JCER Working Paper
AEPR series
No. 2022-1-3

This is the pre-peer- reviewed version of the following article: "The COVID-19 Pandemic and Asia", *Asian Economic Policy Review*, vol. 17, issue 1, which has been published in final form at http://onlinelibrary.wiley.com/doi/10.1111/aepr.12361/abstract and DOI: 10.1111/aepr.12361.

Is There a Trade-Off between COVID-19 Control and Economic Activity? Implications from the Phillips Curve Debate

Mitsuhiro FUKAO
Musashino University

Etsuro SHIOJI
Hitotsubashi University

This paper was prepared for the Thirty-third Asian Economic Policy Review (AEPR) Conference "The COVID-19 Pandemic and Asia", held on April 9 and 10, 2021, via zoom.

January 2022

Asian Economic Policy Review
Japan Center for Economic Research

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April 23, 2021

Is there a Tradeoff Between Covid-19 Control and Economic Activities? Implications from the Phillips Curve Debate[1,2]

Mitsuhiro Fukao (Musashino University)
and Etsuro Shioji (Hitotsubashi University)[3]

[1] This is a revised version of a paper presented at the Thirty Second AEPR Conference (Vol. 17, No. 1) on April 9-10, 2021, titled "Pandemics and the Economy: Lessons from SARS, COVID-19, and After". We would like to thank Takatoshi Ito for his invaluable insights and encouragement. We would also like to thank our discussants Jonathan Skinner and Keiichiro Kobayashi, and all the other participants in the conference for their valuable comments. Shioji acknowledges financial assistance from the Grant-in-aid for scientific research A- 20H00073, B-21H00704, and C-18K01605, Japan Center for Economic Research, and Nomura Foundation.
[2] JEL codes: I18, E12, E31, E52. Key words: covid-19, SIR model, Great Inflation, Pandemic Phillips Curve, Pandemic Taylor Rule.
[3] Corresponding author. E-mail: shioji (at) econ.hit-u.ac.jp.

Abstract

In this paper, we argue that roles of public policies concerning COVID-19 can be better understood in light of the past discussions on the Great Inflation of the 1970s and the 1980s. Like the Phillips curve in macroeconomics, the pandemic presents a trade-off between economic activities and something undesirable, namely infection. Like the Phillips curve, this apparent output-infection trade-off is an elusive one and is lost in the long run. Containing infection calls for a decisive policy action. In this paper, we consider two types of such policies. One is called a "Low for long" policy which requires a permanent suppression of economic activities. The other is called a "Taylor rule" type policy, which allows the normal level of economic activities for the most part, but reacts aggressively to a sign of a virus spread.

1. Introduction

1.1 Background: the Covid-19 Outbreak

The new corona virus infection surfaced in Wuhan in late 2019 became a global pandemic by the spiring of 2020. This new infection, named COVID-19, proved to be highly deadly for older people or people of co-morbidity. The death rate estimated from reported deaths and reported infections has been about 1.5 percent in Japan. Initially, only tools to contain this highly contagious virus was the avoidance of close contacts among people by keeping social distance and facemask wearing. Since some infected people without symptoms can infect others by extremely small droplets within their breathed air, group dining in closed rooms and other social gathering had to be severely restricted to contain this illness. While some office works and schooling could be converted to televised meetings and teaching over internet, distribution, mass transit, hotels, bars, restaurants and other businesses were severely restricted. Table 1.1 summarizes major developments in Japan that are related to the spread of the disease. Figure 1.1 and Figure 1.2 plot the time series evolution of deaths and new cases of infection in Japan.

As the highly effective vaccines were developed in an amazing speed, some countries such as Israel have secured enough doses to inoculate most of their population and are removing many restrictions to keep social distancing. Unfortunately, even if most of the population is inoculated, it is unlikely that we can forget this pandemic in everyday life. Firstly, we do not know how long immunity from vaccination or past infection would last because of the short history of this virus. Secondly, the occasional mutations of virus itself is likely to erode the effectiveness of the current vaccines. Thirdly, the deadliness and/or infectiousness of COVID-19 may change by the mutations of the viris. It is reported that the UK, Brazilian, and South African variants of COVID-19 have some of the second and the third characteristics.

1.2 Insight: Corona virus and the Phillips Curve

The problem of controlling the COVID-19 infection with social-distancing restrictions and that of controlling inflation with macroeconomic policy via unemployment level are similar in structure. The inflation-rate control was analyzed by an economic model called the Phillips curve since 1960s. The Phillips curve analyze the inflation by assuming a negative relationship with the unemployment rate. When unemployment is low, inflation rate tends to accelerate by upward pressure on wage rate. On the other hand, the unemployment is high, inflation rate tends to decelerate by downward pressure on wage rate. When the unemployment is in between, the inflation rate tends to be stable. In this analysis, expansionary monetary and fiscal policies can reduce unemployment in the short run by accepting a higher inflation rate. However, it cannot keep it low for a long time because a higher inflation rate will be built into the expectations of workers and a higher inflation rate will offset the incentive effect on workers to work more under the higher nominal wage increase.

In the COVID-19 infection control, in the short run, the government can stimulate the economic activities by weakening social-distancing restrictions. However, the weakened restrictions will be translated into a higher growth of new infections. Since the average number of newly infected people from one existing infected person, R, is estimated to be about 2.5 under normal economic activities, the number of new infections will rise exponentially. Moreover, the average time lag from the current cohort of the infected people to the next cohort is only about 5 days. As a result, the power of exponential growth is extremely high. In order to reduce the number of new infections, the government must lower R to less than one. For example, by cutting social contacts among people by 70 percent, the R will be 0.75 (2.5 x (1-0.7) = 0.75). Figure 1.3 presents the time series evolution of the effective reproduction number for Japan.

From these observations, we can see the similarity of the two situations. R corresponds to the unemployment and the number of new infections corresponds to the inflation rate. In order to reduce the growth of new infections, the government must reduce R to less than one by imposing restrictions on social interactions. The government can temporality loosen up restrictions to stimulate the economy. However, it will induce a rapid increase of new infections and the number of deaths. In order to reduce the new infections, the government must keep R to less than one for a certain period. The cost measured by the strength of social distancing to keeping the number of new infections will be the same for 1,000 new infections per day or 100,000 new infections per day. Obviously, the best policy is to check the exponential growth at the very start of the pandemic. When the government want to restart the economy by removing social distancing measures, it should do so very cautiously one step at a time.

1.3 Overview of our theory: a dynamic AD-AS model of the pandemics

In order to represent the above insight, we introduce a model developed by Shioji (2021) called a “dynamic AD-AS model of the pandemics”. It is a relatively simple extension of

the original SIR model of the epidemiology, with no optimizing agents. In that sense, it is less structural in comparison to the "behavioral" macro-SIR model of Evans, Rebelo and Trabandt (2020) or Kubota (2021), and is more similar to the "non-behavioral" model of Fujii and Nakata (2021).
The model consists of the following three sectors:

- **Pandemic Phillips Curve** (= a modified SIR or the "SIRQ" model) (PC)
  - Unlike the "real" Phillips Curve, this sector consists of two equations.
- **Pandemic IS Curve** (IS)
- **Pandemic Policy Rule** (PR)

There are four endogenous variables involved:

- "Infected" (***I***): this corresponds to the inflation rate "π" in the original dynamic AD-AS model.
- "Recovered" (***R***)
- "Activities" (***y***): corresponds to GDP gap in the original AD-AS model.
- "Intervention" (or policy stringency, ***i***): corresponds to the nominal interest rate in the original AD-AS model.

The PC part of the model describes how I and R jointly evolve over time, in part in response to the private sector's economic activity level, y. The IS equation describes how y responds to I, and, potentially, also to i. The PR equation describes how the government chooses i. The dynamics is fully backward-looking.
As we shall see, the stability property of the PC part of the model, taken in isolation (that is, if both y and i were constant over time), depends on the underlying value of the reproduction number. If it is sufficiently high, the system has two steady states (thanks to the non-linearity of the PC), called the low/high infection steady state. The low one is unstable. Hence, if we wish to avoid the situation in which the infection explodes to the high steady state, some kind of intervention is necessary, to overturn the stability property of the entire system.
We consider two types of policy rules.

- **Low for Long** (LL): Under this policy, the government raises the level of i to suppress the private sector's economic activities. The policy has to be powerful enough to bring the reproduction number down below 1. The austerity also has to be a permanent one, because, the moment we relax, and the reproduction number crosses the threshold, we shall see an outburst of the epidemic.

- **Pandemic Taylor Rule** (TR): This means that the government sets up a policy reaction function according to which *i* responds to *I*. In normal times in which the disease is contained, there will be no restriction on the private sector's economic activities. However, as soon as we observe a sign of an outbreak, the policy tool will be activated automatically to deter a further spread of the virus.

Like the Taylor Rule in the original AD-AS model, under our Pandemic counterpart, the reaction has to be sufficiently strong to overturn the generic stability property of the underlying economy. We say that the "**Pandemic Taylor Principle**" is satisfied if the response is strong enough so that the low infection steady state turns stable.

1.4 Overview of our empirics: does Tokyo satisfy the Pandemic Taylor Principle?

Shioji (2021) conducts conduct empirical analyses based on the above theory, which will be reviewed in this paper. Our primary focus will be on the estimation of the PC. We shall ask how strong a policy reaction is needed to overturn the stability property of the system to contain the virus. We shall also estimate the IS and the PR, to see if the joint response of the private sector and the government to the pandemic so far has satisfied the conditions for a desirable outcome.

As of this writing (April 2021), it has been only about a year since the pandemic started. We thus could not secure sufficient volume of monthly observations to carry out a statistical analysis. For this reason, in this paper, we rely on daily data. Also, much of the interaction between the epidemic and economic activities take place at a local level: a nation would be just too large as an observation unit for our purposes. Due to this consideration, we shall utilize city-level data.

We study data from three big cities in the world, Tokyo, New York and London. For each of those cities, we estimate evolution of the stock of patients, using data on daily new infections. Daily level of economic activity is measured by people's mobility; when people go out to work or to shop, they are more likely to interact with others, including infected (and possibly a-symptomatic) persons, and this spreads the virus. We utilize Google's mobility index for this purpose. The strength of governmental reaction to the pandemic is measured by Oxford's Stringency Index.

For each city, we estimate to what extent the stock of patients reacts to mobility. Combining this estimate and our theoretical model, we compute the degree of mobility suppression that is required to contain the disease.

We then estimate the response of mobility to both infection and policy. We ask if the reaction has been strong enough to eliminate the possibility of widespread infection. We also estimate the response of policy to the infection.

The rest of the paper is organized as follows. Sections 2 and 3 introduce our theoretical models. Section 4 explains data needed for our empirical analysis. In Section 5, we carry out our empirical studies with the data from Tokyo. We deal with data on New York City in Section 6, and Section 7 is dedicated to the analysis of London. Section 8 concludes.

2. An augmented SIR model

21 Original SIR model

In this sub-section, we briefly review the original SIR model. Let *N* be the total population size, which is assumed to be constant over time Also, S denotes the number of the Susceptibles, I is the number of Infected persons, and R is for the Recovered. The model consists of the following three dynamic equations.

$$S + I + R = N \tag{2.1}$$

$$\Delta I = P \cdot S \cdot I - \gamma I \tag{2.2}$$

$$\Delta R = \gamma I \tag{2.3}$$

In the above, the parameter γ determines the rate at which an infected person recovers. *P* governs the probability of a susceptible person being infected by interacting with an infected individual. If we write

$$P = \rho \cdot \gamma / N \tag{2.4}$$

Then (2..2) can be rewritten as

$$\Delta \frac{I}{N} = \gamma \cdot (\rho \cdot \frac{S}{N} \cdot \frac{I}{N} - \frac{I}{N}) \tag{2.5}$$

This variable ρ is the so-called "Reproduction number".

2.2 Modified SIR or the "SIRQ" model

Shioji (2021) extends the above standard model in two ways. First, we introduce a new variable, *Q*, which stands for "Quarantined". Those are infected people who are moved away from social interaction through, say, hospitalization. Thus, they would not transmit the disease to susceptible people despite that they are being infected.

The second departure from the previous model is that we introduce the concept of "depreciation" to the stock of people who have once recovered. That is, in every period, a constant fraction of the population in the R group lose immunity, and they become susceptible again. In reality, there have been reports of patients who have contracted the new corona virus more than once. Some may lose immunity due to certain types of mutation of the virus. We shall denote this "depreciation rate" by δ.

