the World Health Organization (WHO) officially categorized the COVID–19 outbreak as a global pandemic (WHO, 2020). This pandemic has had a substantial impact on each country and the global economy. The Severe Acute Respiratory Syndrome (SARS), Middle East Respiratory Syndrome, and the Ebola virus disease are referred to as past pandemics.

The June 2020 Global Economic Prospects describe both the immediate and near-term outlook for the impact of the pandemic and the long-term damage. The baseline forecast estimates a 4.3 percent contraction in global gross domestic product in 2020.

Former Prime Minister Shinzo Abe declared a state of emergency for one month from April 7, 2020, covering Tokyo, Osaka, and five other prefec-

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tures (Kanagawa, Saitama, Chiba, Hyogo, and Fukuoka) amid the growing COVID–19 outbreak. This would empower prefectures to impose restrictive measures. However, one month of a state of emergency proved insufficient in controlling the outbreak and the restrictions were extended.

Therefore, on May 4, 2020, the Japanese government encouraged residents to maintain the "new lifestyle" even after the restrictive measures had been relaxed following Prime Minister Abe's extension of the nationwide state of emergency to May 25, 2020. The extension of the state of emergency was not well received by workers in industries such as hospitality and tourism; they appealed to the government for more financial support.

As of May 1, 2020, based on data from the Center for Systems Science and Engineering at Johns Hopkins University, the US ranked first globally in the number of confirmed COVID–19 cases, with over one million patients. Contrastingly, Japan ranked 29th globally, with only 14,027 infections. However, considering Japan's small land size, the "three Cs" (closed spaces, crowded spaces, and close contact) are risk factors that needed to be managed and mitigated. Following the lifting of the state of emergency, infections in Japan increased rapidly, reaching 35,084 cases on July 31, 2020.

To measure risk contagion effect from COVID–19 networks to firm network, the risk parameters affecting infection spread must first be calculated. Hence, as a preliminary analysis, we calculate COVID–19 parameters using a susceptible-infected-recovered-dead (SIRD) model to analyze the impact of COVID–19 infections in Japan.

To offer new insight into the impact of COVID–19 on life insurers' securities investments, this study's research purpose is to assess the contagion effect of COVID-19 on Japanese issuers of securities and evaluate the measures undertaken by the Japanese government to curb the spread of COVID-19, including the first declaration of a state of emergency which lasted from April 7, 2020, to May 25, 2020.[1]

To cope with the research question, two main analyses are conducted:

[1] Japan's version of an emergency is different from the type of "lockdown" seen in Europe. Because of civil liberties enshrined in Japan's postwar constitution, the government has no right to dispatch the police to keep people off the streets, as has happened in countries including France, Italy, and the UK. The main effect was to increase the prefectural governors' powers. Under the emergency, a governor can urge local people to avoid unnecessary outings, but residents would have the right to ignore such requests, and there are no penalties for disobedience.

correlation-based network analysis and credit risk analysis.

Concerning correlation-based network analysis, three analyses are conducted to validate the impact of COVID–19 on Japanese listed firms. First, we examined the interconnection among returns on two TOPIX Sector Indices. This analysis implies that WHO's global pandemic declaration and the state of emergency declaration had significant effects on Japanese firms' stock price performance and the financial performance. Second, we investigated the correlation between the TOPIX return and a COVID–19 parameter using TOPIX Sector Indices[2] and TOPIX data. This analysis suggests that TOPIX bears an inverse relation to the weekly moving average basic reproduction number (BRN) as a COVID–19 parameter. Third, we analyzed the Japanese stock market's network structure around WHO's declaration and the state of emergency declaration, using network centralities and minimum spanning tree (MST). Regarding network structure changes among the industrial sectors, the analysis shows that the connections among related sectors strengthened significantly during the two declarations.

Concerning credit risk analysis, we analyze all the firms listed on the first section of the Tokyo Stock Exchange (TSE). To this end, we verify the significance of net cash as a proxy for a firm's credit risk in the COVID–19 era. COVID–19 parameters are almost the only risk factors impacting a firm's credit risk during this period.

Additionally, regarding a preliminary analysis, we calculate COVID–19 parameters using a mathematical model in epidemiology. Especially, although the BRN is a well-known epidemiological concept to measure the spread of an infectious disease, COVID–19's number in Japan is not published. Hence, to measure the impact of COVID–19 on Japanese firms and the financial market, this study needs to calculate this parameter.

The rest of this study is organized as follows: Section 2 provides a literature review on pandemic mathematical modeling and the application of complex network theory to finance. Section 3 contains modeling and deriving parameters about COVID–19 in Japan. Section 4 presents the correlation-based network analysis of the Japanese stock market. Section 5 explores the credit risk factors of Japanese firms in the COVID–19 era. Section 6 discusses this study's importance. Section 7 presents the conclusions.

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

2. Literature review

Goodell (2020) motivated us to study the relationship between COVID–19 and finance. Goodell considered the possible impacts of COVID–19 on financial markets and institutions, either directly or indirectly, by drawing on various studies.

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

Concerning the relationship between COVID–19 and stock markets, Conlon et al. (2020) discussed cryptocurrencies as a safe haven for stock markets. Ashraf (2020) examined the stock market responses in 64 countries toward COVID–19 from January 20 to April 17, 2020.

Network science is a highly effective approach for examining COVID–19's impact 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 deceased person, and an edge represents the infectious relationship between two persons. In a stock correlation network, a node represents a firm or a sector, and an edge represents the correlational relationship between the two entities.

Concerning the application of a complex network in finance, Kanno (2015a) published one of the first articles in the systemic risk literature, concerning the global financial crisis. Kanno's study (2015b) was the first to apply infectious disease modeling to the financial market. The study assessed the network structure of bilateral exposures in the Japanese interbank market using modified susceptible-infected-removable (SIR) models. Additionally, based on correlation analysis, Zhang et al. (2020) investigated the systemic connections among 12 countries using the graph theory and the MST method, connecting all the nodes in a graph with minimum possible total edge weight and no loops.

As a supplementary analysis, our study explores pandemic mathematical modeling and discusses the literature on infectious disease and pandemics, including COVID–19. Mathematical and complex network models have increasingly been used in infectious disease control. The main applications of such models include predicting effective vaccination impact strategies against common infections and determining the optimal control strategies against an epidemic or pandemic.

Two books offer introductions to infectious disease modeling. Vynnycky and White (2010) provide an introduction for non-specialists in the growing field of mathematical epidemiology. Contrastingly, Brauer et al. (2019) provide a comprehensive, self-contained introduction to the mathematical modeling and analysis of disease transmission models, including a detailed analysis of models for specific diseases, such as tuberculosis, HIV/AIDS, influenza, Ebola virus disease, malaria, dengue fever, and the Zika virus. Kiss et al. (2018) provide the network science featuring a stronger and more methodical link between models and their mathematical origin and explain how these relate to each other, with a special focus on the impact of epidemic spread on networks. Additionally, the book includes the interfaces of graph theory, stochastic processes, and dynamic systems.

3. Preliminary analysis

In this section, the study explores the COVID–19 parameters for financial analyses presented in Sections 4 and 5.

3.1. Positive rates

Positive rate is an important COVID–19 parameter. Testing more people for COVID–19 provides more details on infection rates and enables us to grasp the scale of the COVID–19 spread in Japan. The Ministry of Health, Labor, and Welfare (MHLW) in Japan announced that the maximum capacity for PCR tests was approximately 33,000 persons per day as of July 21, 2020. Currently, the MHLW provides data on the number of people who have tested positive divided by the number of tests conducted nationwide.[3]

A positive daily rate is volatile, it is calculated as the ratio of the past weekly moving average of the number of persons to test positive to the past weekly moving average of the number of tested persons. Thus, the variation can be leveled for short periods. The weekly moving average positive rates for the 11 prefectures ranked high from March 11, 2020, to July 31, 2020, and are shown in Figure 1. Additionally, the weekly moving average for all

[3]It is emphasized that positive rates are not precise, as the number of PCR tests in the denominator relates to the dates the tests were conducted, and the number in the numerator relates to the dates the results were received; moreover, there is no consistency in the rate calculation.

