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

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In this paper, we argue that the 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, which is, in this case, infection. Like the Phillips Curve, this apparent output-infection trade-off is an elusive one and it is lost in the long run. Containing infections calls for decisive policy action. This paper shows that we could design a reaction function, which sets the level of economic activity as a function of the state of infection, in such a way that the possibility of an infection explosion would be eliminated. Our empirical analysis suggests that Tokyo, New York, and London since September 2020 do not satisfy this desirable property.

Key words: COVID-19, output-infection trade-off, pandemic Phillips curve, pandemic Taylor principle, SIR model

JEL codes: I18, E12, E31, E52

1. Introduction

1.1 Background: The COVID-19 outbreak
The new corona virus infection, which surfaced in Wuhan in late 2019, became a global pandemic by the spring of 2020. This new infection, named COVID-19, proved to be highly deadly for older people or people of comorbidity. The death rate from

This is a revised version of a paper presented at the 33rd 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 the Editors, especially 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 thanks So Kubota for his helpful comments and suggestions on an earlier version of the paper. Shioji acknowledges the financial assistance from the Grants-in-aid for Scientific Research A-20H00073, B-21H00704, and C-18 K01605, the Japan Center for Economic Research, and Nomura Foundation.

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COVID-19 estimated from reported deaths and reported infections has been about 1.5% in Japan. Initially, the only tool to contain this highly contagious virus was the avoidance of close contact among people by keeping a social distance and wearing a facemask. Since some infected people without symptoms can infect others by extremely small droplets within the air they have breathed, group dining in closed rooms and other social gathering had to be severely restricted to contain this illness. While some office work and schooling could be converted to online meetings and online teaching, distribution, mass transit, hotels, bars, restaurants, and other businesses were severely restricted. Table 1 summarizes the major developments in Japan that are related to the spread of the COVID-19 disease. Figures 1 and 2 plot the time series evolution of deaths and new cases of infection in Japan.

As highly effective vaccines were developed at 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 a vaccination or past infection will last because of the short history of this virus. Secondly, the occasional mutations of virus itself are likely to erode the effectiveness of current vaccines. Thirdly, the deadliness and/or infectiousness of COVID-19 may change as a result of mutations of the virus. 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 problem has been analyzed by an economic model called the Phillips curve since 1960s. The Phillips curve analyzes the inflation rate by assuming it has a negative relationship with the unemployment rate. When unemployment is low, the inflation rate tends to accelerate as a result of upward pressure on the wage rate. On the other hand, when unemployment is high, inflation rate tends to decelerate due to 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, the inflation rate 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 problem, in the short run, the government can stimulate economic activity 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 with normal economic activity, 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 contact among people by 70%, $R$ will be 0.75 ($2.5 \times [1 - 0.7] = 0.75$). Figure 3 presents the time series evolution of the estimated effective reproduction number for Japan.
Figure 1  Daily deaths (7-day centered moving average).
Source: https://www.mhlw.go.jp/stf/covid-19/open-data.html. [Color figure can be viewed at wileyonlinelibrary.com]

Figure 2  Daily new cases (7-day centered moving average).
Source: https://www.mhlw.go.jp/stf/covid-19/open-data.html. [Color figure can be viewed at wileyonlinelibrary.com]
From these observations, we can see the similarity of the two situations. \( R \) corresponds to 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 in 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 measures to keep the number of new infections will be the same for 1000 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 wants to restart the economy by removing social distancing measures, it should do so very cautiously one step at a time.

1.3 What we do
In this paper, we develop a new model to capture the elusive nature of this “output-infection trade-off.” It is based on an extended version of the standard epidemic model (the SIR model). When the virus is sufficiently transmissible, the model could give rise to two steady states that are locally stable, called the low- and high-infection states, respectively. This model is combined with two additional equations. One is the short-
run “Pandemic Phillips Curve,” which describes how the virus transmission is enhanced when the level of economic activity goes up. The other one specifies how people exercise restraint on their activities in response to the spread of the disease. It is shown that, if this reaction is sufficiently strong, the high-infection steady state can be eliminated. When this happens, we will say that the “Pandemic Taylor Principle” is satisfied.

We estimate the above two equations using data for Tokyo, New York, and London. The results are used to derive the model’s steady state(s) numerically for each city. We find that all three cities ceased to satisfy the Pandemic Taylor Principle since the fall of 2020.