Our "SIRQ" model consists of the following four equations:

$$S + I + R + Q = N \qquad (2.6)$$

$$\Delta I = -\kappa + P \cdot S \cdot I - \gamma I \qquad (2.7)$$

$$\Delta Q = \kappa - \gamma Q \qquad (2.8)$$

$$\Delta R = \gamma(I + Q) - \delta R \qquad (2.9)$$

In the above, κ represents the number of infected persons who are removed from social interaction in each period. We think of this parameter as being determined by governmental health policies as well as other institutional features such as hospital capacity. Using the definition in (2.4), we can rewrite (2.7) as follows:

$$\Delta \frac{I}{N} = \gamma \cdot (-\frac{\kappa}{\gamma} + \rho \cdot \frac{S}{N} \cdot \frac{I}{N} - \frac{I}{N}) \qquad (2.10)$$

We shall keep referring to ρ as the Reproduction number, although, in this model, that would no longer be a precise characterization of this term.

In the remainder of this section, and also in Section 4, we are going to simplify the model by assuming that Q is always at its steady state level:

$$\Delta Q = 0 \ \Rightarrow Q = Q^* = \kappa/\gamma \qquad (2.11)$$

We shall denote the population share of the infected (but not quarantined) as x. Then x is a solution to the following quadratic equation:

$$-\frac{\kappa}{\gamma} + \rho \cdot \left(1 - \left(1 + \frac{\gamma}{\delta}\right)\left(x + \frac{\kappa/\gamma}{N}\right)\right) x - x = 0 \qquad (*)$$

For ρ that is sufficiently high, the model has two steady states. We will call them the low infection steady state (L) and the high infection steady state (H). Typically, H is stable and L is a saddle (which means unstable, as the model is fully backward-looking). If I starts from above L, the model diverges away from L and eventually converges to H.

2.3 An intermediate step = SIRQ model with endogenous infection probability

Before moving on to the full model, it is informative to consider the following slight modification to the above SIRQ Model. Assume that ρ, the Reproduction number, is not a constant but is a variable, and it is an increasing function of *Y*, the level of economic activities. Specifically, we assume the following functional form:

$$\frac{\rho}{\rho^*} = \left(\frac{Y}{Y^*}\right)^{\phi_1} \qquad (2.12)$$

In the above, "*" signifies the steady state value at L (the low one). The parameter ϕ_1 governs by how much a higher level of activities promotes spread of the disease.

In this sub-section, we make a strong assumption that the government can directly control *Y* through policy intervention. Then we can think of two types of policies that could overturn the stability property of the low steady state. We shall now consider them in turn.

2.3.1 Policy 1: "Low for long"

One obvious way to change the model's stability property is to suppress the level of economic activities, *Y*, sufficiently. If ρ becomes small enough, the two steady states in the first quadrant of the phase diagram disappear. And the system would converge to the zero infection situation.

It is worth pointing out that, in reality, this policy is likely to involve a significant social cost. This is because it requires the government to suppress economic activities permanently (or at least until the disease is eliminated completely by vaccines).

2.3.2 Policy 2: "Taylor rule"

An alternative policy would leave the steady state level of economic activity intact, at *Y**. On the other hand, whenever an increase in the number of infected persons is observed, the government activates a policy to reduce the level of economic activity. As an example, in this paper, we consider a policy rule of the following form:

$$\frac{Y}{Y^*} = \left(\frac{I}{I^*}\right)^{-\phi_2} \qquad (2.13)$$

so that, combined with (2.12), we obtain

$$\frac{\rho}{\rho^*} = \left(\frac{I}{I^*}\right)^{-\phi_1\phi_2} = \left(\frac{I}{I^*}\right)^{-\psi} \qquad (2.14)$$

where $\psi = -\phi_1\phi_2$. We shall argue that, when the government makes ϕ_2 sufficiently large, it could flip the stability property of the low steady state.

Shioji (2021) shows that a sufficient (though not necessary) condition for the low infection steady state to be stable is:

$$(\gamma + \kappa/I^*)\psi > \kappa/I^* - P^*I^* \qquad (2.15)$$

That is, the private sector needs to respond strongly enough to the pandemic. This is the idea behind the Pandemic Taylor Principle.

3. A Dynamic AD-AS Model of the Pandemic

In this section, we briefly sketch Shioji (2021)'s full model.

3.1 Pandemic Phillips curve

This sector of the model consists of the following three equations.

$$\Delta I = -\kappa + P \cdot (N - I - R - Q^{*})I - \gamma I \qquad (3.1)$$

$$\Delta R = \gamma(I + Q) - \delta R \qquad (3.2)$$

$$lnP = \phi y \qquad (3.3)$$

In equation (3.3), ln*P* is the log deviation of the infection probability (*P*) from its value at the low steady state. The variable y represents the private sector's chosen level of economic activities, also defined as the log deviation from the low steady state. The parameter $\phi > 0$ represents how strongly the infection probability reacts to such activities.

3.2 Pandemic IS curve

This is represented by the following log-linear equation:

$$y = \rho_y y_{t-1} + (1 - \rho_y)\alpha_\pi \cdot lnI_{t-1} + (1 - \rho_y)\alpha_i \cdot i_{t-1} \qquad (3.4)$$

$$1 > \rho_y \geq 0, \alpha_\pi \leq 0, \alpha_i \leq 0$$

In this equation, *i* on the right hand side represents the level of stringency of governmental policies to discourage private economic activities. The above specification implies that, when the private sector sees either an increase in the level of infection and/or an increased level of governmental regulation, it (potentially) reduces the level of economic activities. The persistence parameter determines delays in such reaction.

3.3 Pandemic Taylor rule

Finally, the policy maker's decision rule is assumed to take either one of the following two forms (or a combination of the two). The first one is the Low for Long policy, under which the government fixes the level of *i* at some high level indefinitely. The second is the Taylor rule, which takes the following form:

$$i = \rho_i i_{t-1} + (1 - \rho_i)\beta_\pi \cdot lnI_{t-1} + (1 - \rho_i)\beta_y \cdot y_{t-1} \qquad (3.5)$$

$$1 > \rho_i \geq 0, \beta_\pi \geq 0, \beta_y \geq 0$$

This equation implies that, when the government sees an increase in the level of infection, it might potentially decide to increase the level (stringency) of governmental intervention (such as ordering a lockdown). On the other hand, when it sees a reduction in economic activities, it might decide to reduce the degree of policy stringency. The persistence parameter governs delays in such policy responses.

4. Data sources

We conduct empirical analyses in the spirit of the theoretical models in the preceding sections[4]. We utilize daily data for three cities, namely Tokyo, New York and London. This section discusses the nature of the data involved in this study, as well as the data source. We need four types of data for our purposes: those related to covid-19 infections, daily proxies for economic activities, measures of the strength of policy intervention, and other types of control variables. We shall discuss them in turn.

4.1 Data on covid-19

Our estimation requires two types of data on covid-19 infections. One is the number of newly infected patients. This will be based on the daily number of new positive test results. The other is the number of people who have been quarantined. For this, we assume that the number of quarantined people is the same as the number of persons who are being hospitalized. This is largely due to lack of better alternatives. We should note that, in reality, within-hospital infections have been a serious problem at times. On the other hand, there have been self-quarantined patients who have imposed strict disciplines on themselves to stay at home or in hotel rooms.

Data on new infections is fairly standard. Data on Tokyo is based on the official report from the Tokyo Metropolitan Government. For New York City, the original data source is the City Government of New York. Data for Greater London is provided by the UK government.

For hospitalization, nature of the data varies across countries, and each requires some explanation. For Tokyo, the Tokyo Metropolitan Government reports the daily number of all the patients who are being hospitalized currently (that is, this is a stock data and is not about new additions or net flows). However, this series only goes back to May 12, 2020. We shall discuss what we did for earlier periods later. For New York, data on new hospitalizations comes from the same source as the number of newly infected patients.

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[4] Shioji conducted the empirical research, and is primarily responsible for any error that might remain in the rest of the paper.

For London, we could find data on the stock of patients that goes back only to August 1 of 2020. We have decided to use data on new hospital admissions: they were obtained from the UK government web site (data starts from August 1) and the Our World in Data web site (which derives the data from the UK government).

4.2 Data on activity levels

We use Google's mobility indices to measure the levels of human activities. This data set consists of six indices, that measure: (1) retail and recreation (denoted "Retail" in this paper), (2) grocery and pharmacy ("Grocery"), (3) parks ("Parks"), (4) transit stations ("Transit"), (5) workplaces ("Work"), and (6) residential ("Residence").

For New York City, the original data is disaggregated between its five boroughs. For each index, we take a weighted average across the boroughs to compute a city-wide index. The weights are based on each borough's population share as of year 2019.

Note that Google reports them in terms of percentage deviation from the baseline period. We transform the original series by first dividing them by 100, then adding 1, and finally taking their logs.

For our purpose, it is more convenient to have a single measure of people' s mobility, rather than six separate ones. For Tokyo and London, we apply the standard principal component analysis on all six indices. We do this on their covariance matrix, rather than the correlation matrix (which is the default with Stata), so that the units would not lose the meaning. We shall call the first principal component (i.e., the one that corresponds to the highest eigenvalue) as "Mobility PCA" and treat this as our mobility index for the two cities. For New York, however, we have found that this index performs poorly in the empirical analysis. For this reason, after some trials and errors, we have decided to use a single index, "Transit", for the analysis of this city.

4.3 Policy stringency

Our measure of the strictness of the governmental responses to covid-19, aimed at restricting people's activities in order to reduce the spread of the virus, is the Oxford COVID-19 Government Response Tracker (OxCGRT)'s Stringency Index, which aggregates nine types of sub-indices, each reflecting different aspects of the governmental responses to the pandemic.

4.4 Weather variables

We also utilize various weather variables for each city. As people are likely to spend longer hours outdoors when the weather is good, we wanted to control for their effects on our mobility indices. For Tokyo, we utilize daily data on the average temperature, precipitation, and sunshine hours, provided by the Japan Meteorological Agency. The temperature is in Celsius, and we add 273.15 to make it the deviation from absolute zero. We also use the square of this temperature variable. For New York, we collected weather data for Central Park from the National Oceanic and Atmospheric Administration (US Commerce Department)'s National Centers for Environmental Information (NCEI). We obtained the daily maximum temperature (converted into Celsius and then taken its deviation from absolute zero), its square, precipitation and snowfall. For London, we got data from Wunderground. The data is for London City Airport Station, and includes the average daily temperature (again, defined as its deviation from absolute zero), its square, and humidity.

5. Evidence from Tokyo

5.1 Overview of data

5.1.1 Infection-related data

In Figure 5.1, panel (A) plots daily evolution of the number of new infections for Tokyo. Panel (B) shows that of the number of patients being hospitalized. As mentioned previously, this data, which measures the stock of patients currently in hospitals, starts from May 12, 2020.

5.1.2 Mobility indices

In Figure 5.2, the blue line represents our mobility index, Mobility PCA (the first principal component), for Tokyo[5]. The red line indicates national holidays for Japan. The six individual indices' factor loadings were 0.4522 for Retail, 0.1117 for Grocery, 0.1682 for Parks, 0.5668 for Transit, 0.6453 for Work, and -0.1308 for Residence. It thus places higher weights on Retail, Work and Transit, and deemphasizes the roles of Grocery, Parks and Residence (which is the only index with a negative weight). This series exhibits a strong weekly seasonality. The impact of holidays on people's tendency to go out is also quite visible. From the figure, it is also evident that the spread of covid-19 has had large negative effects on people's mobility.

[5] As stated earlier, we transform the original six indices prior to applying the principal component analysis. However, to facilitate comparison with the original indices, in this figure, we exponentiate the principal component subtract 1 from the result, and express the outcome in percentage terms.

5.1.3 Stringency Index

Figure 5.3 shows the daily evolution of the Stringency Index. Unfortunately, there is no city-specific index for Tokyo, and what is presented here is for the entire country of Japan. The Tokyo Metropolitan Government did have its own measures to discourage the citizens' mobility, and they are unlikely to be reflected fully in this index. Also, the Japanese Government has deployed some prominent policies to explicitly promote people's movement amid the pandemic, such as the so-called "Go-to" Travel Initiative. They are expected to have the opposite effects to those policies reflected in the index. But they are not taken into consideration in the index's construction. Developing a more suitable index for Tokyo would be an important task for future research.