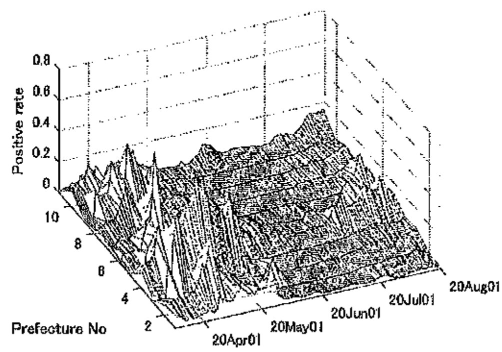

Figure 1: Weekly moving average positive rate curves pertaining to COVID–19 for 11 prefectures ranked high from March 11, 2020 to July 31, 2020

Notes: Each curve shows the high ranked prefecture's positive rate. Prefecture numbers are designated as follows: 1: Hokkaido; 2: Saitama; 3: Chiba; 4: Tokyo; 5: Kanagawa; 6: Ishikawa; 7: Aichi; 8: Kyoto; 9: Osaka; 10: Hyogo; 11: Fukuoka.

prefectures for the entire period is 3.2%. The figures for Tokyo and Kanagawa are at an especially high level, rising as high as above 12%.

3.2. COVID–19 mathematical model and BRN

3.2.1. Susceptible-infected-recovered-dead (SIRD) model

The susceptible-infected-susceptible (SIS) and SIR models are representative infectious disease models. The concept is that a node (i.e., a person) can be in one of two states: either infected or not but is susceptible to becoming infected. This model is a variation on the seminal model in the literature, the SIR model. In the SIR model, 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 they have died. Contrarily, 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, non-fatal diseases without severity but is also useful as a first approximation of the behavior models. In these models, individuals are more likely to undertake a given action as more of their neighbors do the same, but they can also randomly stop acting with the possibility of acting again (Jackson, 2010; Kiss et al., 2018).

Both models are, however, unsuitable for modeling COVID–19, as infected patients who have pre-existing diseases, which become severe, can die suddenly. Thus, the SIRD model is adopted in our study. The SIRD model has four compartments[4] with four states, namely, susceptible (S), infected (I), recovered (R), and dead (D) (Figure 2).

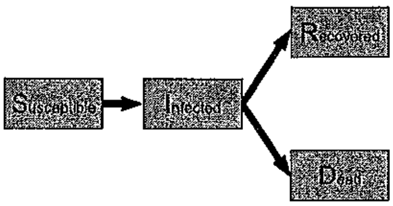

Figure 2: Illustration of susceptible-infected-recovered-dead (SIRD) model

As an assumption, the total of the referenced population is constant (for example, $N = 124$ million in Japan and $N = 13.3$ million in Tokyo) for each state for the period, considering birth and death rates around COVID–19 in the compartment. This is especially applicable for low fatality diseases with large outbreaks. Additionally, we assume that a recovered person cannot be reinfected.

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

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

where initial values at time $t = 0$, which are S_0, I_0, R_0, and D_0 satisfy the following equation: $S_0 + I_0 + R_0 + D_0 = N$ ($N = \mathit{population}$). S_0, I_0, R_0, D_0, and N are obtained from the data published by each prefecture and the MHLW.

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

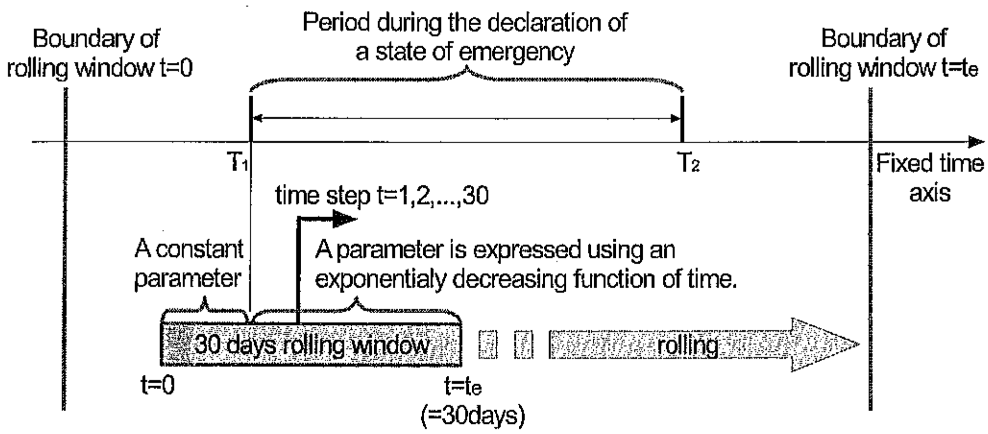

Figure 3: Illustration of calibration

3.2.2. Data for SIRD model

We use data from March 18, 2020, to July 31, 2020, published by the Japanese government (see Table A.9). The main items are infected cases, recovered patients, and the death toll in Japan and in Tokyo.

3.2.3. Parameter modeling

The parameters in the equation (1) need to be modeled for calibration (i.e., optimization) as described in Appendix B. Also, the robustness in the optimization is discussed in Appendix C.

To incorporate the impact of a state of emergency declaration into the SIRD model, we consider a time $t \in [0, t_e]$ in a rolling 30 day window (the window's end date t_e: 30 days), in relation to the period, $[T_1, T_2]$ $(T_1 < T_2)$, for the first state of emergency declaration between the effective date (T_1: April 7, 2020) and the lifting date (T_2: May 25, 2020). If time $t \in [T_1, T_2]$, a suppressing effect works. Otherwise, the parameter values are constant (for reference, see Caccavo (2020)). Figure 3 denotes the relations among the rolling time t, t_e, T_1, and T_2.

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

$$\beta_t = \beta_0 \exp\Big(- \frac{t1_{T_1<t\leq T_2\leq t_e} + (t-T_1)1_{0<T_1\leq \min(t,t_e)<T_2}}{\tau_\beta}\Big) + \beta_1, \tag{2}$$

where $1_{s\in A}$ is a function defined on a set S that indicates membership of an element in a subset A of S, having the value 1 for all elements of S in A and 0 otherwise. 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 time decrease.

Recovery parameters: γ. The recovery rate γ may be time-dependent, but whether it has linearity is unknown. Regarding doctors and drugs, as the resources for treating COVID–19 are inadequate, recovery time is difficult to predict.

However, the infected may show up 2 to 14 days after the infection. These symptoms can vary depending on the person. A small percentage of people who have the SARS-CoV-2 need to stay in the hospital to get help breathing. This might last 2 weeks or more. Some cases become severe and cause death. Therefore, because the recovery rate takes a value between 0 and 1 in a cohort (a country or a district), γ is modeled using a logistic function, following the literature in survival analysis or credit risk modeling (Kleinbaum and Klein, 2010; Trueck and Rachev, 2009; Löeffler and Posch, 2011)[5] as

$$\gamma_t = \gamma_0 + \frac{\gamma_1}{1+\exp(-(t1_{T_1<t\leq T_2\leq t_e} + (t-T_1)1_{0<T_1\leq \min(t,t_e)<T_2}) + \tau_\gamma)}, \tag{3}$$

where γ_0 is the recovery rate at time zero, $\gamma_0 + \gamma_1$ is the recovery rate at a regime, reached after τ_γ days of adaption to the declaration.

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

$$\delta_t = \delta_0 \exp\Big(- \frac{t1_{T_1<t<T_2\leq t_e} + (t-T_1)1_{0<T_1\leq \min(t,t_e)<T_2}}{\tau_\delta}\Big) + \delta_1, \tag{4}$$

[5]Additionally, a probit function is well-known in survival analysis and credit risk modeling.

where δ_1 and τ_δ can be decreased to reduce the number of parameters if the recovery function is a monotonic increasing function without a regime.

