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Analyses of topical policy issues

Convergent movement of COVID-19 outbreak in Japan based on SIR model

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ABSTRACT

The infection dynamics of COVID-19 show frequent phases in which the infection spreads rapidly, resembling explosive infection. However, despite the repeated increases and decreases, there is a process of convergence even within a relatively short period of time. While it is obvious that the growth rate of the cumulative number of infected people slows down as it increases, considering the infectious disease process, we also observe a slowdown in the growth rate of the net number of infected people. Moreover, there exists a special type of convergence whereby areas with initially many infected people exhibit low rates of increase in the numbers of infected people subsequently. This paper uses prefectural panel data from Japan through March 2021 to confirm the convergence process.

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1. Introduction

At the end of December 2019, a case report of pneumonia of unknown cause was sent to the China office of the World Health Organization (WHO), and the first case of COVID-19 imported into Japan was confirmed on January 16, 2020. After that, the WHO declared a global pandemic, and Japan experienced its first wave of infection from mid-March to mid-May. Then, although the initial spread of infection had settled, Japan experienced a second wave around the end of June, followed by a third wave in early November 2020. In this context, it has often been pointed out that the situation in Japan is, in a sense, different from that in other countries, even when focusing only on infection trends. In particular, even before comparing Japan with the United States, Brazil, France, and other countries that have seen extremely serious outbreaks, Japan certainly appears to be unique in comparison with other countries such as Germany that are regarded as having responded relatively successfully to the COVID-19 pandemic.

Having become a major issue in many countries around the world, COVID-19 has had a massive impact not only on human health and health care systems but also on the economy. For example, Fernández-Villaverde and Jones (2020) compared major countries, regions (states), and cities affected by COVID-19 based on two measures for evaluation: (i) economic damage (measured roughly in terms of GDP loss) and (ii) number of deaths due to infection. According to their classification, New York City and the Italian province of Lombardy are among the worst performing in terms of high death tolls and economic damage, whereas the situation is better in East Asian countries, including Japan.

However, for those of us who live in Japan and are currently experiencing the COVID-19 disaster, there is little sense that the government is in control of the disease. There are still many things that we do not understand about COVID-19.
itself and its infection dynamics. Therefore, accounting for the structural characteristics of Japan’s specific medical supply system, we started a research project to assess the COVID-19 disaster by organizing the infection situation in Japan from various perspectives including fact-finding (see Masuhara and Hosoya, 2021).

Apart from Iwamoto (2020) introduced later, our focus on testing the convergence property derived from the characteristics of the SIR (susceptible–infectious–recovered) model is novel, and to our knowledge, there are no empirical studies on convergence as the main research subject. In general, the SIR model is often used for forecasting as well as for policy evaluation in order to simulate trends in infection dynamics, evaluate the impact of policy interventions, analyze economic losses, and so on. In contrast, this paper points out that the analytical characteristics of the SIR model are related to convergent movement in the transmission cycle of infectious diseases and furthermore aims to verify this feature with data.

The spread of infection is still ongoing, and only a few studies have attempted to evaluate the general situation, even if only to produce an interim report. Bassino and Ladmiral (2020) attempted a standard empirical study of Japan’s infection situation, though their study examined only the early stages of the outbreak. In the present study, the determinants of the numbers of positive polymerase chain reaction (PCR) tests were analyzed on the basis of municipalities in each prefecture. High population density, income levels, and behaviors involving human contact (e.g., overseas travel and eating out) were identified as factors contributing to the spread of infection. The working age population (20–64 years old) and the more active elderly (65–79 years old) were more strongly associated with infection than the elderly over 80 years old. These findings provide the basis for the empirical study design of this paper, especially Section 2.

What kind of findings can be obtained from a study using cross-country data? Although previous studies are rather limited, the valuable study by Toya and Skidmore (2021) deserves mention. They found that countries with higher incomes, more freedom, lower population density, and more elderly people had higher infection rates. OECD countries and island countries had lower infection rates. It is surprising that countries with lower population density were more severely affected by cross-country viewpoints, and thus further investigation is warranted. It is also interesting to note that the infection rate is higher in countries with a high degree of freedom. The finding that the levels of freedom and control in civil society affect the spread of infectious diseases will be an important point of discussion.

In relation to the contents of this paper, we would like to briefly mention some research on the SIR model. Research that considers infection dynamics and its impact on the economy based on the SIR model as an epidemiological model has made rapid progress in the wake of the ongoing pandemic and has led to several hundred papers worldwide.1 The SIR model can be divided into two types.2 The key is whether to take into account the rational decision-making of an agent. In conventional SIR models (i.e., non-behavioral SIR models), voluntary behavioral changes in response to the infection situation are not considered. However, that analysis is straightforward and simple in a good sense, and the framework is useful when the results of the analysis need to be promptly disseminated. In this regard, Atkeson (2020) and Alvarez et al. (2021) are well-known studies that consider the connection with macroeconomic models. In addition, Fujii and Nakata (2021) simulated the situation in Japan and their findings were taken up by the Diet.