5.1.4 Others

We constructed the days of week dummies, as well as dummies for national holidays in Japan. We also created other types of festivities dummies, each of which corresponding to each day in mid-August and from late December to early January. This is because many Japanese take summer and winter breaks during those times.

5.2 Estimation of the Pandemic Phillips Curve

In this section, we estimate the Pandemic Phillips Curve for Tokyo. The estimation proceeds in two steps. First, based on the SIRQ model presented in Section 2, we estimate time variations in ρ, which roughly corresponds to the Reproduction number in the regular SIR model, from the data on new infections and hospitalizations. In the second step, we use regression analyses to evaluate how this ρ responds to the mobility index.

5.2.1 Estimation of ρ_t, the time-varying Reproduction number

Construction of I+Q, total number of patients

Under our SIRQ model, the stock of infected patients, both quarantined and outside the quarantines, namely I+Q, follows the following dynamic equation.

$$\Delta(I+Q) = new - \gamma(I+Q) \qquad (5.1)$$

Here, the variable *new* represents new infections. Hence, given the initial stock of I+Q and a choice for the value of the parameter γ, we should be able to construct the entire time series for I+Q if that of *new* is observable, using the perpetual inventory method.

One obvious way to proceed would be to equate the variable *new* with the reported number of new positive test results (i.e., numbers that appear in Figure 5.1). We see two problems with such an approach. First, it is generally understood (correctly, we think) that, for every patient who tests positive, there must be others who have gone undetected, and that they are likely to be spreading the virus. If we ignore them and simply subtract the number of hospitalizations from the number of new infections, we are likely to underestimate the actual threat of contagion that is out there. This is especially true during earlier phases of the pandemic, when the government used to keep a large number of patients at hospitals for fear of contagion. The second and related point is that, if we follow the above approach, we would find that the estimated stock of patients sometimes turns out to be lower than that of hospitalized patients, which is logically impossible. We think this is because the Japanese government back then used to keep practically all the patients who had tested positive, for relatively long time, out of precaution.

For those reasons, and to deal with the missing data on hospitalization prior to May 12, 2020, we make the following assumption.

(Assumption 1) The "detection rate" of infection was less than 100% and was constant over time. Let the number of patients who actually tested positive to be denoted as *positive* and the detection rate to be d, then

$$postive = d \cdot new \qquad (5.2)$$

By combining (5.1) and (5.2), we get

$$\Delta(I + Q) = positive/d - \gamma(I + Q) \qquad (5.3)$$

For this analysis, we (somewhat arbitrarily) set the value of d to be equal to 0.5. That is, for every patient who tests positive, there is another infected person at large. Developing a more data-driven way to determine the value of this parameter is an important task for future research.

The next question is the choice of γ, the daily recovery rate. For this, we rely on the nation-wide data for Japan. In panel (A) of Figure 5.4, the blue line shows the evolution of the number of patients who are deemed to require hospitalization or other types of medical treatment. The red line in the same panel is the number of patients who are discharged from such a status. Panel (B) shows how the latter's ratio to the former has evolved over time. We can see that, after a period of considerable volatility, the share has now stabilized around 0.08-0.09. Based on this observation, we set $\gamma = 0.08$. This value means that about 70 percent of newly hospitalized patients would be discharged within two weeks, which seems reasonable.

Construction of Q, the number of hospitalized patients

Next, we need to deal with the missing data problem for hospitalization for earlier days. We make the following assumption.

(Assumption 2) Until June 12, 2020, when the Japanese Government relaxed its regulations on patient treatments, all the patients who tested positive were being hospitalized. That is,

$$\Delta Q = positive - \gamma Q = d \cdot new - \gamma Q \qquad \text{(until June 12, 2020)} \qquad (5.4)$$

After June 12, we simply equate the reported number of hospitalized patients with Q. In panel (A) of Figure 5.5, the resulting series is shown with the red line. The difference between $I+Q$ and this Q is our estimate for I, which is the green line.

Construction of R, the number of the recovered

In our model, R follows the following equation.

$$\Delta R = \gamma(I + Q) - \delta R \qquad (5.5)$$

We only need to specify the value of δ, the depreciation rate, or the rate at which a recovered person turns susceptible again. It is sometimes said that immunity after contracting covid-19 lasts for half a year or so, although the evidence is scant at this point. We thus set δ to equal 0.016, which means that 95% of immunity is lost in half a year. Panel (B) in Figure 5.5 presents the estimated evolution of R.

Construction of S, the number of the susceptible

By setting N, the total population of Tokyo, to be 1.4 million, we can derive the evolution of S, the size of the susceptible population, over time.

Construction of ρ, the Reproduction number

Finally, using the above results, we obtain our estimates for the time path of ρ. Note that

$$new = P \cdot S \cdot I = \rho \cdot \gamma \cdot S \cdot I/N \qquad (5.6)$$

We thus get:

$$\rho = new \cdot N/(\gamma \cdot S \cdot I) \qquad (5.7)$$

We will utilize this relationship to estimate ρ, by plugging the observed number of new positive test results in *new*. However, there is one problem with this approach. For days on which there was zero new case of infection (which happened often during the earlier stage of the pandemic), our estimated ρ would also be equal to zero. This would prevent us from taking the log of ρ. We have decided to circumvent this problem by simply adding 1 to the observed number of positives. Figure 5.6 presents the time series for ρ thus estimated, in logs. We can see that the log of the Reproduction number has been floating slightly above 0, except for some brief periods when people's mobility was very low.

5.2.2 Estimating the ρ function

Consider the following log-linear relationship between the Reproduction number and the level of economic activity, which is in line with (2.12):

$$ln\rho_t = \phi_1 \cdot y_{t-1} + (constant) \quad (5.8)$$

In practice, this equation is augmented with the lagged dependent variables and lagged *y* as additional explanatory variables. We also include days of week dummies:

$$ln\rho_t = \sum_{j=1}^{J_1} a_{1j} \cdot ln\rho_{t-j} + \sum_{k=1}^{K_1} b_{1k} \cdot y_{t-k} + \sum_{l=1}^{7} d_{1l} \cdot dow_l \quad (5.9)$$

In the above, *dow* means days of week dummies. It is convenient to rewrite the above equation as follows.

$$ln\rho_t = \alpha_{11} \cdot ln\rho_{t-1} - \sum_{j=1}^{J_1-1} \alpha_{1j} \cdot \Delta ln\rho_{t-j}$$

$$+\beta_{11} \cdot y_{t-1} - \sum_{k=1}^{K_1-1} \beta_{1k} \cdot \Delta y_{t-k} + \sum_{l=1}^{7} d_{1l} \cdot dow_l \quad (5.10)$$

where

$$\alpha_{1j} \equiv \sum_{m=j}^{J_1} a_{1m}, \qquad \beta_{1k} \equiv \sum_{n=k}^{K_1} b_{1n}.$$

The long run elasticity of ρ with respect to the level of economic activity is given by $\beta_{11}/(1-\alpha_{11})$, and we shall pay our closest attention to this number.

We report the estimation results in Table 5.1. In all the tables that will be presented below, we follow the STATA convention and express lagged variables by the operator "L.", and differenced variables by "D.". Also, in what follows, "Reproduction" indicates $ln\rho$. For the lagged dependent variables, the order of lags (namely J_1 in (5.10)) is set at 7. The number of lags for the mobility index (that is, K_1 in the same equation) is 14. For their selections, we first decided to require them to be multiples of 7 (the number of days pe week), and based our choice on BIC.

In Table 5.1, we only show the estimated coefficients for Reproduction, lagged by 1 day, and the mobility index, also lagged once. That is, we show only α_{11} and β_{11}, and omit results for all the other variables, to save space. We find that $\alpha_{11} = 0.881$ and β_{11},=0.285, and both are quite significant. They jointly imply the long run elasticity of 2.395.

5.3 Simulation based on the estimated Pandemic Phillips Curve

5.3.1 Steady state analysis

Let us define the "Generic Reproduction Number", denoted $\tilde{\rho}$, as follows:

$$ln\tilde{\rho} = \frac{1}{1-\alpha_{11}} \cdot \frac{\sum_{l=1}^{7} d_{1l}}{7} \ .$$

This is the value of (the log of) ρ that would prevail in the long run if y=0, that is, if activities are at the normal level. Using this notation, we can write

$$ln\rho = ln\tilde{\rho} + [\beta_{11}/(1-\alpha_{11})]y$$

By plugging this relationship into (*) in section 2 and solving the quadratic equation, we can draw the numerical relationship between the level of activities, y, and the infection rate. In this derivation, we set Q*/N to be equal to its sample average, which is 0.00007871.

The result is displayed as locus A in Figure 5.7. In this figure, on the horizontal axis, we measure the steady state percentage of patients who are infected (but not quarantined) as a share of total population. On the vertical axis, we measure the level of activities expressed as a percentage of the normal level. The axes are in a log-log scale. We can see that locus A is U-shaped. Thus, as long as y is sufficiently high, there are two steady states, namely the low- and the high-infection steady states discussed in section 2. As we stressed back then, the low one is dynamically unstable, so the system has a tendency to converge to the high one. When y is at its normal level, the rate of infection at the high-infection steady state is around 14.4% of the entire population. If we can somehow reduce y, the infection ratio at that steady state tends to go down. For example, if y is 75% of the normal level, the population share goes down to around 12%. If y is further reduced to 50% of the normal, the population share goes down to about 5%. When y is below 44% of the normal level, the two steady states disappear altogether, and the system will converge to the zero infection state.

5.4 Estimation of the Pandemic IS Curve without the Stringency Index

5.4.1 Specification of the empirical model

Next, we turn to the estimation of the Pandemic IS Curve. We are interested in analyzing how people's choice of the level of economic activities is affected by the pandemic situation. We can think of two channels. First, individuals may voluntarily reduce their mobility in response to a spread of the virus, either for fear of being infected, or out of concerns for others, realizing that they themselves may be already infected without noticing it. Second, they may decide to respect regulations or recommendations from the government, which is reacting to the outbreak.

In what follows, the dependent variable is going to be the mobility index. The main explanatory variable will be the stock of infected patients, lagged by 1 period. For the moment, the policy variable is not included on the right hand side. We should thus interpret the estimated coefficient on the infection variable as representing the sum of its effects that work through the above two routes.

In addition, we include lagged differences of the dependent variables (lags 1-6). We have considered including lagged differences of the stock of patients, but decided against it based on BIC. In addition, days of week dummies, holiday dummies, other festivities dummies are included. Their coefficients will be omitted from the tables.

5.4.2 Consideration for a structural change

We consider the possibility that there was a structural change in this relationship during one year since the onset of the pandemic. Anecdotal evidence suggests that people might have become less responsive to the spread of covid-19 since around the autumn of 2020. To test this possibility, we allow the coefficients on the infection variable to be different across sub-periods, by including the interaction terms between the infection variable and the first half and the second half dummies. We also add the first half dummy itself as an explanatory variable. We define the first half as the period under the Abe administration (until September 16, 2020), and the second half as the era of the Suga administration. As Shioji (2021) reports, the above specification was favored by the AIC compared to the model without a structural break.

5.4.3 Estimation results and their implications

Estimation results are reported in Table 5.2. The infection variable is significant for the first half but not for the second half. This supports the idea that people's mobility has become unresponsive to the spread of the virus during the second half.

5.4.4 Steady state simulations

Based on those estimates, in Figure 5.7, we draw two additional lines, labeled B and C, each representing the long run response of the level of activity to the infection level for the first half and the second half, respectively. Line B is steeply downward sloping, while line C is even mildly upward sloping.

Notably, line B is so low and steep that it does not intersect with locus A. In other words, there was no steady state with positive infection. That is, during this period, people's activities were suppressed so effectively that the pandemic could be contained. The same cannot be said about the second half. Line C has two intersections with locus A. This means that the system has gained a tendency to converge to the high infection steady state. What explains this structural change? In the next sub-section, we try to see if this is due to changes in people's direct responses to the pandemic, or if it reflects their changing attitudes toward governmental regulations.

5.5 Introducing the Stringency Index into the Pandemic IS Curve

We add the lagged stringency index to the right hand side of the above regression model. We first need to decide whether or not to use cross terms of this variable with the first and second half dummies. We have found that BIC favors allowing the coefficient on the stringency index to differ across the two periods, while restricting the coefficient on the infection variable to be the same between them. It thus appears that the structural change occurred in people's response to the government, not in their natural reaction to the pandemic itself.