The rest of the paper is organized as follows. Section 2 introduces our theoretical model. Section 3 sketches our empirical approach and illustrates the data. Section 4 studies the data from Tokyo, while Section 5 is devoted to an analysis of New York and London. Section 6 concludes the paper.

2. A Dynamic AD-AS Model of the Pandemic

2.1 Overview of the model
In order to capture our insight presented in the introduction, we develop a “dynamic aggregate demand - aggregate supply (AD-AS) model of the pandemic.” Klein et al. (2007) advocate incorporating economic principles into epidemiological models. Following this line of thought, since 2020, we have seen a rapid development of the “SIR-macro” model, which is reviewed in Tanaka (2022). Our approach belongs to this line of research. Unlike the “behavioral” SIR-macro model of Eichenbaum et al. (2021), Hamano et al. (2020), and Kubota (2021), the macroeconomic aspect of the model is a reduced form: in that sense, it is closer to the “nonbehavioral” model of Fujii and Nakata (2021).

Our model consists of the following three blocks:

- Block I is the epidemiological segment and is an extension of the standard SIR model.
- Block II specifies how the pandemic reacts to the level of economic activity.
- Block III depicts how economic activity is influenced by the state of infection.

2.2 How we extend the SIR model
We begin with Block I. In the standard SIR model, people move between three states, susceptible (S), infected (I), and recovered (R). Once recovered, people retain their immunity indefinitely. We modify these settings in two ways.

Kuniya (2021) provides a nice review of various extensions of the SIR model. Ours can be considered as a variant of the SIQR model (Hoppensteadt, 1974) which has been extended to analyze the dynamics of the COVID-19 transmission (Mandal et al., 2020, Ndaïrou et al., 2020, Zeb et al., 2020; Abdullah et al., 2021; Bhadauria...
et al., 2021). Like those models, we introduce the “quarantined” (Q) state, in which an infected person is isolated in a hospital (or a hotel) and stops interacting with S (hence, in this model, the I state means that someone is infected but not quarantined.)

While the usual SIQR model assumes that a constant fraction of people in the I state transit to the Q state in each period, in our model, the number of people in the Q state is treated as a constant. We think this is more appropriate for our purpose. Our experience with COVID-19 has revealed that a municipality’s capacity to isolate patients is often constrained by such factors as the number of hospital beds in the region.

Our model also inherits a feature of the SIRS model (Anderson & May, 1979). Like that model, we assume that people in the R state transit to S at a constant rate. That is, a person who was once infected and has recovered could lose immunity. Hamano and Katayama (2021) develop a full-fledged pandemic-macro model with such a feature.

Thus, our Block I combines characteristics of the SIQR and SIRS models. We shall call this the “SIRQS” part of the model.

### 2.3 Block I: The SIRQS part

Block I consists of the following four equations:

\[
\begin{align*}
S + I + R + Q &= N \quad (1) \\
\Delta I &= -\kappa + P \cdot S \cdot I - \gamma I \quad (2) \\
\Delta Q &= \kappa - \gamma Q \quad (3) \\
\Delta R &= \gamma (I + Q) - \delta R \quad (4)
\end{align*}
\]

where \( N \) is the total population size which is fixed. \( S, I, R, \) and \( Q \) denote the number of people in each state. The parameter \( \kappa \) represents the number of infected persons who are removed from social interaction in each period. The parameter \( \gamma \) determines the rate at which an infected person recovers. \( P \) is the probability of a susceptible person being infected by interacting with an infected individual. If we write

\[
P = \rho \cdot \gamma / N, \quad (5)
\]

the variable \( \rho \) would correspond to the so-called “reproduction number” in the SIR model. Although this terminology would not be strictly applicable in the context of the current model, we shall continue to use it throughout the paper. The parameter \( \delta \) represents the rate at which people who have once recovered become susceptible again.