In contrast, in the behavioral SIR models that incorporate agent optimization, individual behavior changes in response to factors such as the spread of infection and the contents of government policies. Therefore, this is an epidemiological model that implements the concept of dynamic optimization in economics. Eichenbaum et al. (2021), which was published in March 2020 and revised in April 2021, is a pioneering contribution to the study of SIR-Macro models and has already become a basic reference. In their model, pandemic victims decrease consumption and the labor supply, thereby reducing the risk of infection, but they are forced to pay a price for hurting economic growth.3 Hence, SIR-Macro models are useful as a basic framework for considering the trade-off between life and the economy from various perspectives. Hosono (2021) and Kubota (2021a) are two studies that have developed this type of model and simulated the infection situation in Japan. For instance, Hosono (2021) combines a dynamic general equilibrium model and the SIR model with the aim of analyzing the effects of a voluntary lockdown and a request-based lockdown without legal enforcements. Although the economic implications are similar to those of Eichenbaum et al. (2021), it is confirmed that the combination of these two types of lockdowns in the constructed model can approximate the actual share of infected people. This highlights how individual behavior in response to incentives can also play an important role in the spread of infectious disease.

Our study has value as a detailed investigation of the nature and trends of COVID-19 infection dynamics itself in a socioeconomic context through early 2021. Specifically, we focus on some convergent movement of the number of infected people and examine the infection dynamics in detail. We pay particular attention to the rate of increase (growth) in the number of infected people, and we carefully observe the infection dynamics represented by this index. Based on the SIR model, which is the basic model of infectious disease, we examine whether the infection dynamics represented by this index behave in a convergent manner, using data from Japan. The importance of this analysis is discussed in particular detail at the beginning of Section 4 based on the findings obtained through the basic estimation in Section 2.

The rest of the paper is organized as follows. In Section 2, we present some basic estimation results that suggest convergent movement in Japan and provide two testable hypotheses. In Section 3, we briefly examine this theoretical

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1 To follow the details of the analysis, we should review the papers published in traditional journals as well as papers published in Covid Economics, Vetted and Real-Time Papers since March 2020.

2 The following description is essentially based on Kubota (2021b).

3 Because individuals cannot accurately internalize the impact of their economic decisions on the spread of infection, this competitive equilibrium deviates from the social optimum.
relationship. In Section 4, by processing the Japanese prefectural panel data constructed from some data sources on a monthly and daily basis, we visualize the estimation results presented in Section 2 with a focus on time-series trends. We also attempt panel estimation to supplement our hypothesis. This allows us to examine in more detail the possibility of convergent movement. Moreover, the policy implications for Japan based on the estimation results are discussed. In Section 5, we present conclusions and indicate some directions for future research.

2. Signs of convergence in the process of infection spread

In an initial analysis to find the factors affecting the infection dynamics (increase or decrease in the number of infected people), we noticed that the dynamics of the number of COVID-19 cases contained a situation superficially similar to the \( \beta \)-convergence of income, a major topic in neoclassical growth theory. The income convergence hypothesis of growth theory (\( \beta \)-convergence) is the idea that the lower the per capita income is at the initial stage, the higher the growth rate will be during the development process, compared with the steady-state equilibrium determined by the parameters that characterize each country's economy. In the case of the spread of infectious diseases, we assume that the so-called effective reproduction number (ERN) is relatively high in the initial stage when the number of infected people is small, and that it decreases as the spread of infection progresses, eventually leading to the convergence of a single infection cycle. We seek a theoretical basis for this in the SIR model, the details of which will be discussed in Section 3.

2.1. Data description

Before presenting representative estimation results, we briefly describe the data used for the estimation, all of which are generated at the prefectural level in Japan. First, the numbers of positive PCR tests are obtained for the periods from the first confirmed case to the end of June 2020, and then from the beginning of July to the end of August 2020 (cumulative values). Because the difference between these periods captures the infection dynamics from the beginning of July to the end of August, it is used as the dependent variable in the estimation (logarithm of the rate of change in the number of infected people). As an independent variable, the number of positive cases by the end of June (logarithmic value) is included as the most basic variable for verifying the convergence process regarding the number of people with positive PCR tests. If this estimated coefficient is negative, then the subsequent infections are likely to converge to stationary levels. This convergence is similar to the \( \beta \)-convergence of growth theory (income convergence hypothesis) in infectious diseases. In other words, we statistically examine how the number of positive PCR tests at the initial point (beginning of July) affects the rate of increase in the subsequent period.

Other basic independent variables are included in the regression equation according to the following ideas. Various epidemiological surveys have shown that the presence of the “3 Cs” (closed spaces, crowded places, and close-contact settings) greatly increases the risk of infection. In this regard, the inhabitable population density (population per 1 km\(^2\) of inhabitable area) and the ratio of the daytime population to the nighttime population are employed based on the fact that infection is particularly remarkable in nighttime entertainment districts (with alcohol consumption). Epidemiological findings regarding infectious diseases suggest that temperature (and humidity) and the mobility of people are the most fundamental influencing factors. Therefore, the regression equations include the annual average temperature (high temperature acts to suppress infection) and the presence or absence of Shinkansen (super express train) stations in each prefecture as a proxy variable for the latter factor. The number of available intensive care unit (ICU) beds at any point in time is also important in predicting subsequent infection trends, and the estimated coefficient is expected to be positive.