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

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

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

As the number of infected persons increases, $di_t/dt > 0,\ \forall t > 0$ needs to be satisfied as[6]

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

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

$$\mathcal{R}_0 := \frac{\beta_t}{\gamma_t + \delta_t} \frac{S_0}{N} \approx \frac{\beta_0}{\gamma_0 + \delta_0}. \tag{7}$$

3.2.4. Calibration results

The calibration results as of July 31, 2020, on the model parameters and the BRNs are shown in Table 1. As listed in the table, the BRNs in Japan and in Tokyo, are larger than the effective reproduction number announced by a "Novel Coronavirus Expert Meeting" member of the government. Figure 4 indicates the results estimated using the SIRD model for Japan and for

[6]Regarding Japan's COVID–19 measures, the effective reproduction number ($\mathcal{R}$) is emphasized more than the BRN ($\mathcal{R}_0$). $\mathcal{R}$ is defined as the average number of secondary infectious persons resulting from each infectious person in a given population, for example, cases where some individuals may be immune because of previous infection (Vynnycky and White, 2010). $\mathcal{R}$ can be estimated by the product of ($\mathcal{R}_0$) and the fraction of the host population that is susceptible x as $\mathcal{R} = \mathcal{R}_0 \times x$, where x is defined as the proportion of the population that is susceptible.

Tokyo. The upper and lower panels indicate cumulative infection, death, and recovery rates in Japan and Tokyo, respectively.

Anastassopoulou et al. (2020) estimated the BRN ($\mathcal{R}_0$) to be around five as computed by the least-squares using the publicly available epidemiological data for Hubei, China daily from January 11, 2020. Contreras et al. (2020) assessed the evolution of the pandemic in Chile through the effective reproduction number ($\mathcal{R}$), directly estimated from the discrete version of the SIR models. Decoupling the recovered fraction in the SIR model as clinically recovered individuals and deaths, $\mathcal{R}$ was given in the range of 1 to 4. Estimating x is difficult. However, if the fraction x is assumed to be 0.2, $\mathcal{R}$ would be given in the range of 5 to 20. Because $\mathcal{R}$ depends on both $\mathcal{R}_0$ and x, $\mathcal{R}$ is a parameter more uncertain than $\mathcal{R}_0$.

Table 1: SIRD model parameters and BRN $\mathcal{R}_0$ as of July 31, 2020, obtained from an optimization

	β_0	τ_β	δ_0	δ_1	τ_δ	γ_0	γ_1	τ_γ	BRN
Japan	0.034	29.459	2.675E-05	1.675E-05	6.644	0.011	0.043	10.950	3.078
Tokyo	0.039	6.827	1.330E-05	3.283E-06	4.627	0.015	0.035	11.683	2.621

Note: The fitting data points correspond to 30 days from July 2, 2020 to July 31, 2020.

4. Correlation-based network analysis

This section describes the analyses about the correlation-based network to investigate the impact of COVID–19 on Japanese listed firms.

4.1. Correlations among TOPIX Sector Indices

One of the best ways to understand the relationships among firms is to consider how their stock sector index returns are correlated. Generally, firms operating in the same sector show similar price fluctuations. The correlation analysis is conducted using data from TOPIX and TOPIX Sector Indices returns on the Japanese stock market.[7]

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

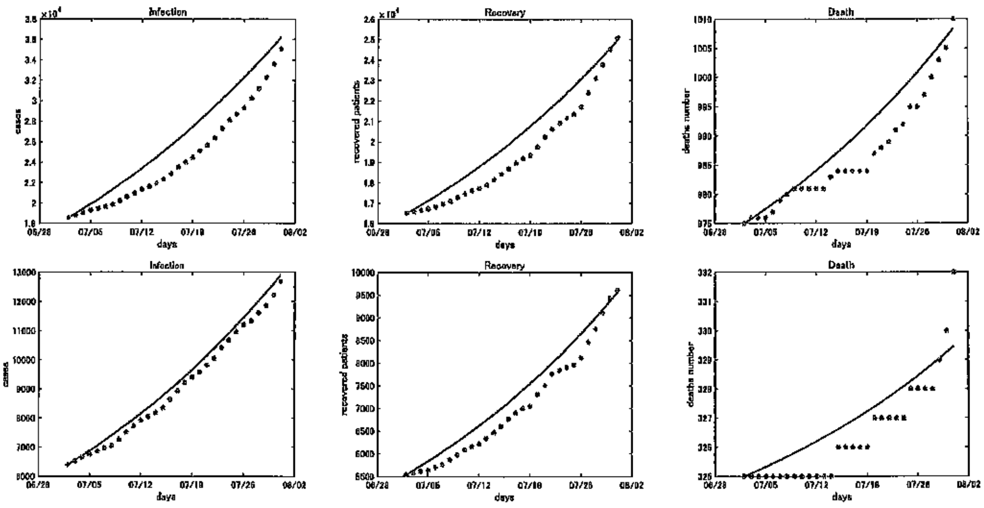

Figure 4: Japan's and Tokyo's COVID–19 curves pertaining infected cases, recovered patients, and deaths as of July 31, 2020, estimated by the SIRD model

Notes: The three upper panels and three lower panels present compartment graphs for infected cases, recovered patients, and deaths in Japan and Tokyo, respectively.

By pairing 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, that is, sector no l and sector no m ($l, m = 1, 2, \ldots, 33$)), over time Δt (e.g., one day) is computed as follows:

$$\rho_{lm}(\Delta t) = \frac{E[r_l r_m] - E[r_l]E[r_m]}{\sqrt{(E[r_l^2] - E[r_l]^2)(E[r_m^2] - E[r_m]^2)}}, \tag{8}$$

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

$$d_{lm} = \sqrt{2(1 - \rho_{lm})}. \tag{9}$$

This distance takes a value between 0 and 2, and, for example, if $\rho_{lm} = 0.5$, then $d_{lm} = 1$. MST is discussed using equation (9) in subsection 4.3.2.

Figure 5 shows the TOPIX returns for the half-year from February 1, 2020, to July 31, 2020. The period is divided by two events (WHO's global pandemic declaration and the state of emergency declaration) into four periods: P_1: February 1 to March 10, P_2: March 11 to April 6, P_3: April 7 to May 25, and P_4: May 26 to July 31 (see Table 2).

Apparent from Figure 5 is a structural break in the stock index return fluctuations resulting from WHO's global pandemic declaration on March 11, 2020. Additionally, Table 2 indicates that the correlations among the TOPIX Sector Indices are significantly impacted by COVID–19; the mean of pairs (the number and ratio of correlation coefficients over 0.9) significantly decreased with the declarations, whereas the standard deviation of pairs sharply increased. This implies that the WHO's global pandemic declaration and the state of emergency declaration had significant effects on the Japanese stock market.

Table 3 denotes the top 10 rankings of TOPIX Sector Indices concerning the mean, the standard deviation, and the Sharpe ratio by period since February 1, 2020. The Sharpe ratio is the expected return earned over the risk-free rate per volatility unit 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 the risk-free rate. However, as its yield is recently negative, the zero rate or a low positive rate is applied as the risk-free rate.

As per the mean, Real Estate and Services sectors are improving their performance from their worst levels, whereas Mining, Wholesale and Trade, Textiles and Apparels, Construction, and Machinery are worsening their performance. By contrast, as per the standard deviation, Foods, Oil and Coal Products, Textiles and Apparels, and Electric Power and Gas show increasing volatilities, whereas Banks and Marine Transportation show decreasing volatilities. The former industries relate to the demand for necessities such as food, clothing, and housing, whereas the latter is related to economic decline and mobility limitations.

