Covid-19 and Output in Japan*

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Abstract

Using a tractable macro-SIRD model, we explore the relationship between the spread of Covid-19 and output in Japan. We also examine the consequences of adopting alternative criteria for ending the state of emergency currently in place in Tokyo. We will update our analysis weekly at `https://Covid19OutputJapan.github.io/`.

Keywords: Covid-19; Emergency Declaration; Japan; Macro-SIRD model; Vaccines.

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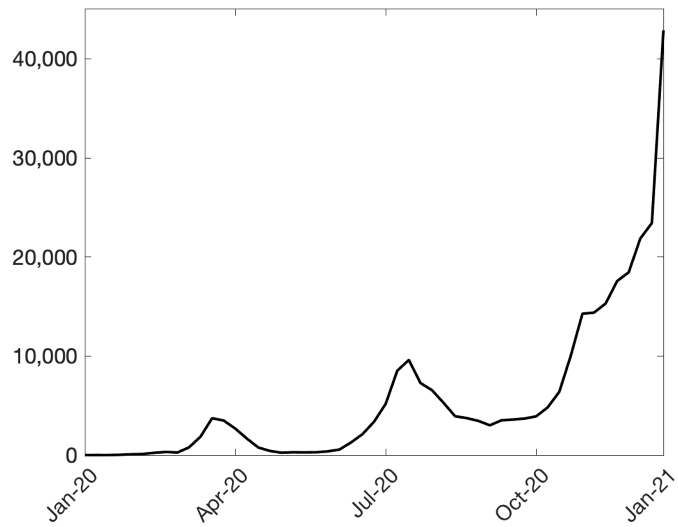
1 Introduction

Figure 1: The weekly number of new Covid-19 cases in Japan



Source: Ministry of Health, Labor, and Welfare.

As shown in Figure 1, the number of new Covid-19 cases in Japan has been on an upward trend since October 2020. The pace of the increase has accelerated in the past few weeks, having led policymakers and public to reassess how vigilant they would like to be against the risk of infection and how much to restrain economic activities. Given unpredictable nature of the evolution of Covid-19, it is likely that policymakers and public will need to frequently reassess the extent to which they would like to restrain economic activities.

In this note, we develop a tractable model of Covid-19 and the economy to assist such reassessment. We use our model to compute projections of Covid-19—conditional on various paths of output—and construct a projected trade-off between Covid-19 and output. We also use our model to examine the effectiveness of alternative strategies for ending the state of emergency currently in place in Tokyo.

2 Model

Our model is formulated in a discrete-time with each period interpreted as a week. It consists of two parts: the epidemiological and economic part. The epidemiological part is given by the following SIRD model:

$$
\begin{aligned}
S_{t+1} - S_t &= -N_t - V_t && (1)\\
I_{t+1} - I_t &= N_t - N_t^{IR} - N_t^{ID} && (2)\\
R_{t+1} - R_t &= N_t^{IR} + V_t && (3)\\
D_{t+1} - D_t &= N_t^{ID} && (4)\\
N_t^{IR} &= \gamma_t I_t && (5)\\
N_t^{ID} &= \delta_t I_t && (6)
\end{aligned}
$$

S_t, I_t, and R_t denote the number of susceptible, infectious, and recovered persons, respectively. D_t denotes the number of cumulative deaths. N_t, N_t^{IR}, and N_t^{ID} are the number of newly infected persons, newly recovered persons, and deaths from Covid-19 between time t and time t+1, respectively. V_t is the number of newly vaccinated persons from time t to time t+1.[1] γ_t and δ_t are time-varying parameters for recovery and death rates, respectively.[2]

The economic part of our model is given by the following linear production function.

$$
\begin{aligned}
Y_t &= (1-\alpha_t)A_t(\{\alpha_t\}_{j=0}^{t-1})(S_t + a_I I_t + R_t)\\
&:= (1-\alpha_t)\bar{Y}_t && (7)
\end{aligned}
$$