Table 1 shows the sources of the data. The number of positive PCR tests obtained from the Toyo Keizai Online “Coronavirus Disease (COVID-19) Situation Report in Japan” is based on data from the Ministry of Health, Labour and Welfare (also in Section 4). Herein, we used the daily data from Toyo Keizai listed in Table 1 for the number of positive PCR tests because this data is compiled as prefectural panel data and is used as the standard among researchers. The total population, population density, average temperature, and day–night population ratio were obtained from the Statistics Bureau of the Ministry of Internal Affairs and Communications; the Nishiura prediction was derived from the materials of the Expert Committee on COVID-19 Infections, explained in detail later; the Shinkansen dummy, which takes a value of 1 when there is a Shinkansen station in the prefecture, was taken from Enpedia’s “Ranking of Shinkansen Stations”; and the number of ICU beds was obtained from website of the Ministry of Health, Labour and Welfare. Note that these explanatory variables are time-invariant and cannot be used practically in the panel data estimation in Section 4. Table 2 shows the descriptive statistics of the dependent and explanatory variables described above. Iwate Prefecture is excluded from the analysis because the number of positive PCR tests was zero as of June 2020. Therefore, the sample size is 46.
Table 1
Sources of the data.

| Variables                              | Sources                                                                 |
|----------------------------------------|-------------------------------------------------------------------------|
| Positive PCR tests                     | Toyo Keizai Online “Coronavirus Disease (COVID-19) Situation Report in Japan” based on the Ministry of Health, Labour and Welfare (also in Section 3) |
| Population density, Day–night population, Temperature Shinkansen dummy Number of available ICU beds Onset (Nishiura), Severe (Nishiura) | Statistics Bureau of the Ministry of Internal Affairs and Communications Enpedia’s “Ranking of Shinkansen Stations” Ministry of Health, Labour and Welfare The Nishiura prediction from the materials of the Expert Committee on COVID-19 Infections |

Table 2
Summary statistics.

| Variables                              | Mean   | SD      | Min    | Max   |
|----------------------------------------|--------|---------|--------|-------|
| Growth rate of positive PCR tests from June to August (logarithmic value) | 4.196  | 6.598   | 0.101  | 38    |
| Positive PCR tests in June 2020 per 100,000 (logarithmic value) | 8.948  | 8.574   | 0.559  | 45.59 |
| Positive PCR tests in August 2020 per 100,000 (logarithmic value) | 3.127  | 3.232   | 2.381  | 152.1 |
| Population density (log)               | 6.842  | 0.764   | 5.465  | 9.182 |
| Day–night population                   | 99.21  | 4.165   | 88.90  | 117.8 |
| Temperature                            | 16.14  | 2.195   | 9.500  | 23.50 |
| Shinkansen dummy                       | 0.630  | 0.488   | 0      | 1     |
| Number of available ICU beds           | 0.185  | 0.382   | 0      | 1.515 |
| Onset (Nishiura)                       | 188.1  | 15.37   | 148.2  | 221.8 |
| Severe (Nishiura)                      | 6.294  | 0.485   | 5.034  | 7.347 |

Note: SD indicates standard deviation.

To curb the rapid spread of infection in Japan, a state of emergency was first declared from April to May 2020. That declaration was decided largely based on the so-called “Nishiura prediction” by Hiroshi Nishiura, then a professor at the Graduate School of Medicine of Hokkaido University. At the end of February 2020, this prediction that around 10% of all people in Japan might develop COVID-19 had a large social impact and also influenced the reorganization of the medical care system in each prefecture. In addition, an estimate that without protection against infection, COVID-19 would render around 850,000 people severely ill and would kill around 420,000 of them, which was announced in mid-April 2020 (around the same time as the declaration of the state of emergency), was received with great surprise. Considering the impact of the Nishiura prediction on the infection dynamics, herein we include in the regression equation the prefectural predictions for the numbers of cases and hospitalized and seriously ill people.

2.2. Preliminary estimation results

Table 3 shows typical estimation results (1)–(6). Of these, we explain the following three as remarkable features: (i) the logarithm of positive PCR tests at the initial time point is negative and significant in all estimates; (ii) the inhabitable population density is positive and significant; and (iii) the predicted values for onset and severely ill patients based on the Nishiura prediction are negative and significant. Point (iii) is particularly interesting because it suggests that surprising predictions may have contributed to infection suppression as a proxy variable for fear, and it must be explored in more detail. Of course, the result that we are particularly interested in is (i). Although these estimates provide only a snapshot of the infection situation up to August 2020, they foreshadow convergence of the number of infected people per 100,000 of the population.

Upon careful consideration, the occurrence of such a phenomenon can be understood as a natural consequence related to the ERN based on the SIR model, which is a well-known epidemiological model for infectious diseases.

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8 In Table 3, columns (5) and (6) are based on Lasso regression. Therefore, the independent variables used in columns (5) and (6) were selected from the viewpoint of statistical prediction.

9 As mentioned earlier, the Nishiura prediction was one of the triggers for the first declaration of the state of emergency in April 2020, which has led to much debate about its validity.
2.3. Convergent process in the infection dynamics of COVID-19

In Japan, the rapid spread of COVID-19 occurred in early April, late July, and mid-November of 2020, and people have been experiencing increasing anxiety about COVID-19 due to the rise in cases reported daily. This is an undeniable fact. However, focusing on the growth rate of the number of infected people is likely to give a different view of the infection dynamics, as suggested by the consequences of the SIR model described below. Specifically, if the basic transmission dynamics of the SIR model are correct, then there exists some clear tendency for the growth rate of the number of infected people to converge over time. Thus, although the number of infected people might exhibit divergent behavior during periods of rapid spread, the growth rate of the number of infected people, when viewed from a global perspective, indicates that the infection dynamics are progressing toward a stationary level.

As mentioned in the previous section, we confirm the verification hypothesis for convergence in this paper. This is divided into the following two basic hypotheses:

(i) In a given country, the growth rate of the number of infected people in the region with the highest number of infected people in the initial stage decreases in the subsequent period.