Finally, concerning the Sharpe ratio, Banks, Mining, and Marine Transportation show improving performance, whereas the Foods sector is declining and Oil and Coal Products are fluctuating at low levels. Although pharmaceutical firms are being driven by the development of a COVID–19 vaccine, their progress is slow; they do not feature in the top 10 rankings. As the remaining industries are typical manufacturing industries, they are largely affected by other industries' activities and by the social environment.

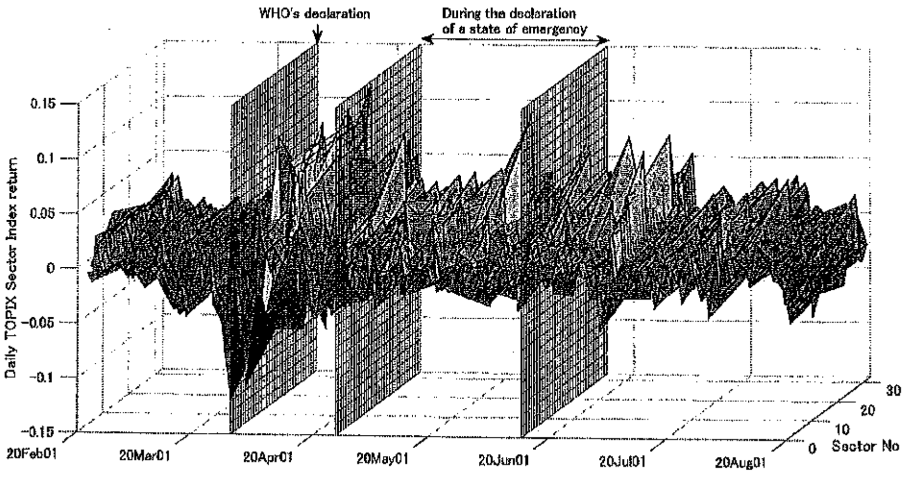

Figure 5: Return transitions of TOPIX Sector indices from February 1, 2020, to July 31, 2020

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

4.2. Correlations between TOPIX and BRN

As the BRN plays an important role in forecasting the outbreak, its correlation with TOPIX needs to be investigated. The left panel of Figure 6 indicates the time-series for both TOPIX and BRN in Tokyo from April 16, 2020,[8] to July 31, 2020, and the right panel of Figure 6 indicates multiple regressions with a binary variable. There were two groups around the state of emergency declaration. The analysis result is described in Table 4. Table 4 suggests that TOPIX is inversely proportional to the weekly moving aver-

[8]In the calibration of BRN, a 30-day time window starting from March 18, 2020, is applied.

Table 2: Correlations among TOPIX Sector Indices from February 1, 2020, to July 31, 2020

	P_1:Before WHO's D	P_2:WHO's D to Gov's DSE	P_3:During Gov's DSE	P_4:After Gov's DSE
Period	February 1 – March 10	March 11 – April 6	April 7 – May 25	May 26 – July 31
Mean	0.846	0.755 (↓)	0.521 (↓)	0.611 (↑)
S.D.	0.075	0.176 (↑)	0.300(↑)	0.321 (↑)
No of pairs ≥ 0.9	281	164 (↓)	61 (↓)	91 (↑)
Ratio of pairs ≥ 0.9	0.258	0.142 (↓)	0.050 (↓)	0.074 (↑)

Notes: Abbreviations: S.D.: standard deviation; D: the declaration; DSE: the declaration of a state of emergency; Gov: Japanese government. The arrow indicates increase or decrease compared to last period.

age BRN. We check for multicollinearity using the variance inflation factor (VIF) and identify all values equal 3.064. The robustness of the estimates is supported by the fact that all the variables and the constant are statistically significant at the 1% level in addition to the adjusted R-squared of 0.890. This suggests that the first state of emergency declaration from April 7, 2020, to May 25, 2020, was effective in curbing the outbreak.[9]

Using daily COVID–19 confirmed cases and deaths as COVID–19 parameters and stock market returns data from 64 countries over the period January 22, 2020, to April 17, 2020, Ashraf (2020) found that stock market returns declined as the number of confirmed cases increased. This result is consistent with our analysis using BRNs as COVID–19 parameters.[10] Also, concerning the state of emergency declaration impact as the government's measure on firms' performance, Narayan et al. (2020) investigated the effect of government responses of G7 countries including Japan to COVID-19 on

[9]The Japanese government prioritized the economy by lifting the state of emergency completely on May 25, 2020. Furthermore, the government embarked on a "Go-To Travel Campaign" on July 22, 2020, to support the declining Japanese tourism industry because of COVID–19. This campaign has been criticized as having accelerated the spread of COVID–19.

[10]The study uses only 58 points as sample data of the Nikkei 225 and confirmed cases since January 22, 2020, when the first COVID–19 case was confirmed in Japan. Correctly, the first confirmed case was on January 15, 2020.

Table 3: TOPIX Sector Indices ranked in the worsening condition: mean, standard deviation, and Sharpe ratio

	Mean (small to large)				Standard deviation (large to small)				Sharpe ratio (small to large)			
R	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
1	33	33	4	4	8	4	6	2	8	4	6	2
2	21	27	3	8	29	7	9	33	29	7	9	33
3	8	3	8	3	3	28	14	22	3	28	14	22
4	19	4	5	27	2	27	21	9	2	27	21	9
5	27	8	33	16	24	32	8	14	24	32	8	14
6	1	21	32	33	32	24	19	23	32	24	19	23
7	3	32	27	12	5	11	22	27	5	11	22	27
8	28	25	16	5	15	8	10	4	15	8	10	4
9	5	5	12	19	4	12	3	24	4	12	3	24
10	7	16	21	21	19	16	2	29	19	16	2	29

Notes: Abbreviation: R: Ranking. P_1, P_2, P_3, and P_4 correspond to the periods from February 1 to March 10, March 11 to April 6, April 7 to May 25, and May 26 to July 31, respectively. The figures in the table are as follows: 1: Fishery, Agriculture & Forest, 2: Foods, 3: Mining, 4: Oil and Coal Products, 5: Construction, 6: Metal Products, 7: Glass and Ceramics Products, 8: Textiles and Apparels, 9: Pulp and Paper, 10: Chemicals, 11: Pharmaceutical, 12: Rubber Products, 13: Transportation Equipment, 14: Iron and Steel, 15: Nonferrous Metals, 16: Machinery, 17: Electric Appliances, 18: Precision Instruments, 19: Other Products, 20: Information & Communication, 21: Services, 22: Electric Power and Gas, 23: Land Transportation, 24: Marine Transportation, 25: Air Transportation, 26: Warehousing and Harbor Transport, 27: Wholesale Trade, 28: Retail Trade, 29: Banks, 30: Securities and Commodities Futures, 31: Insurance, 32: Other Financing Business, and 33: Real Estate.

stock market returns. They showed that lockdowns had a positive effect on the G7 stock markets and were most effective in cushioning the impact of COVID-19. This result is consistent with our study.[11]

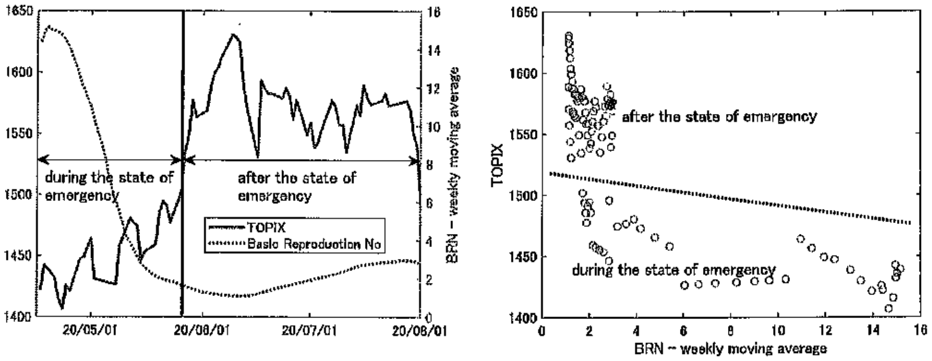

Figure 6: Line plot (left panel) and linear regression (right panel) of TOPIX to BRN in Tokyo from April 22, 2020 to July 31, 2020

Notes: In the left panel, the horizontal line with value 1 indicates the BRN's critical level. Namely, if $\mathcal{R}_0 > 1$, the infection spread, but if $\mathcal{R}_0 < 1$, the infection does not spread.