The estimation results are shown in Table 5.3. The coefficient on the infection variable, which is now constrained to be the same across the two sub-periods, is negative and significant. The coefficient on the stringency variable is negative and significant for the first half, but turns insignificantly different from zero in the second half.

We can thus conclude that the main difference between the sub-periods is that people have "stopped listening to what the government says" in the second half. It should however be noted that the first half dummy is also negative and significant. This implies that people also started to be more "relaxed", independently of their changing attitudes toward to the government.

5.6 Estimation of the Pandemic Taylor Rule

Before leaving the Tokyo case, in Table 5.4, we study the determinants of the stringency index, assuming that the government is following a Taylor-style rule. The dependent variable will be the stringency index. The lagged dependent variable is introduced as a regressor on the right hand side variable. In the first column, the lagged infection variable is introduced as an explanatory variable. In the second column, lagged mobility is added as a regressor. We have considered adding lagged differences of the stringency index and the mobility index on the right hand side, but such specifications were not supported by BIC. No other explanatory variables are included. We have also considered introducing cross terms between the infection variable and the first and the second half dummies, but BIC did not support such a specification, so we kept it simple.

The fist column of the table indicates that an increase in the infection causes the government to relax restrictions, which is the opposite to what one might expect. In the second column, when lagged mobility is added, the infection variable loses the significance. The mobility variable is not significant, either.

The results suggest that the Japanese government did not follow a Taylor-type rule when setting its policies. Hence, although the Japanese public was responding to public policies during the first half of the sample, as previously noted, the government itself was not responding to the pandemic situation.

6. Evidence from New York

Now we turn to data on New York City. As we follow procedures that are basically the same as those in the previous section, our discussion will be brief.

6.1 Estimation of *ρ* and its dependence on the activity level

6.1.1 Estimation of ρ

As the first step, we estimate ρ, the Reproduction number. To avoid the possibility that the estimated Q would exceed the estimated series of I+Q, we assume that, up to March 8, 2020, all the infected patients were hospitalized. Figure 6.1 shows the estimated evolution of I+Q, I and Q. We set N, the city's total population, equal to 8.5 million. Figure 6.2 exhibits the estimated time path of ρ.

6.1.2 Estimation of the ρ function

Next, we regress the estimated ρ on the mobility index. As explained earlier, we use the Transit index, which is plotted in Figure 6.3. The accompanying red line corresponds to the holidays in New York State.

Table 6.1 reports the result from the estimation of the ρ function. As in the previous section, we choose the lag order specification based on the BIC. The short-run elasticity of ρ with respect to Transit is 0.136, and the long-run elasticity is 1.038. Both of them are smaller than the case for Tokyo, suggesting that the infection levels are much less responsive to people's activities in New York.

Based on this estimation result, we draw the steady state relationship between the mobility index and the infection variable, which is locus A in Figure 6.5. Compared with the case of Tokyo, the U-shaped curve is shallower. We "only" need to suppress mobility to down somewhat below 60% of the normal level to eliminate the high infection steady state. This would, however, still cause a significant economic damage.

6.2 Estimating the reaction of the activity level to the pandemic situation

6.2.1 Response of the activity level to the infection variable

We next study the determinants of economic activities. This is done in Table 6.2. Based on the BIC, we allow the coefficients to be different between the first half and the second half. The sample is divided into two, somewhat arbitrarily, in the same way as in the case of Tokyo. The lag structure is also determined by the BIC. In the first column, we see that our mobility variable, Transit, responds negatively to the infection variable, as expected, during the first half. However, for the second half, the coefficient turns positive, which is counterintuitive.

Based on those estimates, in Figure 6.5, we plot the long run responses of the activity levels to infection, separately for the first and the second halves, represented by lines B and C, respectively. Line B does not have an intersection with locus A. That is, during the first half, activities were suppressed so effectively that the high infection steady state was eliminated. On the other hand, line C intersects with locus A twice, partly because of its perverse upward sloping shape.

In the second column of Table 6.2, we add the lagged value of the stringency index (plotted in Figure 6.4) to the right hand side. Its coefficient is insignificant in the first half, but turns significantly positive in the second half, which is also quite puzzling.

6.3 Estimating the policy reaction function

Finally, we estimate the policy reaction function in Table 6.3. The difference between the two columns is that the second column adds the lagged Transit index as an explanatory variable. But this turns out to be insignificant. We shall thus focus on the first column. We find that the infection variable has a significant influence on the governmental decision, in contrast to the case of Tokyo. The response goes down in the second half, though it remains significant. On the other hand, the first half dummy has a negative coefficient. We can thus see that, although the average degree of policy stringency has gone up in the second half, it has also become less responsive to the infection situation.

7. Evidence from London

Now we shall briefly discuss the case of London. We proceed much in the same way as we have done for the other two cities. Hospitalization data was available only since March 19, 2020. We assumed that, until that day, all the patients who were confirmed to be infected were hospitalized. As a proxy for the level of economic activities, we use the first principal component of the six Google mobility index, as we did for Tokyo.

Figure 7.1 shows the estimated evolution of I+Q, I and Q. We set N, the city's total population, equal to 9 million. Figure 7.2 exhibits the estimated evolution of ρ. Figure 7.3 shows the Mobility (PCA). Figure 7.4 is the Stringency Index, though it is for the entire England.

Table 7.1 reports the result from the estimation of the ρ function. The short-run elasticity of ρ with respect to Mobility PCA is 0.062 while the long-run elasticity is 0.663. Both are comparatively small.

Based on those estimates, we derive and depict the steady state relationship between mobility and infection in locus A in Figure 7.5. Note that the slope of this U-shaped curve is steeper on both sides of the bottom, and the bottom is deeper down compared to either Tokyo or New York. To eliminate the high infection steady state, mobility has to be suppressed to almost 20% of the normal level.

In Table 7.2, we study the determinants of economic activities. In the first column, the stringency index is not included as an explanatory variable. Based on BIC, we constrain the coefficient on the infection variable to be the same between the first and the second halves. This coefficient turns out to be significantly negative. The first half dummy is also significantly negative.

Based on those estimates, in Figure 7.5, we draw the long run response of the activity level to infection. Line B is for the first half, and line C is for the second half. As the coefficients are restricted to be the same between the two sub-periods, the slope is common between B and C. But B has a much lower intercept. As a consequence, the high infection steady state is eliminated for the first half, but not for the second half. It should, however, be also noted that, even for the latter half, the infection rate at that high infection steady state is relatively low, thanks to the steep slope of the activity's reaction function to the infection.

In the second column of Table 7.2, we add the stringency index to the right hand side. In this case, BIC supports allowing the coefficient on the infection variable to differ between the first and second halves, while constraining that of the stringency index to be the same. We find the infection variable to be significant only in the first half. The stringency index turns out to be negative and significant.

Table 7.3 shows the estimation results for the policy reaction function. The infection variable is significant, though the coefficient is small. It turns insignificant when the lagged mobility index is added as an explanatory variable.

8. Conclusions

In this paper, we have argued that the pandemic is analogous to the Phillips curve, in several senses:

(1) The pandemic creates a short-run trade-off. If we are willing to accept a greater extent of infection, we could achieve a higher level of economic activities.

(2) This trade-off creates a temptation to policy makers. They have an incentive to relax anti-pandemic restrictions to exploit this relationship.

(3) However, this trade-off is actually an elusive one. If policy makers hesitate to take decisive actions in the face of an outbreak, the infection would explode, possibly doing a great harm to economic activities as well.

We speculate that there is yet another similarity between the two: he importance of credible commitment by policy makers. The fact that the Japanese public stopped responding to governmental regulations in the second half of the sample seems to indicate that they have understood the incentive structure of their government. They might have concluded that, as soon as it sees a sign of improvement with the pandemic situation, their government would be more than eager to relax the restrictions. Such a sequence of policies is unlikely to succeed in containing the epidemic, so, for the Japanese public, it would not be worth the sacrifice to follow its guidance. Incorporating such forward looking behaviors on the side of the private sector would be an important venue for future research.

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Table 1.1 **Timeline of Major Events of COVID-19 Pandemic Related to Japan**

Year 2020	
January 6	Unknown type of severe pneumonia was reported in Wuhan, China
January 16	The first case of COVID-19 infection of a Chinese man in Japan was confirmed
January 30	WHO declared coronavirus outbreak a global health emergency
February 3	A cruise ship, the Diamond Princess, arrives at Yokohama with COVID-19 patients
February 14	The first death from COVID-19 in Japan, a woman in her 80s in Kanagawa
February 27	Prime minister Abe requested all primary and secondary schools to close
March 11	WHO declared COVID-19 a pandemic
March 24	Tokyo Olympic Games in 2020 was postponed for one year
March 29	Well-known comedian, Ken Shimura, died from COVID-19
April 7	State of Emergency was declared for seven prefectures
April 16	State of Emergency was declared for all the prefectures of Japan
May 14	State of Emergency was removed for 39 prefectures but 8 remained
May 25	State of Emergency was abolished for all the prefectures
June 19	Voluntary travel restrictions were abolished
July 22	Government starts subsides for traveling except for Tokyo region (so-called "Go to travel campaign")
October 1	Government starts subsides for eat-outs (so-called "Go to eat campaign"); Tokyo region was added for subsides for travelling
November 5	Surging COVID-19 infection was reported in some prefectures including Hokkaido
November 10	Governmental panel on COVID-19 warned a rapid expansion of new infections
November 18	The number of new cases recorded a new peak in Japan
November 20	Governmental panel on COVID-19 advised to stop subsides for traveling and eat-outs
December 3	Osaka declared a medical emergency
December 15	Government stopped "Go to travel campaign"
Year 2021	
January 7	State of Emergency was declared for Tokyo and nearby three prefectures

Note: In the tables, L. and D. represent lag and differencing operators, respectively.

Table 5.1 Estimation results for the determinants of $\ln \rho$ for Tokyo

	(1) Reproduction
L.Reproduction	0.881***
	(22.08)
L.Mobility(PCA)	0.285***
	(4.05)
Observations	369
Adjusted R-squared	0.779

t statistics in parentheses

(Note) Also included: days of week dummies
lag 1-6 of D.Reproduction
lag 1-13 of D.Mobility(PCA))

* p<0.05, ** p<0.01, *** p<0.001

Table 5.2 Determinants of mobility for Tokyo

	Mob.(PCA)
Infected*H1	-0.0417***
	(-4.92)
Infected*H2	0.000991
	(0.05)
L.Mobility(PCA)	0.742***
	(25.81)
H1	0.161
	(0.89)
Observations	375
Adjusted R-squared	0.975

t statistics in parentheses

(Note) Also included: days of week dummies,
holidays and festivities dummmies, weather variables,
and D.Mobility(PCA) (lags 1-6)

(Note) H1 = 1st Half Dummy, H2 = 2nd Half Dummy

* p<0.05, ** p<0.01, *** p<0.001

Table 5.3 Determinants of mobility for Tokyo
(with Stringency Index added as an explanatory vaiable)

	Mob.(PCA)
L.Mobility(PCA)	0.684***
	(22.63)
L.Infected	-0.0389***
	(-4.68)
L.Stringency*H1	-0.185***
	(-4.45)
L.Stringency*H2	0.00713
	(0.13)
H1	-0.303***
	(-6.38)
Observations	375
Adjusted R-squared	0.977

t statistics in parentheses

(Note) Also included: days of week dummies, holidays and festivities dummmies, weather variables, and D.Mobility(PCA) (lags 1-6)

(Note) H1 = 1st Half Dummy, H2 = 2nd Half Dummy

* p<0.05, ** p<0.01, *** p<0.001

Table 5.4 Determinants of the Stringency Index for Japan

LHS=Stringency

	Stringency	Stringency
L.Stringency	0.963***	0.983***
	(155.58)	(145.23)
L.Infected	-0.00172*	-0.000446
	(-2.53)	(-0.53)
L.Mobility PCA		0.00250
		(0.35)
Observations	406	382

t statistics in parentheses

(Note) No other variables included.

* p<0.05, ** p<0.01, *** p<0.001

Table 6.1 Estimation of the ρ function for New York City.