We shall simplify the model by assuming that \( Q \) is always at its steady-state level:

\[
\Delta Q = 0 \implies Q = Q^* = \kappa / \gamma \quad (6)
\]
Using Equations (1), (5), and (6), we can rewrite Equation (2) as follows:

$$\Delta \frac{I}{N} = \gamma \cdot \left( -\frac{\kappa}{\gamma} + \rho \cdot \left( 1 - \frac{R}{N} - \frac{\kappa/\gamma}{N} \right) \cdot \frac{I}{N} - \frac{I}{N} \right)$$  \hspace{1cm} (7)

Also, we can write Equation (4) as:

$$\Delta \frac{R}{N} = \gamma \left( \frac{I}{N} + \frac{\kappa/\gamma}{N} \right) - \delta \frac{R}{N}$$  \hspace{1cm} (8)

Thus, Equations (7) and (8) jointly determine the dynamics of infection. Let $x$ be the steady-state value of $I/N$. It is a solution to the following quadratic equation:

$$-\frac{\kappa}{\gamma} + \rho \cdot \left( 1 - \left( 1 + \frac{\gamma}{\delta} \right) \left( x + \frac{\kappa/\gamma}{N} \right) \right) x - x = 0$$  \hspace{1cm} (9)

For a value of $\rho$ that is sufficiently high, Equation (9) has two solutions. This is depicted in Figure 4, where we draw the phase diagram for Equations (7) and (8). Each of the loci [7] and [8] sets the left-hand side of Equations (7) and (8) to zero, respectively. From Figure 4, we can see that there is actually a third steady state, which is a state with zero infections. Point $H$, which will be called the high-infection state (or the “endemic”

![Figure 4](wileyonlinelibrary.com)
state, in the terminology of the SIRS model), is stable. Point U is unstable (it is a saddle). The zero infection situation, which will be called the low-infection state, is also stable.

As we lower the value of $\rho$, locus [7] in Figure 4 shifts downward and the two intersection points move closer to each other. When it is below certain threshold, points H and U would disappear, and the low-infection one will be the unique steady state.

2.4 Block II: The short-run trade-off equation or the pandemic Phillips curve

Now we move on to Block II. It represents the idea of the short run output-infection trade-off or the short-run pandemic Phillips curve. It specifies $\rho$, the reproduction number, as an increasing function of $Y$, the level of economic activity. It is assumed to be log-linear:

$$\frac{\rho}{\rho^*} = \left(\frac{Y}{Y^*}\right)^{\phi_1}, \text{ where } \phi_1 > 0. \quad (10)$$

In Equation (10), both $\rho^*$ and $Y^*$ are positive constants. The parameter $\phi_1$, which is also assumed to be positive, governs the rate at which the level of activity promotes the spread of the virus. It would thus correspond to the slope of the short-run Phillips curve in macroeconomics. In what follows, we shall simply call Equation (10) the “trade-off equation.”

2.5 Lack of a long-run trade-off

Figure 4 shows that the above trade-off is an elusive one. Unless $Y$ is maintained at a sufficiently low level, $\rho$ will exceed a threshold value, and there is no natural force to prevent the economy from going to the high-infection state through an infection explosion. A strong intervention would be needed to eliminate this possibility. One obvious solution would be to impose a strict upper limit on $Y$, so that $\rho$ would never exceed the threshold. In fact, this would be the only possibility in the standard SIR model. But such a “low for long” policy would exert a sizable economic cost. Fortunately, thanks to the presence of the Q state in our model, there is a possibility that a more flexible “Taylor-rule type” policy could achieve the same goal. We shall specify this in the next subsection.

2.6 Block III: The reaction function

Block III describes how the level of activity reacts to the state of infection. It reflects both the spontaneous response of the private sector to the threat of the virus (“voluntary lockdown” in the terminology of Watanabe & Yabu, 2020, 2021), and the readiness of the government to impose restrictions on people’s activities in response to rising infection numbers (and people’s willingness to respect them). It is also assumed to be log-linear:
\[
\frac{Y}{Y^*} = \left( \frac{I}{I^*} \right)^{-\phi_2}, \quad \text{where } \phi_2 > 0,
\]  

where \( I^* \) is a positive constant. If this reaction is sufficiently strong, it would eliminate the high-infection state, and ensure that the economy will converge to the low-infection state. In such a case, we shall say that the function satisfies the “Pandemic Taylor Principle.”

3. Sketch of the Empirical Analysis and Related Studies

3.1 Our data and estimation

In what follows, we study if the Pandemic Taylor Principle is satisfied in three cities, Tokyo, New York, and London.\(^1\) We focus on cities rather than nations, because we believe that much of the interaction between the pandemic and economic activity takes place at a local level. We first estimate the empirical counterparts of Blocks II and III. Then the entire model will be simulated numerically, with appropriate parameter values chosen for Block I, to obtain the steady-state conditions.

For the estimation, we use daily data. Details can be found in the Appendix A-C in the Supporting Information. Briefly speaking, we mainly use the following two sets of data.