4.3. Stock networks

This subsection analyzes the change of the network structure of the Japanese stock market around WHO's global pandemic declaration and the state of emergency declaration, using four correlation matrixes calculated in Subsection 4.1.

[11]However, a lockdown could not be imposed in Japan on March 13, 2020, as the enforcement date corresponds to the date when the law (an amendment to the Act on Special Measures for Pandemic Influenza and New Infectious Diseases Preparedness and Response) was determined. Although national lockdown is assumed in their study, the first declaration was issued only for seven prefectures out of 47 prefectures (later, six prefectures added). Dummy variables that control for day-of-week effect are all not significant, even at the 10% level. From the perspectives of these issues, their analysis result might be coincidental with our result.

Table 4: Multiple regression result and its robustness

Variables	Non-std coef	VIF
BRN(WMA)	-4.004***	3.064
	(0.000)	
dummy	-97.164***	3.064
	(0.000)	
Constant	1580.127***	
	(0.000)	
Observations	107	
Adjusted R-squared	0.890	

Notes: Non-std coef: Non-standardized coefficients. P-values are given in parenthesis. *** represents statistical significance at the 1% level. BRN is expressed in weekly moving average (WMA). The regression equation is expressed as $TOPIX = B \cdot BRN + dummy_i + Constant \quad (i = 0, 1)$.

4.3.1. Weighted degree

Because a correlation coefficient has no direction, its analysis results in an undirected graph. Additionally, 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

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

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

Table 5 indicates the weighted degrees regarding metric distance in the TSE sector network for the four periods divided by WHO's global pandemic declaration and the state of emergency declaration, respectively.

In a correlation-based network, the weighted degrees increased following the increasing metric distances expressed in equation (9), during the periods of P_2 and P_3 from WHO's declaration to the lifting of the state of emergency (DSE), whereas the statistics reverse after the lifting of the DSE. This result indicates that the average connections among related sectors are significantly strengthened by two consecutive declarations during the periods of P_2 and

P_3.

Table 5: Descriptive statistics of weighted degrees concerning metric distances around WHO's declaration and the state of emergency declaration

Period	P_1	P_2	P_3	P_4
Mean	17.6	20.5 (↑)	28.3 (↑)	24.0 (↓)
Standard deviation	2.4	3.2 (↑)	4.5 (↑)	4.2 (↓)

4.3.2. Minimum spanning tree

A network graph draws all edges between nodes, making it difficult to understand the correlational relationship between nodes. Contrastingly, a spanning tree of that graph is a subgraph, that is, a tree that connects all the nodes. A single graph can have many different spanning trees. An MST for a weighted, connected, undirected graph is a spanning tree with a weightless than or equal to the weight of every other spanning tree. In a correlation-based network, correlation is associated with the metric distance expressed in the equation (9). The weight of a spanning tree is the sum of the weights given to each edge of the spanning tree (Caldarelli, 2013).

Figure 7 indicates that the connections among related sectors strengthened much during the two declarations (P_3) whereas there were almost no connections among related sectors during P_1 and P_2. In other words, the subgraphs during P_3 indicate that the clustering of stocks correspond to related industries (for example, sets of {Rubber Products, Transportation Equipment}, {Mining, Oil & Coal Products, Glass & Ceramics Products}, {Air Transportation, Land Transportation}, {Pharmaceutical, Precision Instruments, Other Products}, {Retail, Foods, Fishery–Agriculture–Forestry}, {Securities & Commodities Futures, Other Financing Business}). Also after the state of emergency declaration (P_4), strong connections are continuously seen in some related sectors (for example, sets of {Rubber Products, Transportation Equipment, Iron & Steel}, {Mining, Oil & Coal Products}, {Pharmaceutical, Precision Instruments}, {Retail, Foods}, {Banks, Insurance}).

Zhang et al. (2020) showed the MST before and after the pandemic announcement in the top 12 infected countries selected by the number of confirmed cases. Before the announcement, European stock markets are strongly connected. France, Germany, and the Netherlands are the core of the MST. The US market and the China Mainland stock market are rather isolated in the system. By contrast, the MST after the announcement shows that the European group remains highly connected. The UK and Spain replaced Germany and the Netherlands to become the core members.

Contrarily, our study focuses on industry sectors in Japan. The MST before the state of emergency declaration showed a low correlation among similar sectors whereas the MST after the declaration did high connection among related sectors.

5. Credit risk analysis

This section explores the credit risk factors in the COVID–19 era, using financial data for all firms listed on the first section of TOPIX. To this end, we conducted a panel regression analysis.

5.1. Data for panel analysis

For the panel regression analysis, we used firm-level financial data (2,170 firms), market data, and macroeconomic data, in addition to COVID–19 data in Tokyo, where the economic and political activities are concentrated. We obtained the financial and market data from the Refinitiv DATASTREAM database, offering cash, deposits, and short-term investment (short lending and security investment) reports for all firms of the TSE first section. Macroeconomic data were obtained from the Japanese government and IHS Markit (Table 6). Because the BRN is calibrated over the past 30 days, the period has been shortened by one month compared to the original data length, resulting in the timeframe being April 16 to July 31, 2020.

Table 7 shows the expected sign, mean, standard deviation, mode, and quartile, relating to the values for market and macroeconomic variables along with COVID–19 parameters used as control variables (Panel 1) and the cross-correlation matrix (Panel 2). In Panel 1, the sign ($\pm$) indicates that the variable can take any sign, and "Number" indicates the effective number of the data. Panel 2 shows the correlations among net cash amount calculated as the sum for all firms of the TSE first section, COVID–19 parameters, market variables, and macroeconomic variables. The correlations among macroeconomic variables, such as core consumer price index (CPI), purchasing managers index (PMI), and industrial production index (IPI), are all significantly high (above 0.9). Contrastingly, correlations among COVID–19 parameters and