LHS=Reproduction

	Reproduction
L.Reproduction	0.869***
	(39.00)
L.Transit	0.136*
	(2.13)
Observations	351
Adjusted R-squared	0.896

t statistics in parentheses

(Note) Also included: days of week dummies
lag 1-6 of D.LHS
lag 1-1 of D.(mobility index)

* p<0.05, ** p<0.01, *** p<0.001

Table 6.2 Estimation of the determinants of mobility for New York

LHS=Tansit

	Transit	Transit
L.Transit	0.666***	0.656***
	(23.93)	(20.71)
H1	0.459***	0.495***
	(6.32)	(5.93)
L.Infected*H1	-0.0409***	-0.0413***
	(-10.39)	(-5.75)
L.Infected*H2	0.0178*	0.0145*
	(2.58)	(2.05)
L.Stringency*H1		-0.00218
		(-0.09)
L.Stringency*H2		0.0890*
		(2.10)
Observations	357	357
Adjusted R-squared	0.995	0.995
AIC	-1042.5	-1043.5
BIC	-887.4	-880.6

t statistics in parentheses

(Note) Also included: days of week dummies,
holidays and festivities dummmies, weather variables,
and D.LHS (lags 1-6)

* p<0.05, ** p<0.01, *** p<0.001

Table 6.3 Estimation of the policy reaction function for New York

LHS=Stringency

	Stringency	Stringency
L.Stringency	0.835***	0.833***
	(32.98)	(32.94)
L.Infected*H1	0.0496***	0.0552***
	(6.40)	(6.46)
L.Infected*H2	0.0114***	0.0139***
	(6.24)	(5.69)
H1	-0.315***	-0.338***
	(-5.92)	(-6.13)
L.Transit		0.0394
		(1.53)
Observations	356	356
Adjusted R-squared	0.995	0.995
AIC	-872.2	-872.6
BIC	-849.0	-845.5

t statistics in parentheses

(Note) Also included: D.Transit (lag 1)

* p<0.05, ** p<0.01, *** p<0.001

Table 7.1 Estimation of the ρ function for London

LHS=Reproduction

	Reproduction
L.Reproduction	0.906***
	(40.80)
L.Mobility (PCA)	0.0623**
	(2.81)
Observations	366
Adjusted R-squared	0.928

t statistics in parentheses

(Note) Also included: days of week dummies
lag 1-6 of D.LHS
lag 1-13 of D.(mobility index)

* p<0.05, ** p<0.01, *** p<0.001

Table 7.2 Estimation of the determinants of mobility for London

	Mob.(PCA)	Mob.(PCA)
L.Mobility (PCA)	0.909***	0.882***
	(50.31)	(34.05)
L.Infected	-0.0267***	
	(-4.04)	
H1	-0.144***	0.165
	(-4.32)	(1.03)
L.Infected*H1		-0.0194*
		(-2.56)
L.Infected*H2		0.0118
		(0.75)
L.Stringency		-0.0466*
		(-2.14)
Observations	377	361
Adjusted R-squared	0.992	0.992
AIC	-366.0	-362.2
BIC	-259.8	-245.5

t statistics in parentheses

(Note) Also included:
days of week dummies,
holidays and festivities dummmies, weather variables,
and D.LHS (lags 1-6)

* p<0.05, ** p<0.01, *** p<0.001

Table 7.3 Estimation of the policy reaction function for London

LHS=Stringency

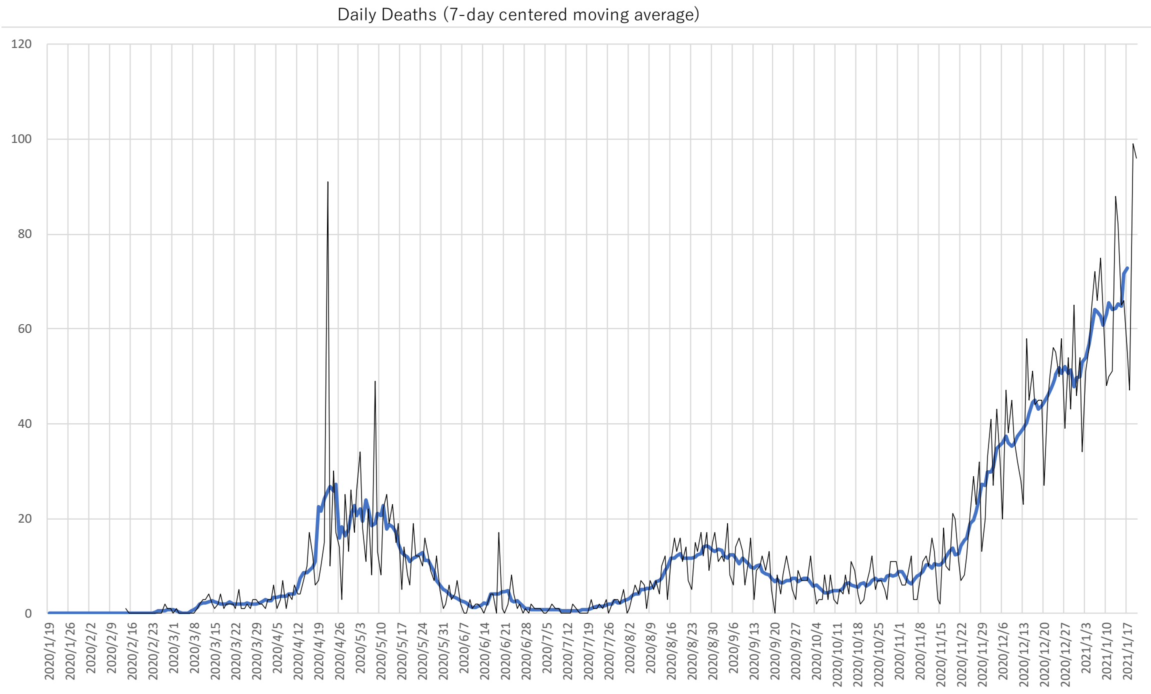
	Stringency	Stringency
L.Stringency	0.976***	0.974***
	(131.18)	(116.50)
L.Infected	0.00316**	0.00303
	(3.28)	(1.72)
L.Mobility PCA		-0.00209
		(-0.20)
Observations	365	361
Adjusted R-squared	0.990	0.989
AIC	-513.2	-502.3
BIC	-501.5	-486.7

t statistics in parentheses

(Note) Also included:
first half dummy
and D.LHS (lag 1)

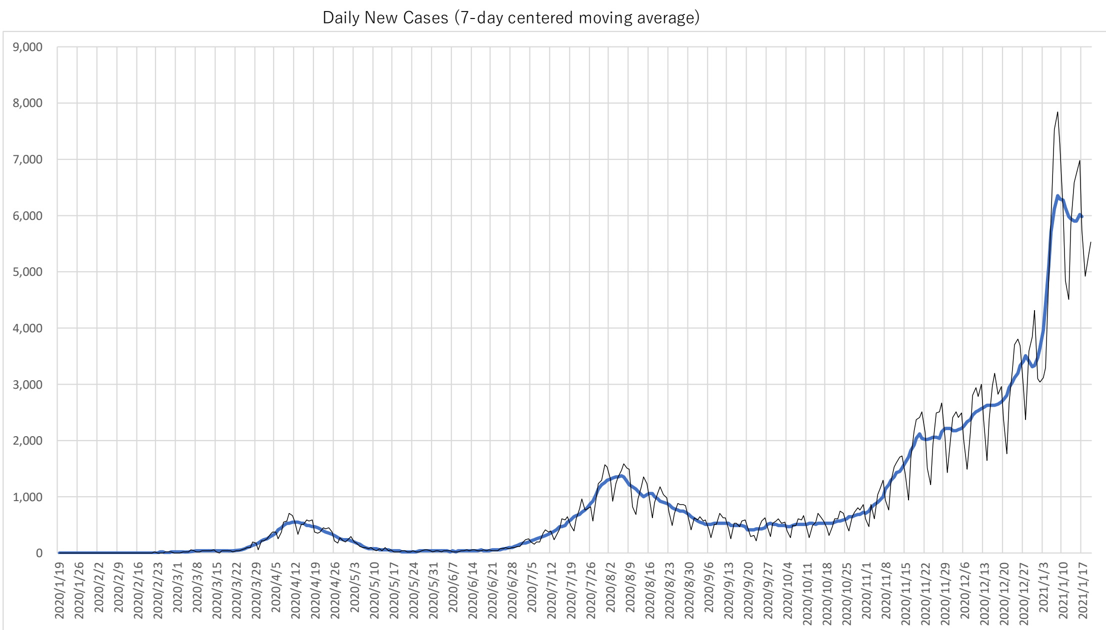
* p<0.05, ** p<0.01, *** p<0.001

Figure 1.1



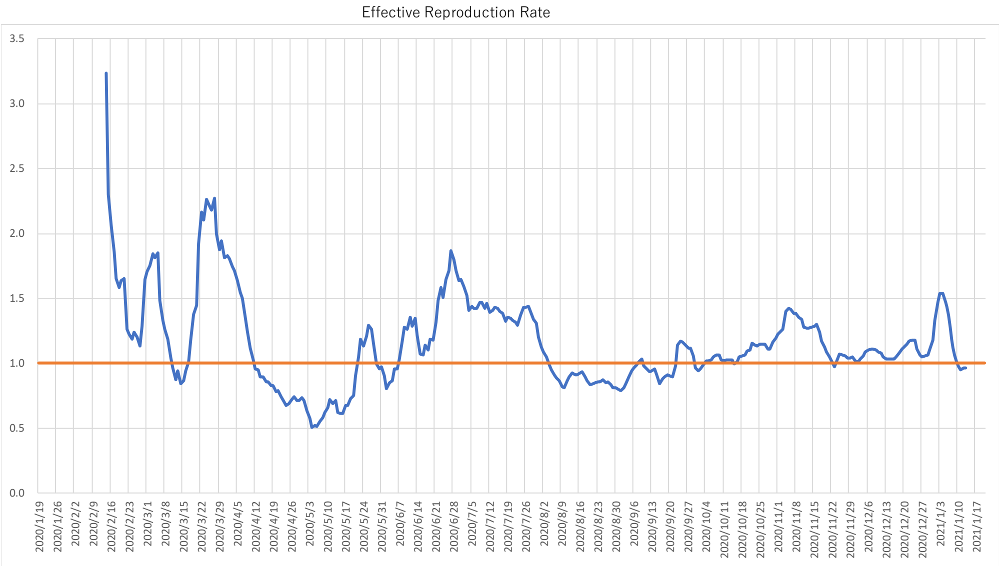
Note: https://www.mhlw.go.jp/stf/covid-19/open-data.html

Figure 1.2



Note:https://www.mhlw.go.jp/stf/covid-19/open-data.html

Figure 1.3

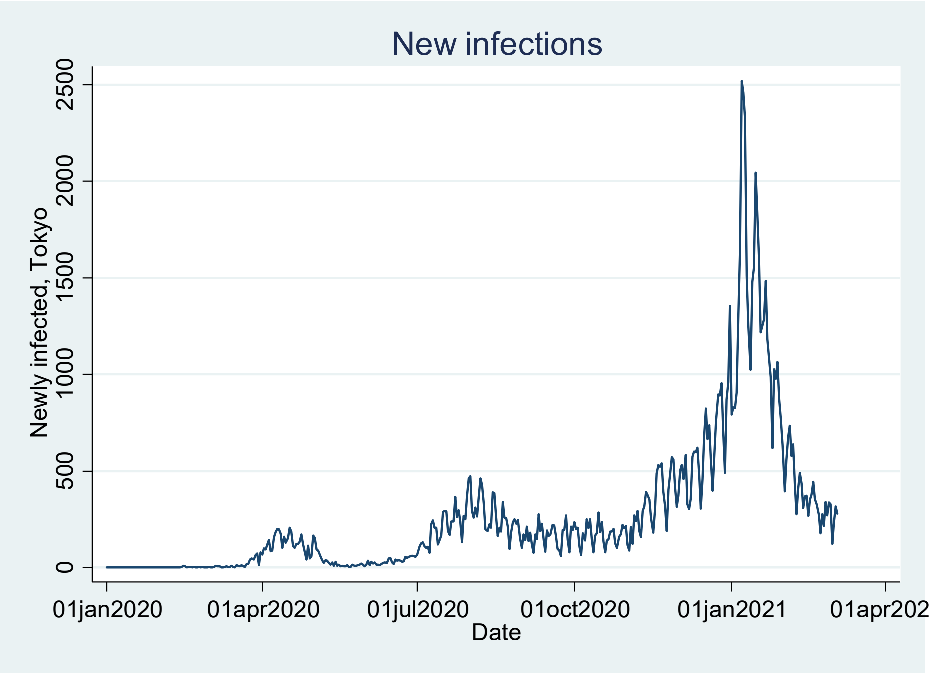


Effective Reproduction Rate = (Average(Xt+1…Xt+8)/Average(Xt-7…Xt))^(5/7)