(ii) Focusing on the growth rate of the number of infected people in a given country as a whole over time, we observe a high growth rate in the early stages of infection when the cumulative number of infected people is small, and a gradually declining growth rate as the cumulative number of infected people increases.

If the data support these results, then we conclude convergence of COVID-19 infection, at least under the same variant. Although in the next section we investigate these hypotheses using Japanese infection data, we find the following positive implications for this type of study. First, the data do indeed support the unexpected convergence described above (the analysis in this paper focuses on this issue). Second, even if the overall convergent movement is confirmed, some deviations from the convergence path (or the expected path of variation) may be observed due to, for example, the rapid spread of mutated viruses or changes in an infectious-disease control program by the government. The impact of artificial and natural events on transmission dynamics, especially if linked visually and quantitatively, provides important information for efforts to prepare for future COVID-19 outbreaks or the arrival of new, unknown infectious diseases. This paper emphasizes the importance of a preliminary status report and does not analyze such details. However, we reason strongly that these are very important issues to be analyzed in the near future.

3. Convergent movement and the SIR model

As discussed in Section 2, the income convergence hypothesis states that the lower the per capita income is at the initial stage, the higher the growth rate will be. This mechanism is due to the scarcity of capital stock per capita at the

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Table 3

| Table 3 Preliminary estimation results for the convergent infection dynamics of the COVID-19 outbreak in Japan. |
|------------------------------------------------|
| (1) | (2) | (3) | (4) | (5) | (6) |
| Log of number of positive PCR tests | –0.483*** | –0.858*** | –0.933*** | –0.760*** | –0.689*** | –0.843*** |
| Population density | 0.974*** | 0.972*** | 0.972*** | 0.545** | 0.522** | 0.522** |
| Day–night population | –0.005 | –0.011 | –0.011 | 0.019 | 0.015 | 0.015 |
| Temperature | 0.252*** | 0.252*** | 0.252*** | 0.252*** | 0.252*** | 0.252*** |
| Shinkansen dummy | –0.356 | –0.155 | –0.155 | –0.452 | –0.395 | –0.395 |
| Number of available ICU beds | –0.075*** | –0.075*** | –0.075*** | 0.024 | 0.024 | 0.024 |
| Onset (Nishiura) | –1.070*** | –1.070*** | –1.070*** | (0.310) | (0.310) | (0.310) |
| Severe (Nishiura) | 1.593*** | 1.593*** | 1.593*** | 6.098* | 6.098* | 6.098* |
| Constant | 0.731*** | 0.731*** | 0.731*** | 0.731*** | 0.731*** | 0.731*** |
| adj. R² | 0.145 | 0.428 | 0.428 | 0.479 | 0.479 | 0.479 |
| N | 46 | 46 | 46 | 46 | 46 | 46 |

Notes: Robust standard errors (White) appear in parentheses; significance levels: 1% (**), 5% (**), 10% (*).
initial stage, which results in higher marginal productivity of that limited capital. A similar argument can be observed for infectious diseases. In the initial stage when the number of infected people is small, the ERN is relatively high, and as the spread of infection progresses, it decreases and eventually the cycle of infection begins to converge. By using the SIR model, we can describe this process in terms of convergence.

Let $S(t)$, $I(t)$, and $R(t)$ be the numbers of susceptible, infectious, and recovered people, respectively. Then, using the SIR model, the spread of COVID-19 is described by

$$N = S(t) + I(t) + R(t),$$

$$\frac{dS(t)}{dt} = -\eta(t) \frac{S(t)}{N},$$

$$\frac{dR(t)}{dt} = \gamma I(t),$$

where $N$ is the total number of population, $\gamma$ is the combined recovery and mortality rate from COVID-19, and $\eta(t)$ contains information about the encounter rate and the infection rate (in the standard SIR model, this parameter is given as $\beta(t)$, but we use $\eta(t)$ to avoid confusion). Differentiating Eq. (1) with respect to time $t$ and noting that $N$ is constant over time, we obtain $dS(t) + dI(t) + dR(t) = 0$. Then, Eqs. (1)-(3) yield

$$\frac{dl(t)}{dt} = \eta(t) \frac{S(t)}{N} I(t) - \gamma I(t) \Rightarrow \frac{dl(t)}{I(t)} = \frac{\eta(t) S(t)}{\gamma N} - 1 \gamma.$$

Here, $\eta(t) S(t)/\gamma N$ is the ERN. From Eq. (4), the growth rate of the number of infected people is equal to the ERN minus one and multiplied by the recovery rate $\gamma$. The value of the recovery rate may be small in the early stage of a pandemic because standardized treatment is yet to be established, but it will become constant as treatment strategies are established. Therefore, the ERN and the growth rate of the number of infected people are linearly related.

Moreover, in Eq. (4), the ERN decreases with time because of the following factors. First, as the infections spread, the spread of the infection progresses, it decreases and eventually the cycle of infection begins to converge. By using the SIR model, we can describe this process in terms of convergence.