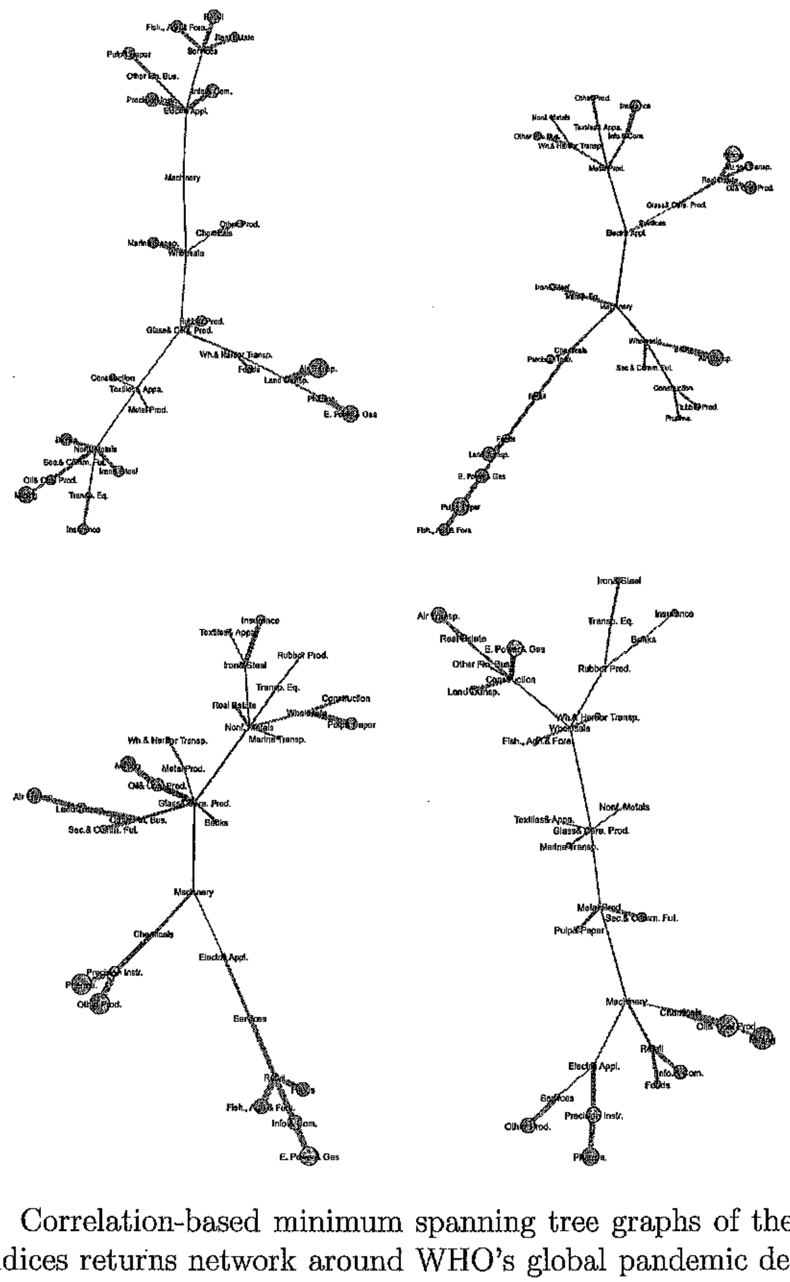

Figure 7: Correlation-based minimum spanning tree graphs of the TOPIX Sector Indices returns network around WHO's global pandemic declaration and the state of emergency declaration

Notes: These graphs are drawn by the Yifan Hu algorithm in accordance with Kruskal's minimum spanning tree algorithm. The size of a node (a circle) is proportional to weighted degrees, that is, the total number of links weighted by metric distances, in the correlation-based network. The upper-left panel shows the undirected graph for the period P_1: February 1 to March 10, the upper-right panel corresponds to P_2: March 11 to April 6, the lower-left panel corresponds to P_3: April 7 to May 25, and the lower right panel corresponds to P_4: May 26 to July 31.

market variables (except for Nikkei 225 VIX), COVID–19 parameters and macroeconomic variables (except for Vacancy rate and Unemployment rate), net cash and market variables, and net cash and macroeconomic variables are low.

The definitions of the variables listed in Table 7 are as follows: Net cash is calculated for a firm's total of cash & deposits and short-term holding securities minus interest-bearing liabilities reported in its financial statement. In this analysis, each firm's net cash is summed over all firms per day. Net cash is relevant regarding default risk triggered by liquidity shortages in the COVID–19 era.

Because there is no volatility index for TOPIX, the Nikkei 225 VI is used. This index is a volatility index calculated using the Nikkei 225 option, the other stock index on the Japanese stock market.

The core CPI for the Ku-area of Tokyo indicates average fluctuations in commodity prices (goods and services) purchased by households from the previous month on a seasonally adjusted basis. The core CPI is calculated by excluding fresh food from the CPI and is different from the national index (Ministry of Public Management).

The PMI reflects the business environment in the Japanese industrial sector. The index is calculated monthly based on surveys of manufacturing company managers regarding new orders, sales, inventory, suppliers, and the industry outlook. This measures the purchasing managers' activity level in the manufacturing sector. The PMI surveys serve to indicate business change at an earlier time than other economic indicators. A figure above 50 indicates expansion in the sector, whereas one below 50 indicates contraction (IHS Markit's survey).

The vacancy rate indicates the ratio of jobs offered to job hunters. Furthermore, the unemployment rate is defined as the percentage of the unemployed to the total labor force (sum of the employed and unemployed), calculated as Unemployment rate (%) = (Unemployed / Labor force) $\times$ 100 (MHLW).

The IPI is a monthly macroeconomic indicator measuring real output in the Manufacturing, Mining, Electric, and Gas industries, relative to a base year (Ministry of Economy, Trade, and Industry).

The fixed-effects dummy equals 1 if the day falls in the state of emergency period and 0 otherwise.

The expected sign for each variable listed in Panel 1 of Table 7 is explained as follows: The higher the TOPIX returns as a proxy for the performance of all the firms listed on the TSE first section, the greater the net cash. Thus, we expect a positive sign on the TOPIX return. The Nikkei 225 VI provides a measure of market risk and investors' sentiment. It bears other informal names, such as "Fear Gauge" or "Fear Index," and has no directional impact on a firm's credit risk, and therefore, can be either positive or negative. The higher the COVID–19 parameters (BRN (WMA) and positive rate), the worse the firms' performances. Thus, we expect a negative sign on COVID–19 parameters. A higher Core CPI (Ku-area of Tokyo) is the result of increased consumption. Thus, we expect a positive sign on the core CPI.

The PMI is an index indicative of the prevailing economic activity direction in the manufacturing and service sectors. The PMI's purpose is to provide information about current and future business conditions to a firm's decision-makers, analysts, and investors. Thus, as there is a time gap between the current economic condition and the PMI, the expected PMI sign is positive. A higher vacancy rate does not necessarily lead to enough net cash whereas a lower unemployment rate can lead to firms' abundant net cash. Thus, the expected vacancy rate sign is either positive or negative and the expected unemployment rate sign can be positive. The higher the IPI, the higher the performance by manufacturing firms. Hence, the expected IPI sign is positive; however, it depends on the ratio of the manufacturing firms to all firms.

5.2. Methodology

A firm's credit risk is driven by its net cash as a proxy for its liquidity in the COVID–19 era. Depending on the industry (for example air transportation and hotel), the business opportunity has suddenly fallen. As such, net cash strongly affects a firm's financial health. Net cash is a proxy variable for credit risk.

We estimate variables by using a stepwise method based on the panel regression model as follows:

$$\begin{aligned} Netcash_t = \beta_0 + \sum_i \beta_i Controls_{i,t} + \sum_j \beta_j market_{j,t} \\ + \sum_k \beta_k macroeconomic_{k,t} + \sum_l dummy_{l,t} + \epsilon_t, \end{aligned} \tag{11}$$

where the left-hand side is the net cash, as the sum of the 2,170 firms listed on the TSE first section. On the right-hand side, the TOPIX return and the

Table 6: Financial ratios and other related variables

Item	Description	Updating cycle	Sources
Financial ratios	Net cash as the sum for 2,170 firms of TSE first section	Semi-annualy*	DATASTREAM
COVID–19 parameters	BRN (WMA) and positive rate	Daily	Calculation in Section 3
Stock related data	TOPIX, TOPIX Sector Indices, and Nikkei 225 VI	Daily	DATASTREAM
Macroeconomic data	Core CPI (ku-area of Tokyo), PMI, vacancy rate, unemployment rate, and IPI	Monthly	Japanese Government and IHS Markit

Notes: Each variable is set to a constant till the next updating time. Though each firm's net cash cycle is semi-annual, the net cash aggregated as the entire firm is updated almost daily.

Nikkei 225 VI reflect the market performance of all the firms listed on the TSE first section. Core CPI, PMI, vacancy rate, unemployment rate, and IPI are especially COVID–19-related macroeconomic variables. The control vectors include the following COVID–19 variables: positive rates or BRNs calculated in Section 3. Additionally, a dummy variable is used for the state of emergency declaration by the government. ϵ is an error term.

5.3. Analytical results

Table 8 reports the results ((2), (3), (5), (6)) estimated by the stepwise variable selection method, based on equation (11) for April 16 to July 31, 2020. Table 8 also shows the results ((1), (4)) of the forced entry method, in contrast to the results of the stepwise variable selection method.