1. **COVID-related data**: We use the daily number of newly reported positive test results. The number of people in the Q state will be measured by the number of persons who are being hospitalized.

2. **Measure of economic activity**: We use Google’s mobility indices at the city level for Tokyo and London, and those for the five boroughs of New York. Google provides six types of indices (6*5 = 30 in the case of New York), and we take their weighted average, based on principal component analysis, to obtain a single measure of activity for each city.

In addition, we use the Oxford COVID-19 Government Response Tracker’s Stringency Index. It should be noted that they do not provide city-level indices. Consequently, we use the national-level index in the analysis of Tokyo, the statewide index for New York, and that for England when studying London. We also use various types of weather variables to control for their effects on mobility.

3.2 Related empirical work

Our estimation of Block II, the trade-off equation, is related to Glaeser et al. (2020), who use zip-code-level data from five US cities to estimate the impact of mobility on the number of new cases of COVID-19. Among studies using Japanese data, Tomura (2021) conducts a Bayesian estimation of a model in which the effective reproduction number is a function of past consumption expenditures as well as people’s mobility. Kajitani and Hatayama (2021) estimate the impact of mobility on the effective reproduction number at
the prefecture-level. Kurita et al. (2021) estimate the impact of the Japanese government’s state of emergency declarations on the evolution of the effective reproduction number.

Our estimation of Block III, the reaction function, is related to Watanabe and Yabu (2020, 2021), who use prefecture-level data to estimate how mobility responds to both information on and the actual occurrence of COVID-19 in Japan, and compare the results with those from the USA presented by Goolsbee and Syverson (2021).

Our entire empirical framework is also related to Hosono (2021) who estimates the impact of mobility on the transmission of the disease as well as the response of mobility to infection risk. The results are incorporated into a dynamic model. Unlike this paper, Hosono uses a full-fledged, optimization-based version of the SIR-macro model.

4. Evidence from Tokyo

4.1 Daily estimation of the reproduction number
To estimate Equation (10), the trade-off equation, we first need to obtain daily estimates for $\rho$, the reproduction number. We do this based on the SIRQS part of our model, using data on new infections and hospitalizations.

Again, the details of this procedure are relegated to the Appendix in Supporting Information. Briefly, we assume that, on each day, a constant fraction of the people who are newly infected are detected. The Institute for Health Metrics and Evaluation (IHME) of the University of Washington estimates the actual number of new infections at the national level. By taking the average ratio between the official number and this estimate, we set the detection rate equal to 0.2.² By dividing the daily number of reported cases at the city level by this detection rate, we obtain our estimate of the daily inflows into the pool of the infected (i.e. $I + Q$), which will be denoted as “new.” We estimate $\gamma$, the daily recovery rate, to be equal to 0.08, based on the national aggregate data. Then, by the perpetual inventory method, we obtain an estimated daily series for $I + Q$.

We equate $Q$ with the reported number of hospitalized patients, except in the very early periods. This would also give us $I$. Once we know $I + Q$, $R$ can be computed from Equation (4), with an appropriate value of $\delta$. We set it equal to 0.016, which means that 95% of immunity is lost in half a year. By setting $N$, the total population of Tokyo, to be 14 million, we can derive the evolution of $S$, the size of the susceptible population, over time. Finally, using these results, we obtain our estimates for the time path of $\rho$:

$$\rho = \text{new} \cdot \frac{N}{(\gamma \cdot S \cdot I)}.$$

4.2 Estimation of Block II, the trade-off equation
We estimate an empirical version of Equation (10). The log of our proxy for the level of economic activity will be denoted by $y$. Basically, we regress the log of $\rho$ on lagged $y$. The median incubation period for COVID-19 is believed to be 4–5 days.
this, we take 4-day lags of $y$. This basic specification is augmented with lagged dependent variables and further lagged values of $y$ as additional explanatory variables. We also include day of the week dummies, dow:

$$\ln \rho_t = \sum_{j=1}^{8} a_{1j} \cdot \ln \rho_{t-j} + \sum_{k=4}^{11} b_{1k} \cdot y_{t-k} + \sum_{l=1}^{7} d_{1l} \cdot \text{dow}_l + \epsilon_t$$

(13)

It is convenient to rewrite the above equation as follows.