This means that the growth rate of the number of infected people and the cumulative number of infected people are negatively correlated as an inductive system, which describes one aspect of the convergent movement in infection dynamics. The same argument holds when the left-hand side of Eq. (4) is converted into the growth rate of the cumulative number of infected people. Using Eq. (4), we obtain

$$\frac{dl(t)/dt + dR(t)/dt}{I(t) + R(t)} = \eta(t) \frac{N - (I(t) + R(t))}{N} \frac{I(t)}{I(t) + R(t)}.$$

Therefore, under $I(t) > 0$, we observe a negative correlation between the growth rate of the cumulative number of infected people and the cumulative number of infected people. Second, given individual differences in the risk of infection, those who are more likely to be infected first will be infected, and those who have a lower risk of infection remain in the uninfected population in large numbers, further reducing the average rate of infection. In the presence of heterogeneity in infection risk, herd immunity arises more quickly.

The two results explained above are obtained from the nature of the SIR model, but Iwamoto (2020) mentions three more possibilities: (i) individuals and firms take precautions to protect themselves (voluntary prevention); (ii) the government either encourages behavioral changes (requests for self-restraint) or restricts people’s behavior (lockdown); (iii) seasonality of infectiousness (increased infections in winter, decreased infections in summer). All these are factors that shift $\eta(t)/\gamma$. Conversely, the loosening of voluntary prevention by individuals and firms, the easing of government restrictions on behavior, and the shift from summer to winter increase not only the ERN but also the growth rate of infected people. This is a typical “hammer and dance,” and the growth rate of infected people is cyclical in the short term, like economic fluctuations. Meanwhile, the growth rate of the number of infected people always has a decreasing trend according to the nature of the SIR model. In the long run, as the cumulative number of infected people increases, the growth rate of infected people decreases.

11 See Acemoglu et al. (2020), Atkeson (2020), and Avery et al. (2020) for details.
However, regarding the long-term trend based on the SIR model and the short-term cyclicity, the length of the trend and the fluctuations may differ among countries. In Japan, we observed a hammer from April 2020 that suppressed the increase in the number of infected people in the first wave, a dance from late May to June, a second wave from June to July, and a convergence from August to October. It is not appropriate to conclude that a decrease in \( S(t)/N \) is the only factor. Rather, the change is caused by a decline (hammer) in \( \eta(t)/\gamma \) due to policy and citizens’ efforts to change their behavior, followed by some relaxation (dance). Fluctuations may be larger in the United States, and a decrease in the growth rate of infected people is not observable until vaccination against COVID-19 decreases \( S(t)/N \) or \( \eta(t) \). However, if \( \eta(t) \) remains constant or if people prefer to make less contact with each other than they did before the pandemic \( (\eta(t) > \eta(0)) \), then we conclude that the long-term trend is parallel to the convergence process. In Japan, the situation of \( \eta(t) < \eta(0) \) is considered to be established because using masks and avoiding the 3 Cs (i.e., observing social distancing) has spread to a certain extent at least in 2020, and the “new normal” is accepted, albeit incompletely. Thus, although infection may appear to be explosive in the short term, there will be a tendency toward convergence in the long term.

If, in the SIR model, reinfection becomes non-negligible, then \( S(t) \) is no longer a non-increasing function of \( t \), and in some cases may even become an increasing function of \( t \). In the most extreme case, \( R(t) \) is instantly included in \( S(t) \), and the behavior of the model is determined by \( \eta(t)/\gamma \) in Eq. (4). In this case, if \( \eta(t) < \gamma \), the number of new infections decreases, but if \( \eta(t) > \gamma \), the number of infections continues to increase until it reaches \( N \). However, although the extreme cases described above have not occurred thus far, we cannot exclude the possibility that such cases will occur due to mutations leading to new variants of the coronavirus.\(^{12} \)

### 4. Case of Japan

We examine the convergence of the rate of increase (growth) in the number of infected people predicted by the SIR model using data from Japan. Assuming that the total population does not change much over a period of time (which is a reasonable assumption, and not an extremely strange one in Japan, where the total number of deaths from COVID-19 was around 10,000 as of April 2021), it is obvious that there will be a convergence of the growth rate in the big picture, as explained in Eq. (5). Therefore, it is also obvious that the rate of growth in the cumulative number of infected people decreases gradually. However, for a fairly long-term infection such as COVID-19, it is worth checking whether convergent movement can be observed in a period of several months to a year. Section 4.1 contains an analysis for this purpose, and it is the cornerstone for the analysis in the next section, which is the aspect of this paper that deserves the most emphasis. Section 4.2 contains the highlight analysis of this paper and examines the convergence of the growth rate of the number of infected people based on the net infected patients, excluding those who have been discharged from hospitals. It is difficult to predict how the net growth rate will evolve, especially when the survey period is limited. In light of the structure of the SIR model discussed earlier, signs of convergence are suggested, and convergence is verified using actual data.

#### 4.1. Gross analysis

In this section, we assess whether the convergence property in the SIR model presented briefly in Section 3 is established from prefecture-level data in Japan. Using the daily data throughout Japan, Fig. 1 shows the relationship between the logarithm of cumulative positive PCR tests per 100,000 population in the previous week (horizontal axis) and the logarithm of daily average of the weekly growth rate in cumulative positive PCR tests (vertical axis).\(^{13} \) This confirms that the growth rate of the cumulative number of positive PCR tests in Japan tends to decrease gradually, albeit with some fluctuation, with the convergent movement explained. However, the background of such fluctuation may be the effect of policy intervention by the Japanese government. In the following, we examine the process in detail.