In cases ((2), (3), (5), (6)), using the stepwise variable selection method, we checked for multicollinearity using the VIF and identified no values above nine. The preliminarily predicted signs of the independent variables are all as projected in Table 7. The estimates of the constant and positive rate in cases (5) and (6) are all significant at the 1% level. Additionally, the estimates on BRN (WMA) in cases (2) and (3) are significant at the 5% level. Hence, it is to be noted that BRN (WMA), including a positive rate, are important explanatory variables. By contrast, concerning the market and macroeconomic variables, there is no significant variable even at the

Table 7: Summary statistics of variables

Panel 1: Descriptive statistics

	Sign	Mean	SD	Mode	25%	50%(Median)	75%	Max	Number
Net Cash (thousands)		186,192,372	729	186,192,475	186,192,475	186,192,475	186,192,475	186,192,872	107
TOPIX return	+	0.000	0.009	-0.028	-0.004	0.000	0.005	0.041	107
Nikkei 225 VI	±	29.266	5.479	27.600	24.243	28.530	33.340	42.020	107
BRN(WMA)	−	4.158	4.267	1.099	1.581	2.376	3.542	15.152	107
Positive rate	−	0.115	0.167	0.006	0.015	0.040	0.077	0.635	107
Core CPI	+	0.002	0.002	0.001	0.000	0.001	0.004	0.004	107
PMI	+	31.636	9.524	26.500	21.500	26.500	45.000	45.400	107
Vacancy rate	±	1.230	0.101	1.110	1.110	1.200	1.320	1.390	107
Unemp. rate	−	2.736	0.148	2.800	2.600	2.800	2.900	2.900	107
IPI	±	-0.048	0.052	-0.089	-0.091	-0.089	0.027	0.027	107

Panel 2: Correlation matrix

	Net Cash	TOPIX return	Nikkei225 VIX	BRN (WMA)	Positive rate	Core CPI	PMI	Vacancy rate	Unemp. rate	IPI
Net Cash	1	0.008	-0.240*	-0.374**	-0.438**	0.054	-0.032	-0.224*	0.228*	-0.03
TOPIX return	0.008	1	-0.119	-0.017	-0.033	-0.098	-0.124	0.144	-0.135	-0.1
Nikkei225 VIX	-0.240*	-0.119	1	0.652**	0.663**	-0.671**	-0.543**	0.767**	-0.495**	-0.542**
BRN (WMA)	-0.374**	-0.017	0.652**	1	0.980**	-0.207*	0.014	0.672**	-0.755**	0.055
Positive rate	-0.438**	-0.033	0.663**	0.980**	1	-0.191*	0.018	0.625**	-0.695**	0.053
Core CPI	0.054	-0.098	-0.671**	-0.207*	-0.191*	1	0.963**	-0.815**	0.398**	0.940**
PMI	-0.032	-0.124	-0.543**	0.014	0.018	0.963**	1	-0.667**	0.223*	0.983**
Vacancy rate	-0.224*	0.144	0.767**	0.672**	0.625**	-0.815**	-0.667**	1	-0.814**	-0.601**
Unemp. rate	0.228*	-0.135	-0.495**	-0.755**	-0.695**	0.398**	0.223*	-0.814**	1	0.088
IPI	-0.03	-0.1	-0.542**	0.055	0.053	0.940**	0.983**	-0.601**	0.088	1

Notes: Abbreviations: S.D.: standard deviation; Med: Median; WMA; Weekly Moving Average: PMI: Purchasing Managers' Index; Unemp.: Unemployment; IPI: Industrial Production Index. Net Cash is expressed in units of 1000 yen. Net cash quartiles are somewhat similar because Japanese firm's accounting month concentrates on March. The upper panel provides the descriptive statistics for financial variables, market variables, COVID–19 variables, and macroeconomic variables. The expected sign is positive if net cash increases with the increases in the variable. Otherwise, the expected sign is negative. ± means that the variable can be either positive or negative. The lower panel shows the correlation matrix among net cash, market variables, COVID–19 variables, and macroeconomic variables. ** and * represent two-sided significance at the 1% and 5% levels, respectively.

10% level. The adjusted R-squared values are 0.116 to 0.186, supporting the model's goodness-of-fit.

Contrastingly, in cases (1) and (4), using the forced entry method, we found that all market and macroeconomic variables are not significant, and in such cases, some variables have multicollinearity while others have no expected signs.

Kanno (2015c) assessed firms' default risk through a multi-level regression based on simultaneous estimates of the impacts of company-specific, macroeconomic, and sector-specific risk factors using panel and time-series data of Japanese listed firms from April 2001 to March 2012, which includes the time of the global financial crisis. In the study, the macroeconomic factors, such as the core CPI growth rate, overall unemployment rate, overnight call rate, and ten-year long-term JGB yield to subscribers, and the sector-specific risk factors are all significant at the 5% level, in addition to the financial ratios such as EBITDA (logarithmic transformation), current ratio, and fixed assets to fixed liability ratio.

Although Kanno's (2015c) multi-level regression model differs from this study's regression model regarding model structure, in addition to the difference between both datasets employed, it is notable that the some macroeconomic factors are significant at the 1% or 5% level in this study. Contrarily, the COVID–19 parameters (BRN (WMA) and positive rate) are virtually the only risk factors that affect a firm's credit risk during the beginning period of the COVID–19 crisis. In other words, the COVID–19 parameters can be called systemic risk factors in managing the pandemic's systemic risk.

6. Discussion

We discuss the importance of our research from the analytical results.

Concerning assessing the contagion effect on firms in a pandemic, our correlation-based network analysis using network centralities and MST found that the connections among related sectors become stronger during the beginning of the COVID–19 crisis. From the financial network perspective, such network indicators would be helpful in regional and sectoral analyses, in addition to the investment analysis in financial markets.

Additionally, regarding the impact of the state of emergency declaration as the government's measure on firms' performance, stock markets move in inverse proportion to the BRN, which is used as a forecasting indicator of the COVID–19 outbreak. Our network and credit risk analyses explored

Table 8: Impact of COVID–19 on net cash for listed firms

Variables	Net cash					
	(1)	(2)	(3)	(4)	(5)	(6)
Method	Forced entry	Stepwise	Stepwise	Forced entry	Stepwise	Stepwise
BRN(WMA)	-63	-59**	-85**			
	(0.214)	(0.021)	(0.020)			
Positive rate				-3049***	-3184***	-3217***
				(0.002)	(0.000)	(0.000)
TOPIX return	-463			535	144	1151
	(0.955)			(0.946)	(0.985)	(0.881)
N225 VIX	3	-6	1	32	30	29
	(0.902)	(0.809)	(0.956)	(0.232)	(0.245)	(0.255)
PMI		-4	5		11	15
		(0.705)	(0.726)		(0.328)	(0.257)
Core CPI	3591			5272		
	(0.992)			(0.988)		
Vacancy rate	-3012			-735		
	(0.550)			(0.858)		
Unemployment rate	-1793			-1147	-992	-334
	(0.400)			(0.557)	(0.144)	(0.800)
Industrial production	-3114			1207		
	(0.777)			(0.906)		
Constant	186201***	186193***	186192***	186196***	186194***	186192***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed-effects dummy			Yes			Yes
Observations	107	107	107	107	107	107
Adj. R-squared	0.090	0.116	0.116	0.169	0.147	0.186

Notes: P-values are given in parenthesis. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

that the BRN, as an epidemiological indicator, plays an important role as a systemic risk factor of a pandemic in business economies. In forecasting the spread of a pandemic such as COVID–19, in the future, this finding would be implicative in firms' making adaptive business plans for a pandemic era and thereby improving their financial health.

Furthermore, concerning financial institution's risk management, it became evident that pandemic indicators, such as the COVID–19 parameters (reproduction number, positive rate), are important risk factors in stress tests.

7. Conclusions

Our study contributes to the literature by assessing the contagion effect of COVID–19 on Japanese listed firms.