Note: https://www.mhlw.go.jp/stf/covid-19/open-data.html

Figure 5.1 Covid data for Tokyo

(A)



(B)

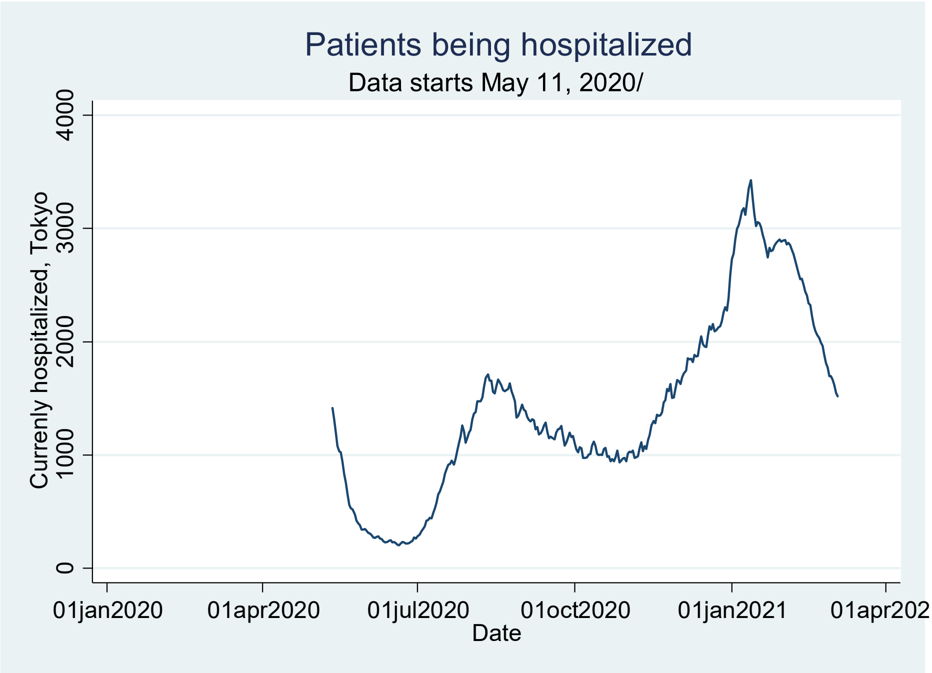


Figure 5.2 Google mobility index for Tokyo (red lines correspond to holidays)

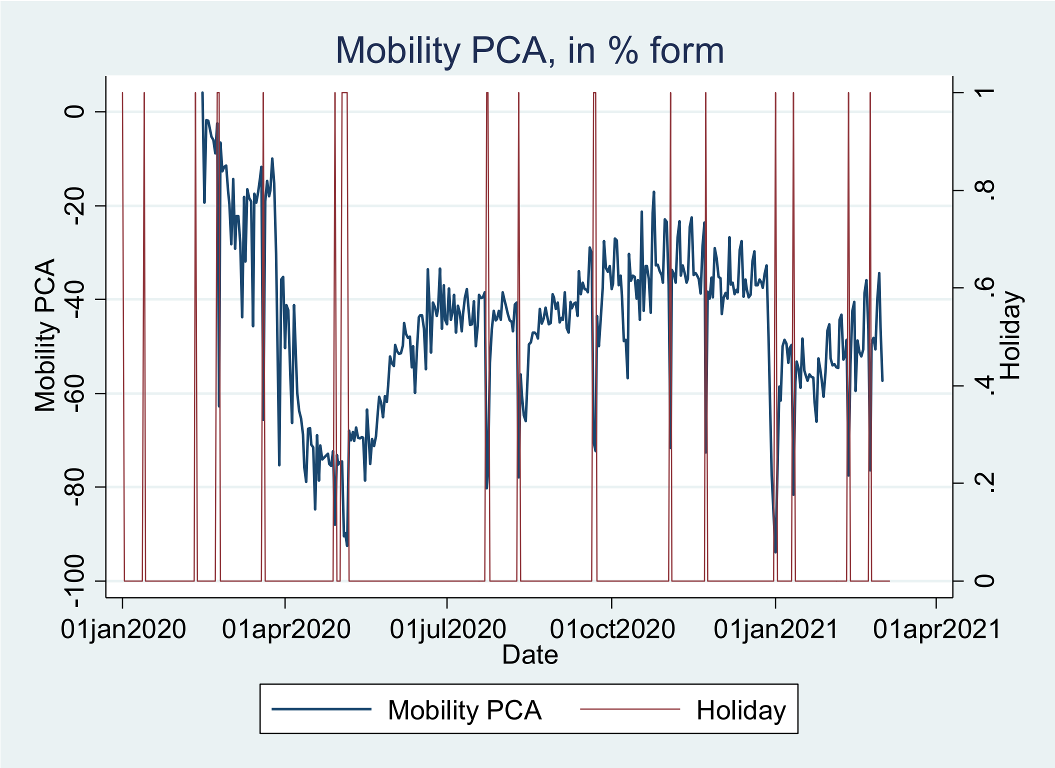


Figure 5.3 Stringency index for Japan

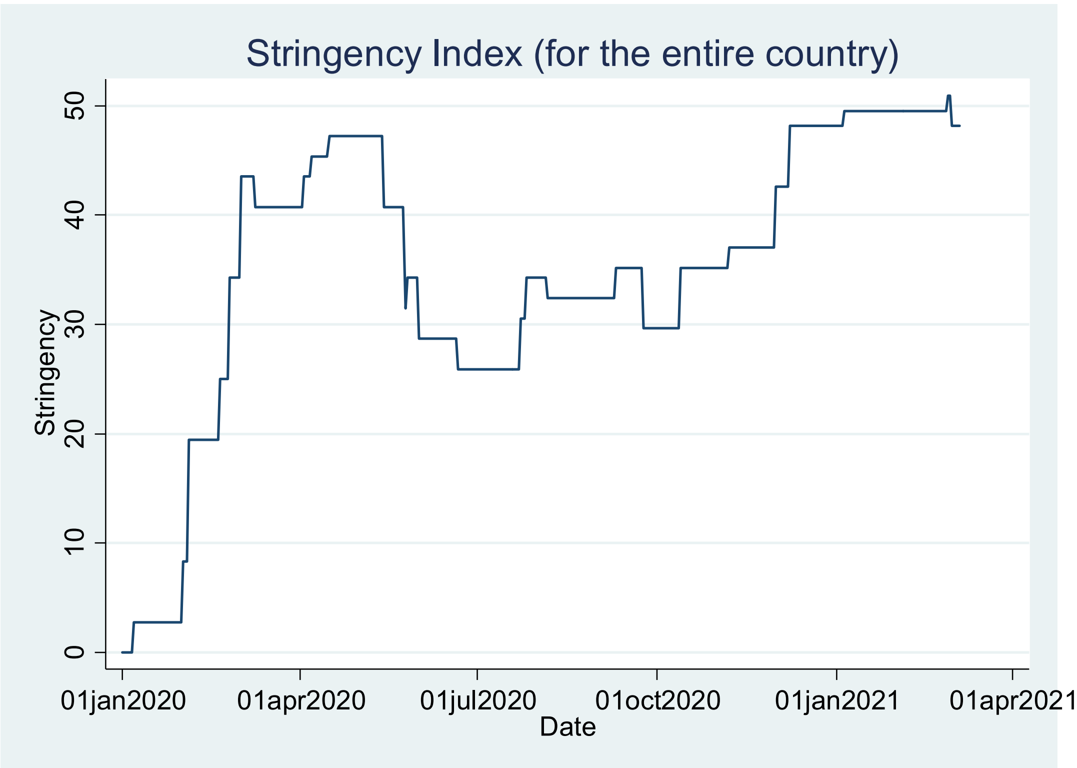
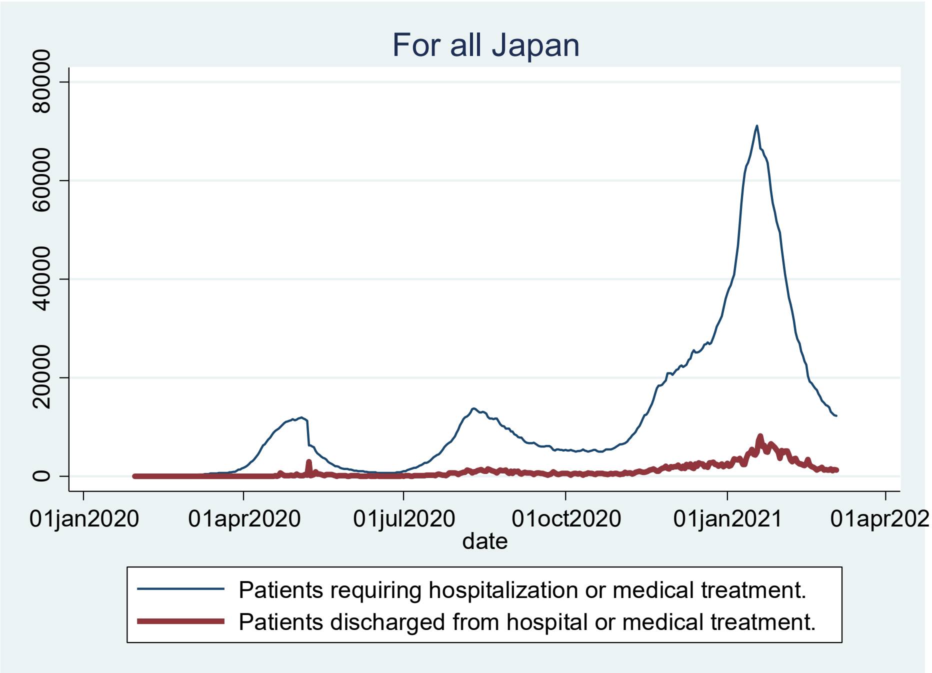


Figure 5.4 Estimating the recovery rate using Japanese data

(A)



(B)