Given that \( 1.05^7 \approx 1.41 \) (1.1\(^7 \approx 1.95 \)), this means that the cumulative number of positive PCR tests roughly doubled within a week in early April 2020. The growth rate then decreased sharply in June, but this was largely because of the declaration of the state of emergency on April 7, 2020. The declaration asked people to refrain from going out or traveling between prefectures, and it included a request to restrict the use of facilities where clusters of infection were occurring. Although it was a lockdown without the penalties imposed in other countries such as the United Kingdom and France, the declaration may have played an important role in controlling the growth rate of infections in Japan. Initially, the declaration of emergency was set to expire on May 6, 2020, but the continuing increase in the number of infections led to an extension being announced on May 1. On May 25, the state of emergency was lifted in all prefectures, and on June 18 the request to refrain from traveling between prefectures was relaxed.

With the state of emergency lifted, the growth rate of the number of infected people increased again after June 2020. In addition, the “Go To Travel” program was launched on July 22 to support the tourism industry by subsidizing travelers’

\(^{12} \) At least in 2020, the probability of being infected with COVID-19 and then reinfection after recovery was very low, according to results reported by Vitale et al. (2021). Using results of PCR tests during the first wave of the COVID-19 pandemic in Italy (February–July 2020), the authors examined the incidence of initial infection and reinfection with COVID-19, defining reinfection as “a second positive test result at an interval of at least 90 days after recovery from infection”. The results are scientifically reliable and consistent with the data period used in our paper. On this basis, it is concerning that the SIR model does not take reinfection into account, given the mathematical nature of the model, but it is still valid as a model that approximates reality.

\(^{13} \) In Fig. 1, the \( \ln(5) \) and \( \ln(10) \) lines indicate a daily growth rate of 5% and 10%, respectively.
Fig. 1. Log of daily average of weekly growth rate of cumulative positive PCR tests.

accommodation fees. The growth rate of infected people then continued to increase until the beginning of August, probably because of that program. In Japan, the national Obon holiday occurs in mid-August, and the growth rate began to decrease around that time, probably because of the government’s “verbal intervention” concerning the spread of infection to non-urban areas.\footnote{Along with the New Year’s holiday, the Obon holiday is an important event in Japan during which it is customary to spend time with one’s family and, for many people, involves traveling to the family home in another prefecture.}

After September 2020, the daily growth rate was around 1%, and COVID-19 remained under control. On October 1, in addition to the “Go To Travel” program, the “Go To Eat” program was launched to support restaurants by subsidizing the cost of food and beverages. Restaurants were thought to be areas in which the 3 Cs were unavoidable and conducive to the spread of COVID-19, but in situations where the increase in infection was controlled, the policy was deemed feasible to implement.

In November 2020, the growth rate of the cumulative number of positive PCR tests increased, and the number of new infections per day exceeded 1,500; in particular, the number of new infections per day in Tokyo exceeded 500. On November 17, the “Go To Eat” program was limited to a maximum of four people over fears over tightening hospital capacity, and on November 27 the program was canceled in central Tokyo. However, the spread of COVID-19 did not slow down, and by the beginning of January 2021 the number of new infections per day in Tokyo exceeded 2,000. In response to this situation, a second emergency declaration was announced for the Tokyo metropolitan area on January 7, 2021, and another 11 prefectures were added on January 13, 2021; the state of emergency continued until March 7, 2021.\footnote{This was later extended until March 21.}

Since the declaration of the state of emergency, the growth rate of the cumulative number of positive PCR tests has decreased sharply, falling below 1% in February. Vaccinations against COVID-19 for healthcare workers began on February 17, 2021, and the second state of emergency was lifted on March 21.

The growth rate of the cumulative number of positive PCR tests in Japan has shown a decreasing trend, as explained by the SIR model, although with fluctuations. Next, we investigate the convergent movement hypothesis between prefectures at the same point in time. In other words, we examine the tendency for prefectures with a high (resp. low) cumulative number of positive PCR tests at a given point in time to have a lower (resp. higher) rate of growth subsequently. Because the daily panel data by prefecture lead to large variations, we use the growth rate of the cumulative number of positive PCR tests during one month, converted to a daily average.

Fig. 2 plots the growth rate of the cumulative number of positive PCR tests versus the cumulative number of positive PCR tests, colored by month from April 2020 to March 2021, while Fig. 3 shows a monthly decomposition of Fig. 2. As shown in Fig. 1, the cumulative number of positive PCR tests fluctuates from month to month, with rises and falls.

In Fig. 2, however, the growth rate is lower in January 2021 than in April 2020. Furthermore, in Fig. 3, the convergence property within the same month is confirmed. This is especially true in April 2020 and January 2021, when the state of emergency was declared, and in July, August, and December 2020, when the number of infected people increased sharply. In contrast, no remarkable convergence is observed in May, June, September, or October 2020, when the spread of infection had subsided temporarily.
4.2. Net analysis

The arguments regarding Figs. 1–3 use the relationship between the growth rate of the cumulative number of positive PCR tests and the log of those cases, which corresponds to Eq. (5) regarding the SIR model. These results involve using the cumulative number on both the vertical and horizontal axes, and considering that there has not yet been explosive spread of infection in Japan, the decrease in the growth rate of the stock (gross positive PCR tests) is an important result, but in a sense an obvious one. However, the SIR model in Eq. (4) shows the same trend for the cumulative number of positive PCR tests and for the net number of those cases excluding discharged patients. Next, we examine the relationship between the net growth rate of the number of positive PCR tests and the cumulative number of those cases. This is shown in
Fig. 4 shows no explosion in the growth rate of the cumulative number of positive PCR tests, and the growth rate is not as pronounced as in Fig. 1. Figs. 5 and 6 also show the convergent process in terms of cross-sectional units at the same point in time, although it is not as clear as in Figs. 2 and 3.