$$\ln \rho_t = \alpha_{11} \cdot \ln \rho_{t-1} - \sum_{j=1}^{8} a_{ij} \cdot \Delta \ln \rho_{t-j} + \beta_{14} \cdot y_{t-4} - \sum_{k=4}^{11} b_{1k} \cdot \Delta y_{t-k} + \sum_{l=1}^{7} d_{1l} \cdot \text{dow}_l + \epsilon_t$$

(14)

where

$$\alpha_{ij} \equiv \sum_{m=j}^{8} a_{1m}, \quad \beta_{1k} \equiv \sum_{n=k}^{11} b_{1n}.$$ 

The long-run elasticity of $\rho$ with respect to the level of economic activity is given by $\beta_{14}/(1 - \alpha_{11})$, and we shall pay our closest attention to this number.

We report the estimation results in the first column of Table 2. The sample period is from February 25, 2020 to March 4, 2021. In all the tables that will be presented below, we follow the STATA convention and denote lagged variables by the operator “L.”, and differenced variables by “D.”. Also, in the tables, “Reproduction” indicates $\ln \rho$, and “Mobility” indicates $y$. In Table 2, we only show the estimates of $\alpha_{11}$ and $\beta_{14}$, to save space. We find that $\alpha_{11} = 0.824$ and $\beta_{14} = 0.641$, and both are quite significant. They jointly imply a long-run elasticity of 3.642.

4.3 Steady-state simulation for Blocks I and II

Let us define the “generic reproduction number,” denoted $\bar{\rho}$, as follows:

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

(15)

This is the value of (the log of) $\rho$ that would prevail in the long run if $y = 0$, that is, if activity is at its normal level. Using this notation, the following relationship holds in the steady state:

$$\ln \rho = \ln \bar{\rho} + [\beta_{14}/(1 - \alpha_{11})] y.$$ 

(16)

We can then solve Equation (9), using the parameter values we set in the previous subsection, and by setting $Q^e/N$ equal to its sample average (which is 0.00007871), to
obtain a pair of steady state values for \( I/N \) (if they exist) for different levels of \( y \). The result is the U-shaped curve (denoted “A”) in Figure 5, which puts \( y \) on the vertical axis and the log of \( I/N \) on the horizontal axis. The dotted line, which constitutes the

![Figure 5](https://wileyonlinelibrary.com)
left half of locus A, corresponds to the unstable steady state, and the solid line, which makes up the right half of the same locus, is for the high-infection state.

Figure 5 indicates that, if we can suppress activities to be below 72% of its normal level permanently, the high-infection state, as well as the unstable one, would disappear altogether, and the system will converge to the low-infection state. But such austerity would carry a large economic cost.

4.4 Estimation of Block III, the reaction function

We next estimate an equation which corresponds to Equation (11). Basically, we regress $y_t$ on the log of $I_t$. The latter is lagged by 1 day. This basic specification is augmented by including lagged dependent variables and further lagged values of the log of $I_t$ as additional explanatory variables. We also control for other factors that might affect mobility by including day of week dummies (dow$_i$), holiday dummies (each denoted as holiday$_m$, $m = 1, 2, \ldots, M$, where $M$ is the number of holidays in the sample) and various weather variables (each denoted as weather$_n$, $n = 1, 2, \ldots, N$ with $N$ being the number of weather variables included, which is four in the case of Tokyo):

$$y_t = \alpha_2 \cdot y_{t-1} + \beta_{21} \cdot \ln I_{t-1} + \sum_{k=2}^{7} \beta_{2k} \cdot \Delta \ln I_{t-k} + \sum_{l=1}^{7} d_{2l} \cdot \text{dow}_l + \sum_{m=1}^{M} e_{2m} \cdot \text{holiday}_m$$

$$\quad + \sum_{n=1}^{N} f_{2n} \cdot \text{weather}_n + \eta_t.$$  \hfill (17)

In estimating Equation (17), we consider the possibility that there was a structural change in the middle of the sample. Anecdotal evidence suggests that people’s behavior might have become less responsive to the spread of COVID-19 since around the autumn of 2020. To test this possibility, we allow $\beta_{21}$ to be different across the two sub-periods. Let $H_1$ and $H_2$ be dummy variables for the first and the second half, respectively. We extend Equation (17) in the following way:

$$y_t = \alpha_2 \cdot y_{t-1} + c \cdot H_1 + \beta_{21}^1 \cdot (\ln I_{t-1} \cdot H_1) + \beta_{21}^2 \cdot (\ln I_{t-1} \cdot H_2) + \ldots.$$  \hfill (18)

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.