First, as a preliminary analysis, we proposed a COVID–19 SIRD model and derived COVID–19 parameters using a robust method eliminating outliers about Japan nationally and Tokyo locally. In pandemic risk management, needless to say, that the pandemic parameters are essential and sensitive in assessing firms' credit risk.

Second, we analyzed the impact of COVID–19 on the Japanese stock market through correlation-based network analysis. The analysis on the correlation between the TOPIX and BRN shows an inverse relationship around the state of emergency declaration. This supports the validity of the declaration. Additionally, the analysis showed that the government's COVID–19 measures drove the contagion effect in the Japanese stock market. Furthermore, the analysis by MST showed the change of the network structures among the industrial sectors; specifically, the small subgraphs indicate that the clustering of stocks corresponds to related industries. This shows that firms' stock price performance depends on the industry sectors to which they belong.

Third, we analyzed credit risk in the COVID–19 era and found that net cash was a proxy for credit risk and COVID–19 parameters (the BRN and positive rates) were essentially the only factors that affected a firm's credit risk during the COVID–19 period, using panel regression analysis. In other words, market variables and macroeconomic variables were insignificant as credit risk factors for the period of being exposed to a systemic event such as COVID–19.

Finally, this study's analysis of risk contagion effect based on the interconnection between the COVID–19 infection network and the Japanese firms' stock market network, contributed to the existing knowledge regarding risk management in the global pandemic context, one of the most severe systemic risks in human history.

In conclusion, because our data are related to Japan's firms and the stock market, it would be advisable to apply our methodology to other financial markets for further studies. An important limitation for such future studies is that the analyses require outstanding data with bilateral firm names and financial data for at least one accounting year.

Acknowledgments

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Appendix A. List for the number of cumulative infected cases for the period from March 11, 2020, to July 31, 2020.

The cumulative cases are listed in Tables A.9.

Appendix B. Optimization

The calibration (i.e., optimization) of the parameters of the SIRD model is conducted using MATLAB 2020a version as follows:

$$\min_{x} f(x) \quad \text{subject to} \begin{cases} c(x) \leq 0 \\ ceq(x) = 0 \\ A \cdot x \leq b \\ Aeq \cdot x = beq \\ lb \leq x \leq ub \end{cases} \tag{B.1}$$

where $x = (\beta_0, \tau_\beta, \delta_0, \delta_1, \tau_\delta, \gamma_0, \gamma_1, \tau_\gamma)$, b and beq are vectors, A and Aeq are matrixes, $c(x)$ and $ceq(x)$ are functions returning vectors, and $f(x)$ is a function returning a scalar. Using equation (B.1), the optimization is based on the minimization of the residuals between the model's objective function and the officially published epidemiological data. After several trials, β_1 in equation (2) is set to zero.

Table A.9: Cumulative number of persons as the sum of infected cases, recovered patients, and death toll for the period from March 11, 2020 to July 31, 2020

C cases	Hokkaido	Aomori	Iwate	Miyagi	Akita	Yamagata	Fukushima	Ibaraki	Tochigi	Gunma	Saitama	Chiba
25%-Q	451	22	0	84	16	64	64	143	49	124	662	683
Median	1,047	27	0	88	16	69	81	168	65	149	999	904
75%-Q	1,221	27	0	92	16	69	82	172	69	152	1,103	947
Maximum	1,413	32	3	158	18	76	89	280	195	190	2,313	1,656
Mean	884.0	23.2	0.0	80.3	14.2	56.9	65.6	150.6	64.4	126.1	941.4	811.2
SD	427.1	8.3	0.3	37.2	4.5	25.1	28.2	63.8	38.9	52.2	535.7	375.5
C cases	Tokyo	Kanagawa	Niigata	Toyama	Ishikawa	Fukui	Yamanashi	Nagano	Gifu	Shizuoka	Aichi	Mie
25%-Q	3,276	802	56	114	180	113	49	52	139	52	406	39
Median	5,156	1,328	83	227	295	122	60	76	150	75	507	45
75%-Q	6,069	1,457	84	227	300	122	72	77	156	80	523	46
Maximum	12,691	2,484	111	238	321	139	94	105	331	269	1,609	91
Mean	4,994.6	1,172.8	70.9	171.1	231.4	103.9	54.9	62.2	137.0	70.5	486.3	39.9
SD	2,920.0	609.4	22.9	89.3	106.3	38.8	24.6	27.5	60.0	43.4	226.8	17.2
C cases	Shiga	Kyoto	Osaka	Hyogo	Nara	Wakayama	Tottori	Shimane	Okayama	Hiroshima	Yamaguchi	Tokushima
25%-Q	72	259	1,297	524	64	46	3	16	19	137	30	3
Median	100	358	1,781	699	91	63	3	24	25	167	37	5
75%-Q	101	366	1,815	705	92	64	3	24	26	168	37	6
Maximum	171	758	4,057	1,158	235	150	15	29	79	312	53	25
Mean	85.0	325.1	1,579.5	602.2	86.2	59.5	2.9	18.9	24.2	141.0	31.5	5.6
SD	39.9	155.5	780.5	243.4	48.7	27.0	2.1	9.5	14.0	71.7	12.7	3.8
C cases	Kagawa	Ehime	Kochi	Fukuoka	Saga	Nagasaki	Kumamoto	Oita	Miyazaki	Kagoshima	Okinawa	Nationwide
25%-Q	26	46	69	524	17	16	40	55	17	10	121	11,052
Median	28	81	74	664	47	17	48	60	17	10	142	16,276
75%-Q	28	82	74	844	47	17	49	60	17	11	142	17,941
Maximum	46	89	80	1,756	82	74	191	66	121	236	395	35,084
Mean	24.6	59.8	64.0	662.6	37.1	18.6	44.4	52.8	18.7	39.9	120.9	14,918.4
SD	12.4	28.4	21.1	359.1	19.2	12.9	25.0	14.7	17.2	65.9	61.0	7,618.7

Notes: Abbreviations: SD: standard deviation; C: Cumulative; Q: Quartile.

Additionally, the calibration of $\mathcal{R}_0$ needs daily data sufficient for covering one infection wave. Evidently, it is almost impossible to obtain a flexible curve that fits the data with two or more waves. As a result of several trials, we found that a 30-day (i.e., one-month) time-series data fits the infection cases most closely.

Appendix C. Robust estimator in optimization

To obtain the model parameters, the minimization is performed for the objective function, assigning to it the residual between the model value and the COVID–19 data. The ordinary least-squares method is sensitive to the outliers. The maximum likelihood estimation method also produces an estimator with the same nature as the least-squares method. Both non-linear least-squares and maximum likelihood estimation are special cases of M-estimators. Hence, a robust regression method needs a fitting criterion that is not as vulnerable as least-squares or maximum likelihood. To this end, the Tukey bi-square weight function, also referred to as the bi-weight function, produces an M-estimator that is more resistant to regression outliers (Andersen, 2008).

Given n observation data y_i at a time point i $(i = 1, \dots, n)$, the corresponding model value is $\hat{y}_i$. Because the residuals are expressed by $\epsilon_i = y_i - \hat{y}_i$, a class of robust estimator is defined as

$$T(\epsilon_i) = \begin{cases} \frac{k^2}{6}\left\{1 - \left[1 - \left(\frac{\epsilon_i}{k}\right)^2\right]^3\right\}, \text{for } |\epsilon_i| \leq k \\ \frac{k^2}{6}, \text{for } |\epsilon_i| > k \end{cases}, \tag{C.1}$$

where $k = 4.685 \times MAD(\epsilon)$ which is the mean absolute deviation of the residuals. If $|\epsilon_i| > k$, the outlier effects are removed. The objective function $f(\cdot)$ in equation (B.1) is defined as the sum of $T(\epsilon_i)$ $(i = 1, \dots, n)$ to ensure goodness-of-fit between the model value and the epidemiological data.

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