4.3. Simple panel results of estimation

Finally, as an addendum, we present the results of the panel data estimation. We linearize the transition equations of the SIR model expressed in Eqs. (4) and (5) and estimate these directly, using prefectural panel data in Japan. Because

If some prefectures have positive PCR test cases but recover quickly in several months and at the same time the number of new positive cases is zero in the next month, then the net growth rate is \(-100\%\). We treated such instances as outliers and excluded them from the analysis.
our data do not contain time-varying daily or monthly covariates for the medical system in Japan, we use only monthly dummies for estimating conditional convergence. Moreover, the data have gaps and consist of an unbalanced panel and a fixed number of individuals, and we do not apply any panel unit root test.

The estimation results for the gross (logarithmic) and net growth rates of the cumulative number of positive PCR tests are shown in the second and third columns of Table 4, respectively. The standard F-test, Breusch–Pagan Lagrange multiplier (LM) test, and Hausman test were used to determine the fixed-effects model in both models. The results in
second column show that a 1% increase in the number of cumulative positive PCR tests at the end of the previous month results in a 0.659% decrease in the growth rate of the number of those cases. Similarly, the results in third column show that a 1% increase in the cumulative number of positive PCR tests at the end of the previous month decreases the net growth rate of the number of positive PCR tests by 2.851% point.\footnote{When we include not only a monthly dummy but also a coefficient dummy for the logarithm of the cumulative number of positive PCR tests at the ends of previous months, the coefficients of the gross (logarithmic) and net growth rates of the cumulative number of positive PCR tests are \(-0.537\) and \(-2.851\), respectively.}

Next, we analyze the relationship between the infection control measures implemented in Japan and monthly dummies (based on April). In Japan, the first state of emergency was declared on April 7, which led people to refrain from taking action. The effect of this policy reveals May and June dummies for negative gross and net values that were significant at the 1% level. After the state of emergency was lifted on May 25, the movement of people out of the prefecture was lifted on June 18, and the Go To Travel program started on July 22, the number of infected people started to increase. This is reflected in the positive and significant July and August dummies of net values. However, the July dummy of gross value was not significant because the dependent variable is the growth rate of the cumulative number of infected people and it is the stock variable, so the effect of the dummy is not readily apparent. From August onward, the October and November dummies of net values were positive and significant, reflecting the influence of the Go To Eat program. From December 2020 and especially from January 2021, the dummy variables of net values were still positive and significant, although they were expected to have a negative coefficient, due to the effect of the second state of emergency. However, when these month-specific effects are excluded, the results show a converging trend and are negative and significant for both gross and net values.

From these two estimates, we obtain the following two results in the context of Japan: (i) the growth rate of the number of infected people in the prefectures with the highest numbers of infected people increases initially and decreases subsequently; (ii) regarding the growth rate of the number of infected people throughout Japan over time, the growth rate is high in the early stages of infection when the cumulative number of infected people is small, and it decreases gradually as the cumulative number of infected people increases. Therefore, as shown in Section 2.3, we conclude that the convergence property in the number of positive PCR tests is established in the infection situation in Japan.

### 4.4. Factors in deviation from the natural convergence rate

The convergence result obtained in Section 4.3 is actually a property of the SIR model, and the results of \(-0.659\) (gross) and \(-2.851\) (net) are convergence rates inherent to this infectious disease. In this paper, unless otherwise noted, we refer to this convergence rate as the “natural convergence rate”. We can clarify what factors caused the deviation from the natural convergence rate, based on policy outcomes and voluntary behavior changes in Japan as well as the results of previous studies that analyzed these two factors. However, the results of the previous studies mentioned below include the natural convergence rate, and even if there is an effect of policy or voluntary prevention, it might not necessarily correspond to the natural convergence rate. This paper identifies the natural convergence rate and the monthly variation (deviation from the natural convergence rate) and uses these two factors to reinterpret the results of previous studies.

To begin the discussion, we first refer to the “intervention effect” and the “information effect” identified by Watanabe and Yabu (2021). The intervention effect is a change caused by the government’s request for a change in behavior, and the information effect is a voluntary change in behavior based on information about the pandemic. Using big data, Watanabe and Yabu (2021) reported that, contrary to expectations, older people at a higher risk of serious illness and death were less likely to refrain from going out. As for the information effect, it was found that the degree to which people stay at home on weekends and holidays tends to increase with age. This indicates that the Japanese government’s intervention had a policy effect in terms of reducing the number of outings among the young, while for the elderly, it was not a policy effect but rather an information effect that led to self-restraint. In addition, the information effect tended to weaken after the summer of 2020, and this weakening was relatively more pronounced in the younger age group. Based on these intervention and information effects identified by Watanabe and Yabu (2021) and other previous studies, we examined factors in deviation from the natural convergence rate estimated in this paper.

From Table 4, we observed a significant downward deviation from the natural convergence rate from May to June 2020, in both gross and net values. This was due to the “fear” of unknown events, especially in the initial stage, as well as the “behavioral change” triggered by this fear. Muto et al. (2020) revealed that social distancing among residents of Japan (especially women and those over the age of 40 years) changed in response to the infection situation on the Diamond Princess cruise ship. Behavioral changes generally included “voluntary self-restraint”, “wearing masks”, “hand washing”, and “avoiding crowded places”, and these effects were also observed by Chernozhukov et al. (2021) and Shoji et al. (2020). These reinforce the effect of information, and together with the effect of policy interventions (Watanabe and Yabu, 2021), they strongly encouraged the downward deviation. However, even in June 2020, when the state of emergency was lifted, our estimates show a deviation below the natural convergence rate. This implies that the information effect may have persisted only until June 2020.