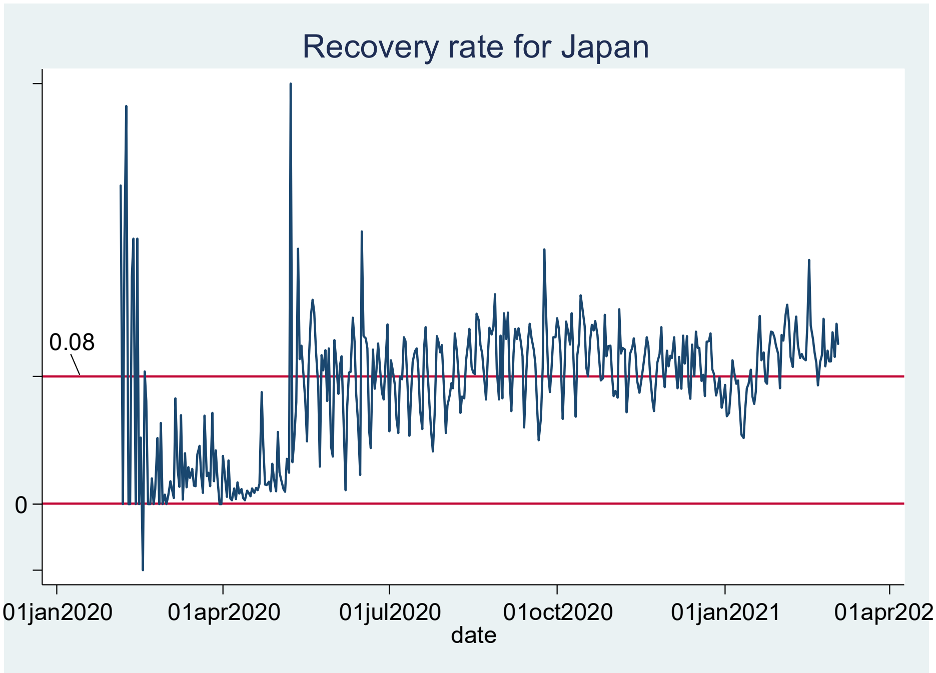
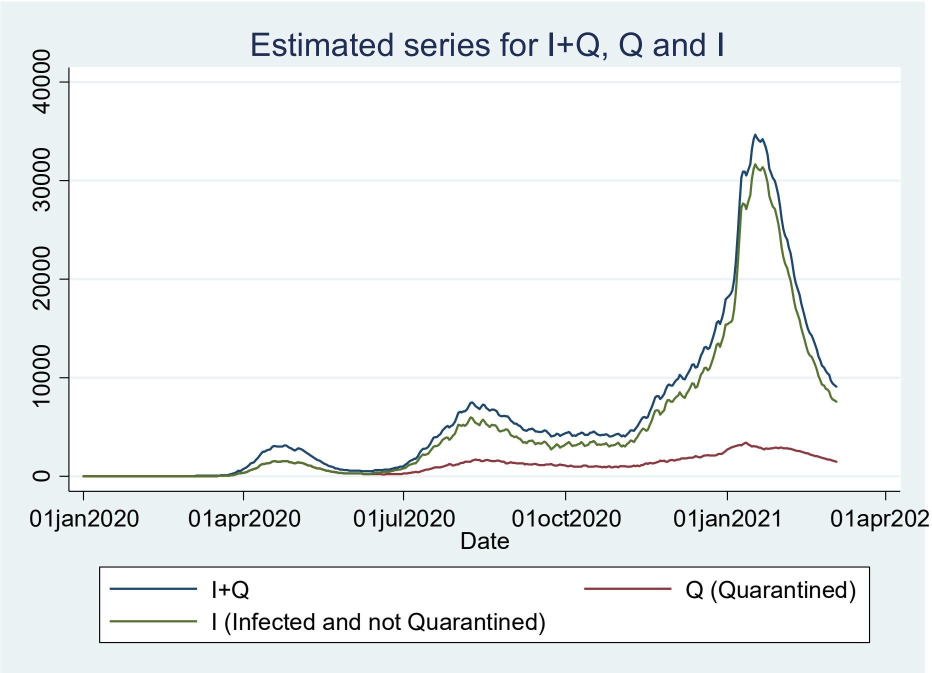


Figure 5.5 Estimation results for Tokyo

(A)



(B)

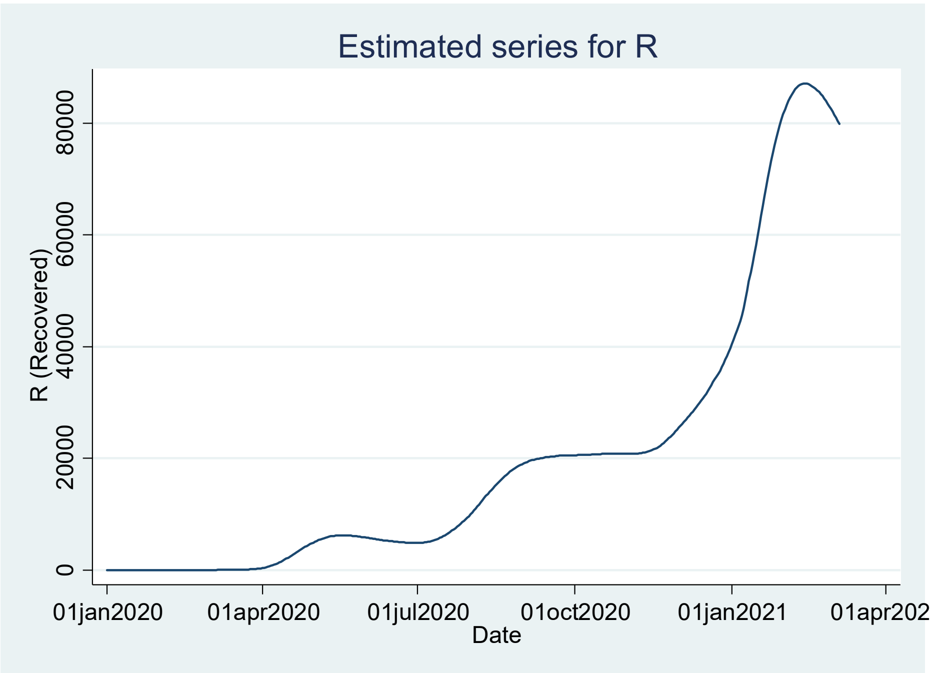


Figure 5.6 Estimation result for Tokyo

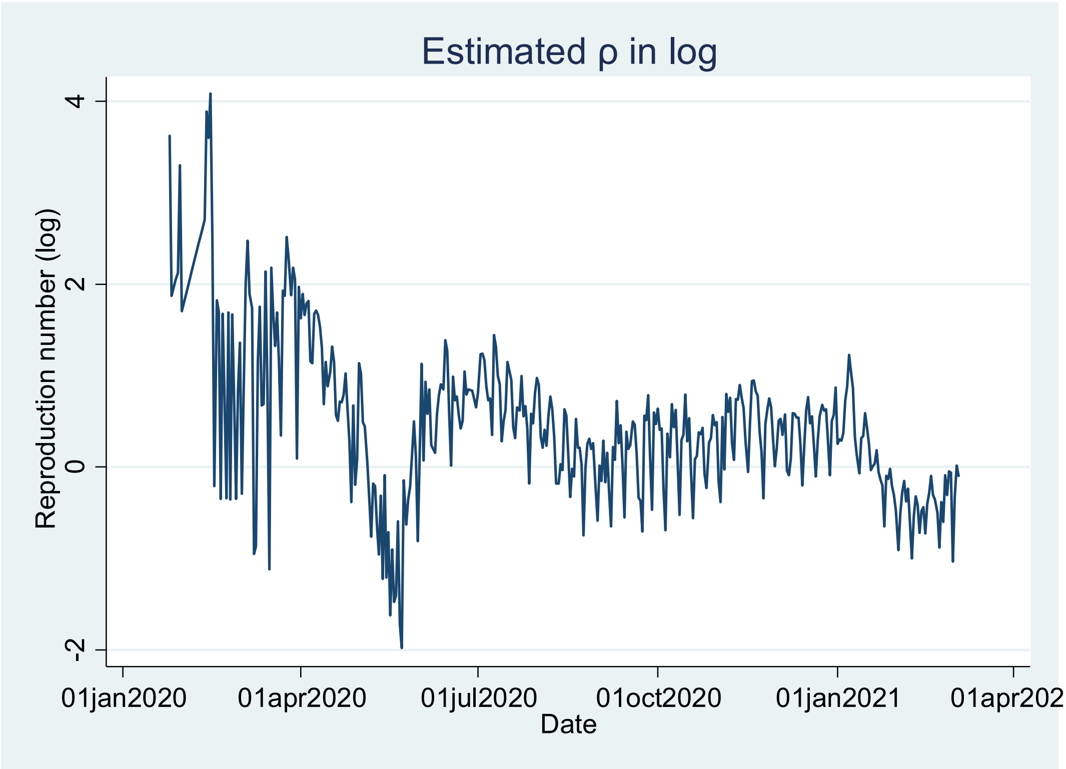


Figure 5.7 Steady state relationship between the level of activities and the infection rate for Tokyo, in log-log scale.