Estimates are reported in the first column of Table 3. The entire sample spans the period of February 23, 2020 to March 2, 2021. 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 a rise of infection since fall 2020.

4.5 Steady-state simulation for Block III

Based on those estimates, we derive the long-run version of the reaction function for the first half (for a non-holiday) as follows:
Table 3 Estimation of the reaction function

|                  | Tokyo     | New York City | London    |
|------------------|-----------|---------------|-----------|
| L. Mobility      | 0.730***  | 0.605***      | 0.920***  |
| | (24.75)    | (17.60)    | (51.39)     |
| Infected*H1      | -0.0237***| -0.0438***    | -0.0133***|
| | (−5.52)    | (−9.90)    | (−3.40)     |
| Infected*H2      | 0.00126 (0.13) | 0.0335***   | -0.00143 (−0.20) |
| | (0.13)     | (3.80)     | (−0.20)    |
| H1               | 0.135 (1.32) | 0.697***    | 0.0570 (0.75) |
| | (1.32)     | (7.12)     | (0.75)     |
| Observations     | 374       | 357          | 371       |
| Adjusted R²      | 0.973     | 0.981        | 0.992     |

*P < 0.05; **P < 0.01; ***P < 0.001.

The table includes L. represents the lag operator, and D. stands for the difference operator.

\[
y = \frac{\beta_{21}}{1 - \alpha_2} \ln I + \left[ \sum_{l=1}^{7} d_{2l} + \sum_{n=1}^{N} f_{2n} \cdot \overline{\text{weather}_n} + c \right] / (1 - \alpha_2) \tag{19}
\]

In the above, \( \overline{\text{weather}_n} \) is the average of the value of the \( n \)th weather variable across the entire sample. For the second half, we just replace \( \beta_{21} \) with \( \beta_{21}^2 \) and replace \( c \) with zero.

In Figure 5, we add two lines, labeled B and C, each representing the long-run reaction function for the first and the second half, respectively: B (the solid line) is steeply downward sloping, while C (the dashed line) is even mildly upward sloping.

Note that line B is so low and steep that it does not intersect with locus A. In other words, the Pandemic Taylor Principle is satisfied for the first half of the sample. This is not the case for the second half of the sample, as line C has two intersections with locus A.

To gain some insights into the cause of the structural change in the reaction function, in the first column of Table 4, we add the policy stringency index (for Japan as a whole) to our previous analysis. We allow its coefficient to vary between the two periods. It is negative and significant for the first half, but turns insignificant in the second half. It appears that people have “stopped listening to what the government says.”

On the other hand, the coefficient on lagged infection remains negative. Although it is still significant for the first half and insignificant for the second, the size of the coefficient is almost the same. It seems that, after controlling for the Japanese people’s changing attitude
toward their government, their responsiveness to the virus itself did not change. Finally, in the first column of Table 5, we study the determinants of the stringency index. As explanatory variables, we include the lagged dependent variable and the lagged infection variable. The sample period is January 25, 2020 to March 5, 2021. Our estimates indicate that the government was always unresponsive. Perhaps the citizens sensed this tendency during the first half and stopped responding to government policies in the second half.

Table 4 Estimation of the reaction function (with Stringency Index added as an explanatory variable)

| LHS = Mobility | Tokyo | New York City | London |
|----------------|-------|---------------|--------|
| L.Mobility     | 0.674*** (21.36) | 0.592*** (15.90) | 0.887*** (34.15) |
| Infected*H1    | −0.0219*** (−5.06) | −0.0382*** (−4.21) | −0.0105 (−2.23) |
| Infected*H2    | −0.0234 (−1.51) | 0.0317*** (3.51) | 0.00231 (0.26) |
| L.Stringency*H1| −0.0867*** (−4.17) | −0.0204 (−0.75) | −0.0169 (−1.47) |
| L.Stringency*H2| 0.0117 (0.33) | 0.0617 (1.16) | −0.0221 (−1.26) |
| H1             | −0.168 (−1.02) | 0.680*** (5.97) | 0.0559 (0.60) |
| Observations   | 374 | 357 | 355 |
| Adjusted $R^2$ | 0.974 | 0.981 | 0.992 |

* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

$t$ statistics in parentheses. Note: Also included: day of the week dummies, holidays and festivities dummies, weather variables, and D.Mobility (lags 1–7). H1 = first half dummy; H2 = second half dummy. In the above, L. represents the lag operator, and D. stands for the difference operator.