In Table 4, we find deviations significantly above the natural convergence rate for gross values in August 2020 and for net values in July and August. This is consistent with the negative aspect of the Go To Travel program shown by Miyawaki.
et al. (2021) and Anzai and Nishiura (2021), which contributed to the spread of PCR-confirmed infections nationwide. In addition, the decrease in the effectiveness of information among young people, as pointed out by Watanabe and Yabu (2021), may have also contributed to the spread of infections. In other words, the policy effect of increasing the number of positive PCR tests that counteracted or exceeded the natural convergence rate was not only triggered but was also partially accelerated by the decline in the information effect among the young.

In addition, in Table 4, there are significant deviations from the natural convergence rate in gross values from November 2020 to January 2021 and in net values from October to December. This is a consequence of the policy effect of the Go To Eat program, which contributed to the increased number of positive PCR tests, and, combined with the 3 Cs and a decrease in the information effect on young people, resulted in the spread of infection beyond the Go To Travel program. With the declaration of a new state of emergency in January 2021, the gross rate returned to the natural convergence rate, but the net rate continued to exceed it.

In summary, the combination of the information effect and the policy effect helped Japan to achieve a level of infection control below the natural convergence rate. However, the information effect lasted only until June 2020, which was extremely short. After that, there was a possibility that the natural convergence rate might be achieved through the policy effect alone, but it is thought that the natural convergence rate could not be achieved because of policies that encouraged people to go out to eat and to travel outside their home prefecture (Go To Eat and Go To Travel), which resulted in disregard for the 3 Cs.

4.5. Policy implications based on our estimation of Japan’s COVID-19 experiences

As described in Section 4.3, the natural convergence rate of COVID-19 in Japan by March 2021 was $-0.659$ on a gross (logarithmic) basis and $-2.851$ on a net basis. Of course, the estimates in this paper were obtained before the introduction of variants into Japan, and the results may be different for the Alpha and Delta variants, which are more infectious than the original virus. Therefore, under the condition that infectivity is relatively moderate, the following policy implications can be obtained.

First, even taking into account the natural convergence rate, the number of infected people in Japan rises or falls depending on the policy measures implemented. If we evaluate the states of emergency, the increase in the number of infected people was greater during the second state of emergency than it was in the first, partly because the effect of information on infection control was not long-lasting. Infection control based on voluntary self-restraint, as in Japan, has a smaller effect than predicted because of the large influence of people’s routines and habits. Second, even if the variants of COVID-19 were as equally infectious as the original virus, the effect of declaring a state of emergency would be weakened by the absence of a strong intervention. To sustain the information effect, we have to consider how to appeal to the public, and if their cooperation cannot be obtained, a strong intervention must be considered in some cases. In April and May of 2020, weak interventions were sufficient to control the disease because it was still a relative unknown, but in 2021, people had learned much more about COVID-19 and weak interventions no longer served to improve the infection situation. This learning effect was not desirable for the government.

These two results suggest that to bring COVID-19 under control in a voluntarily manner as much as possible without resorting to strong measures such as lockdowns, we must either gradually increase interventions with a focus on demonstrating policy effects or implement stronger policies that encourage people to change their behavior with the aim of sustaining information effects for as long as possible. The declaration of the first state of emergency in April 2020 not only suspended in-person learning at educational institutions, but also strongly promoted remote work. Commuting by train in urban areas was also curtailed, and by keeping people from going out, it can be said that the infection control measures were temporarily successful. However, when the second state of emergency was declared in January 2021, fewer efforts were made to work remotely, and people’s consideration of the 3 Cs likely diminished. Japan’s inherent inability to break away from its traditional ways of working and living may have been mitigated somewhat by the policy. Japan’s biggest problem lies in the fact that it initially thought of COVID-19 as a temporary disruption and failed to see it as a sign indicating the need for permanent change.

5. Conclusion

In this paper, we analyzed the convergent movement of COVID-19 cases in Japan. Using cross-sectional data from prefectures and controlling for supply and epidemiological factors, we found that conditional convergence was observed for positive PCR tests in Japan. We used the SIR model (a basic model of infection) to demonstrate that both the net growth rate of the number of infected people and the gross growth rate of the cumulative number of infected people decrease over time, and we discussed the idea that short-term fluctuations are caused by the ERN. Using daily panel data from prefectures in Japan, we confirmed the long-term convergence and short-term fluctuations of the growth rate of the cumulative number of infected people, and monthly data showed the convergence in the cross section at the same point in

However, the Alpha and Delta variants are said to differ significantly from the original virus in terms of their infectivity and the speed with which they cause serious illness, so it may be appropriate to regard them as infections with different dimensions.
time. In the results of the panel fixed-effects model, the coefficient of the logarithm of the cumulative number of infected people in the previous month was negative when controlled for monthly dummies, proving statistical convergence. Such convergence may be observed in countries other than Japan, but the cycle of short-term fluctuations is different. Meanwhile, both the natural convergence rate and the steady state defined by the nature of the infection may be different. Policy interventions can control the magnitude of the fluctuations and can achieve the desired steady state. In the near future, it will be necessary to perform estimations for various countries and identify effective policy interventions.

Declaration of competing interest

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

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