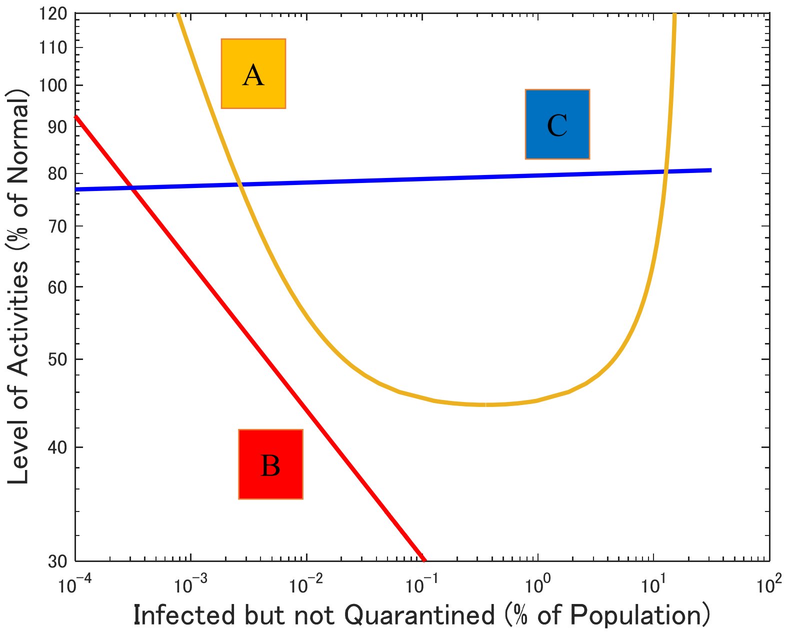


Figure 6.1 Estimation results for New York City

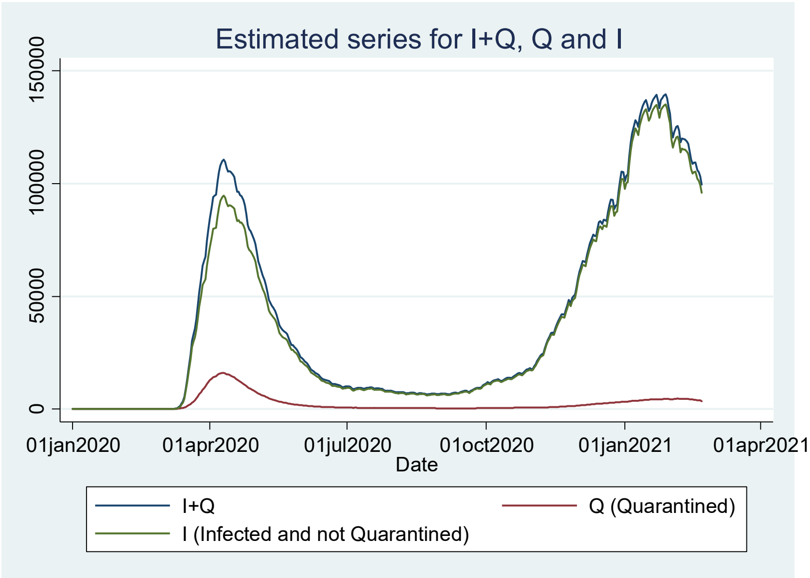


Figure 6.2 Estimation result for New York City

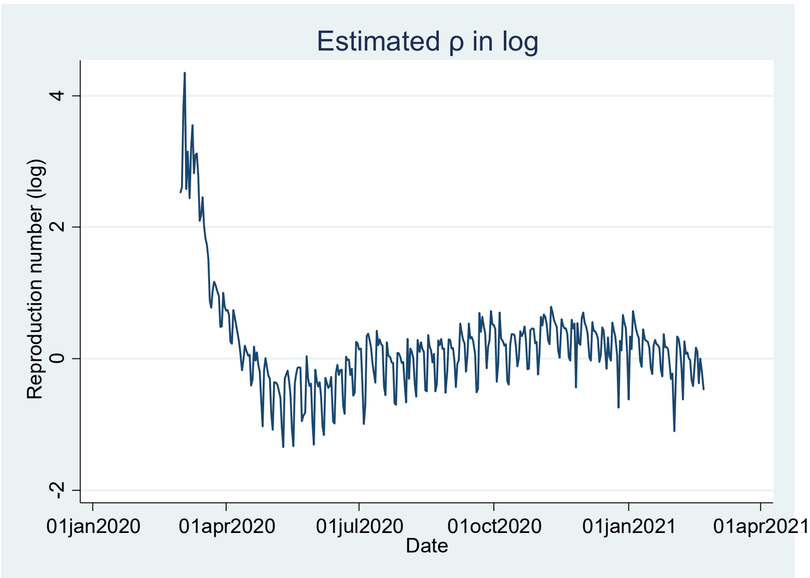


Figure 6.3 Mobility index (Transit), New York City

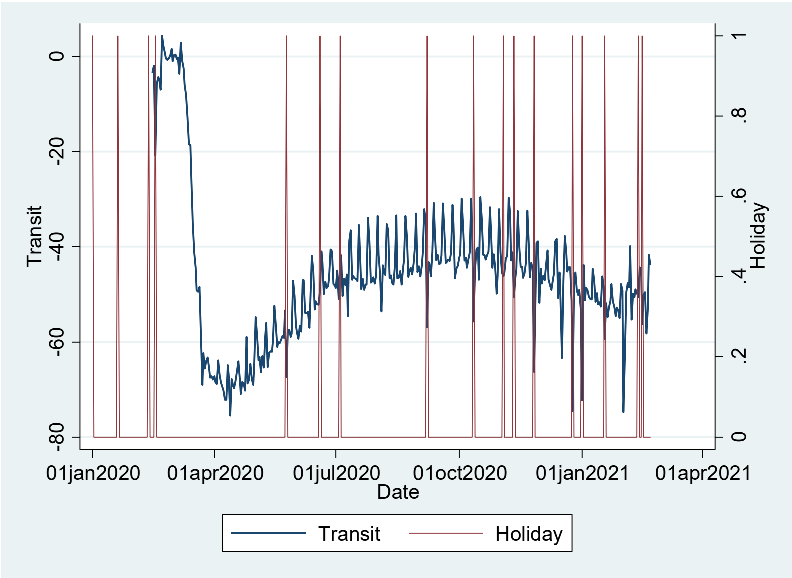


Figure 6.4 Stringency Index, New York State

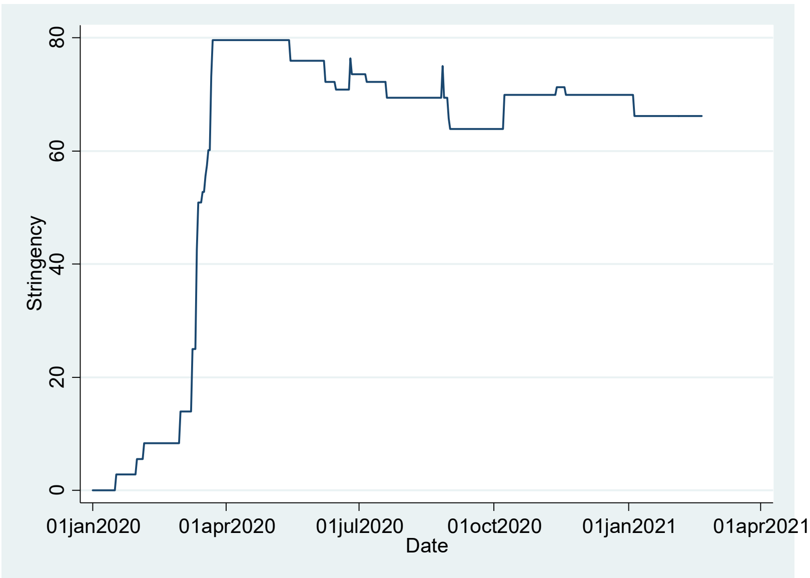


Figure 6.5 Steady state relationship between the level of activities and the infection rate for New York City, in log-log scale.

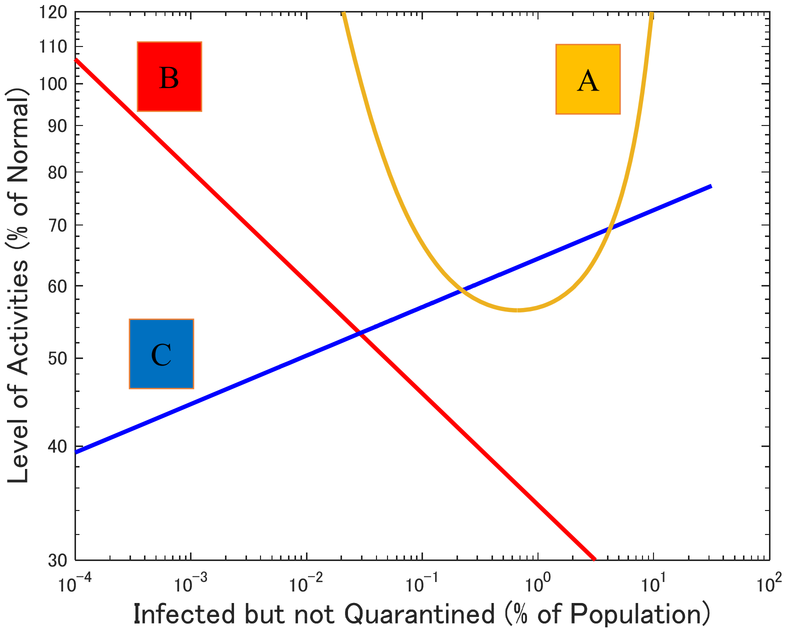


Figure 7.1 Estimation results for London

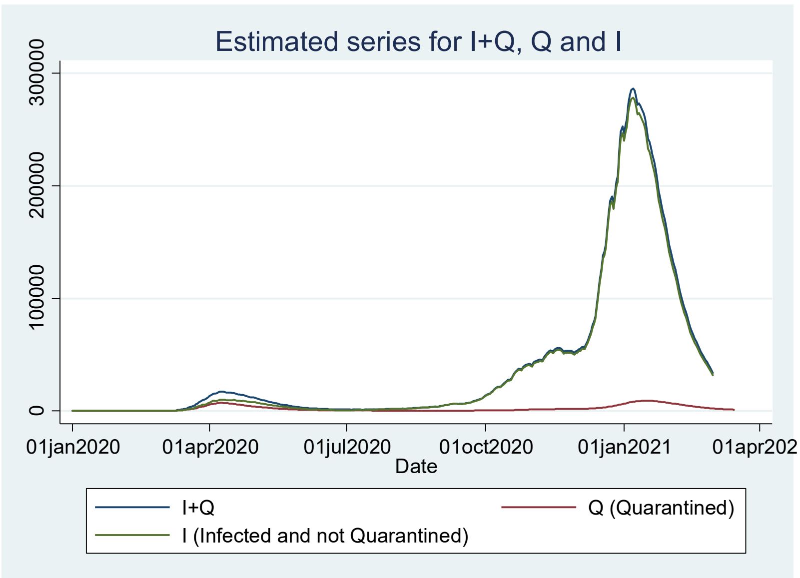


Figure 7.2 Estimation result for London

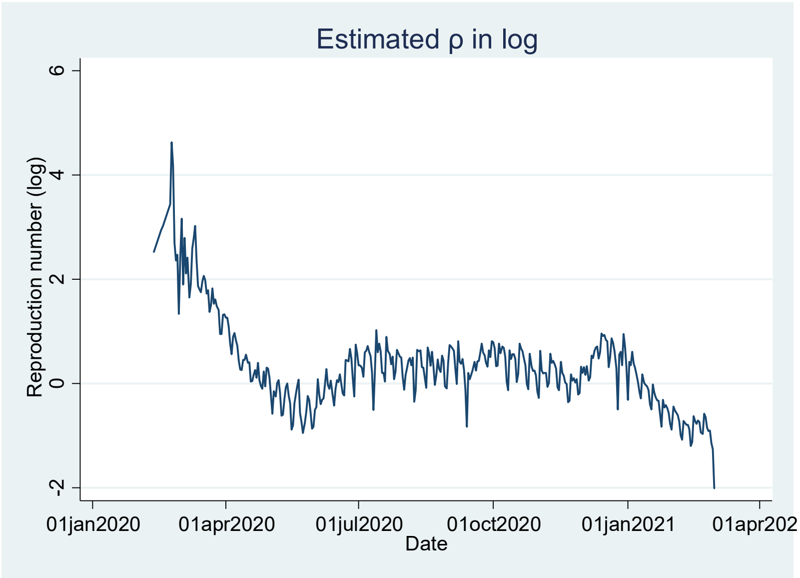


Figure 7.3 Mobility index (PCA) for London

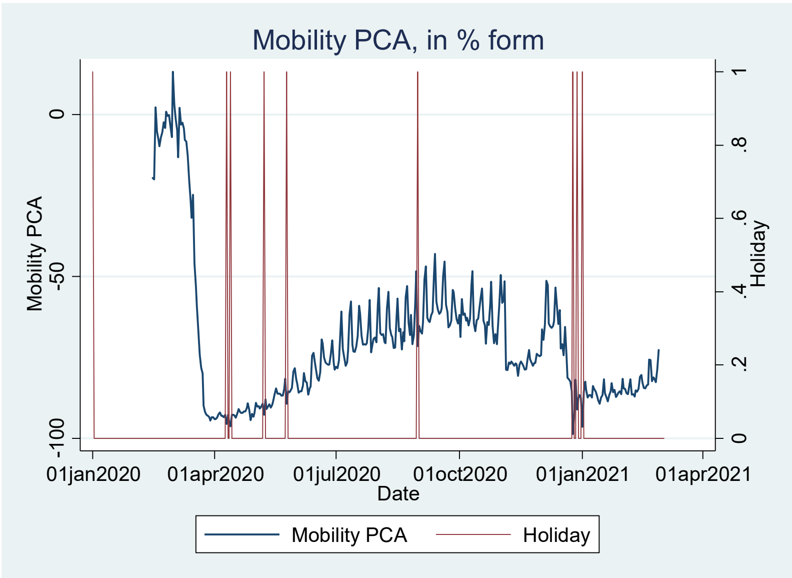


Figure 7.4 Stringency index for England

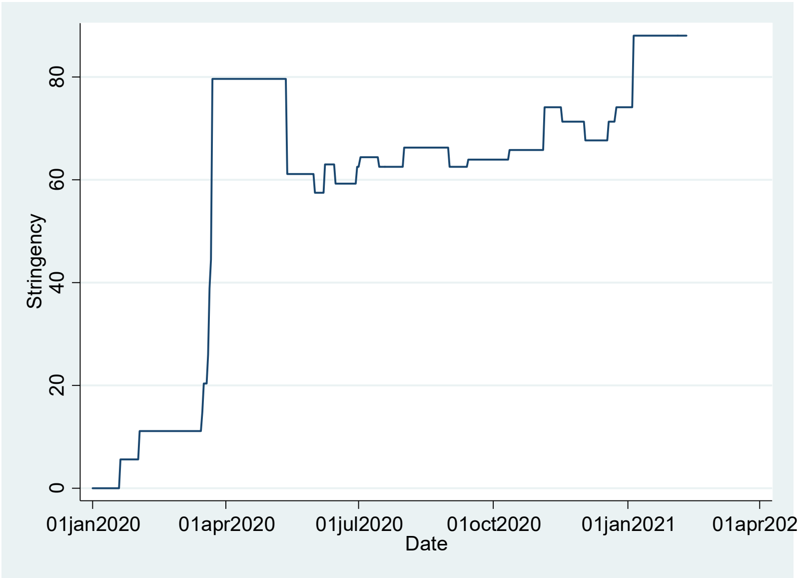
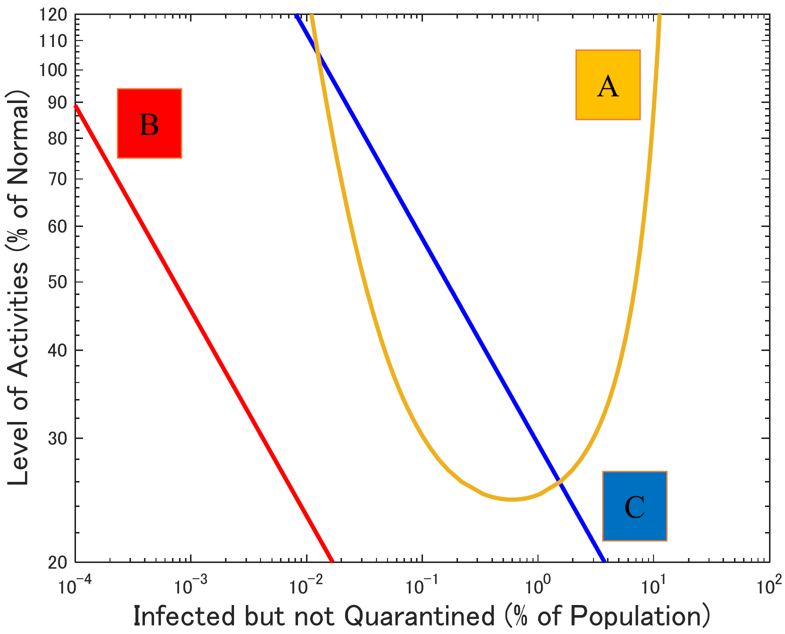


Figure 7.5 Steady state relationship between the level of activities and the infection rate for London, in log-log scale.



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