Table 5 Determinants of the Stringency Index

| LHS = Stringency | Tokyo | New York City | London |
|------------------|-------|---------------|--------|
| L.Stringency     | 0.961*** (103.37) | 0.816*** (40.09) | 0.949*** (83.43) |
| Infected*H1      | −0.00401 (−1.42) | 0.0506*** (6.83) | 0.0204*** (3.65) |
| Infected*H2      | −0.00843 (−1.15) | 0.0126*** (8.81) | 0.00596*** (4.17) |
| H1               | 0.0110 (0.43) | −0.336*** (−5.65) | −0.121*** (−3.13) |
| Observations     | 406 | 357 | 365 |
| Adjusted $R^2$   | 0.988 | 0.994 | 0.990 |

* $P < 0.05$; ** $P < 0.01$, *** $P < 0.001$.

$t$ statistics in parentheses. Note: No other variables included. In the above, L. represents the lag operator.
5. Evidence from New York and London

Now we turn to the data for New York City and London. Since we follow procedures that are basically the same as those discussed in the previous section, our discussion will be brief.

In the estimation of the daily reproduction number, most of the parameter values are the same as those for Tokyo, except that $N$, the city’s total population, equals 8.5 million for New York, and 9 million for London. The detection rate of infection is estimated to be 0.25 for New York based on state-level data, and around 0.45 for London using data for England as a whole.

The estimation results for the trade-off equation are shown in the second and third columns of Table 2 for New York and London, respectively. Lagged mobility is significant for both cities, though the point estimates are much smaller than that for Tokyo. This implies that Tokyo was facing a more favorable short-run trade-off.

The corresponding columns in Table 3 show the estimated reaction function. For both cities, the lagged infection variable is significantly negative for the first half. Paradoxically, it turns positive for New York during the second half (though the intercept

![Figure 6](https://wileyonlinelibrary.com)  
**Figure 6** Steady-state relationship between the level of activity and the infection rate for New York City (log–log scale). [Color figure can be viewed at wileyonlinelibrary.com]
goes down). For London, it remains negative but turns insignificant, as in the case of Tokyo. This tendency is unchanged when we add the stringency index in Table 4. The index itself is always insignificant, implying that much of the slowdown in activity came from people exercising voluntary restraints. Table 5 suggests that their governments were responding to the pandemic situation, unlike their Japanese counterparts: policies became less responsive to infection during the second half, but the level of stringency went up, as indicated by the intercept terms.

Steady-state simulation results are shown in Figure 6 for New York and Figure 7 for London, respectively. The value of $Q^*/N$ is set at 0.0002868 for New York, and it is 0.00029 for London. As in the case of Tokyo, during the first half, people’s response to the pandemic was strong enough to eliminate the high-infection steady state. However, during the second half, the reaction weakens, and the cities can no longer evade the possibility of an infection explosion. It appears that “stay-at-home fatigue” put them in dangerous circumstances, which continued until the eventual arrival of vaccines.

Figure 7 Steady-state relationship between the level of activity and the infection rate for London (log-log scale). [Color figure can be viewed at wileyonlinelibrary.com]
6. Conclusions

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

1. It 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 activity. Policymakers may be tempted to exploit this relationship.
2. However, this trade-off is elusive. If decisive actions are not taken in the face of an outbreak, infections will explode.

We have estimated both the pandemic’s response to the level of activity and people’s reaction to the state of infection using data for Tokyo, New York, and London. We incorporate the results into our dynamic model. We find that, until the fall 2020, people were so responsive to the pandemic that the possibility of an infection explosion was being eliminated. However, since then, the response has weakened considerably.

An important topic for future research is to incorporate the public’s forward-looking behavior, just as macroeconomic studies on the expectation-augmented Phillips Curve did. We can hypothesize that, when the government is more committed to virus containment, households would be more incentivized to cooperate. Such an analysis could shed light on the causes behind the changes in people’s behavior that we have found.

Notes

1 Shioji conducted the empirical research, and is primarily responsible for any errors that might remain in the rest of the paper.
2 We thank Keiichiro Kobayashi for bringing this data source and estimation method to our attention.

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Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: Infection data and estimation of S, I, R, Q

Appendix B: Measures of economic activity

Appendix C: Stringency Index and Weather variables

Appendix D: Full Estimation Results

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