Y_t is output and depends on (i) the number of persons adjusted for the fact that some infected persons cannot work or are less productive—given by $(S_t + a_I I_t + R_t)$—and (ii) output per person—given by $(1-\alpha_t)A_t(\{\alpha_t\}_{j=0}^{t-1})$. Output per person consists of two components. The first component, $(1-\alpha_t)$, captures the reduction in output per person due to social-distancing or other measures aimed at reducing the risk of infection. The second component, A_t, is output per person that would prevail if no person takes measures against the risk of infection at time t. The dependence of A_t on the history of α_t is intended to capture possible hysteresis effects of having restrained economic activities in the past. We use $\bar{Y}_t$ to denote the level of output that would prevail if no one restrained his or her economic activities at time t and refer to it as the *reference level of output*. Appendix A describes in detail what we intend to capture by the reference level of output as well as how we construct it.[3]

[1]As we will discuss later, we assume that a person becomes vaccinated with a 80 percent probability after they receive two shots of vaccines.

[2]See Atkeson (2020) and Moll (2020) for exposition of SIR models.

[3]Our model abstracts from optimizing behaviors of individuals. See Eichenbaum, Rebelo, and Trabandt (2020) for an example of optimization-based macro-SIRD models, among many others.

The epidemiological part of our model is linked to the economic part through the following matching function for newly infected persons.

$$N_t = \frac{\tilde{\beta}_t}{POP_0} I_t S_t \tag{8}$$

where

$$\tilde{\beta}_t = \beta_t (1 - h\alpha_t)^2 \tag{9}$$

and $POP_0 := S_0 + I_0$. $\tilde{\beta}_t$ denotes the infection rate. β_t denotes the "output-adjusted" or "raw" infection rate that would prevail in the absence of any decline in economic activity. β_t falls if people take actions that reduce the infection risk but do not directly affect their economic activities. For example, β_t falls if people wear masks or wash their hands when they return home. β_t also reflects the intrinsic infection rate of Covid-19. If a coronavirus variant with a higher infectious capacity spreads, it will appear as a higher value of β_t.

$(1 - h\alpha_t)^2$ captures the effect of a decline in economic activity on the infection rate.[4] It is helpful to think of this term as a proxy of people's mobility. While some mobility is necessary for households to consume and businesses to produce goods and services, it leads to interactions between susceptible and infectious persons and thus helps spread the disease. A high value of h means that the infection rate can be reduced a lot without reducing output that much. The value of h captures, among others, teleworkability of office work, abilities of restaurants to raise revenues through take-out services, or consumers' willingness to switch from movie theaters to online streaming services.

Our model is not micro-founded, unlike many macro-epidemiological models recently developed in the economics profession. The advantages of our modelling approach are that the absence of tight cross-equation restrictions makes it easy for our model to fit the past data and solve the model quickly and allows us to conduct a broad set of policy experiments in a short amount of time. The disadvantage of our approach is that our analysis is subject to the Lucas critique. We judged that the advantages outweigh the disadvantage in our work because the main goal of our project is to provide with policy-makers and public a back-of-the-envelope calculation of the effects of various policies in a timely manner.[5]

[4]See Alvarez, Argente, and Lippi (2020) and Farboodi, Jarosch, and Shimer (2020) for similar matching functions.

[5]Our use of a reduced-form model is similar in spirit to the widespread use of semi-structural models for policy analysis in central banks. For example, the FRB/US model—a semi-structural model of the U.S. economy—is used prominently for the analysis of forward guidance policies at the Federal Reserve, whereas DSGE models—which suffer from the so-called forward guidance puzzle—are not as frequently used as the FRB/US model. See Chung (2015) and Chung, Nakata, and Paustian (2018).

3 Data, assumptions, and identification of unobserved variables and time-varying parameters

We use data on N_t, N_t^{ID}, and Y_t to recover the paths of the model variables and time-varying parameters. N_t and N_t^{ID} are the number of new positive PCR test cases and the number of deaths due to Covid-19, respectively, from the Ministry of Health, Labour and Welfare in Japan. Y_t is based on monthly estimates of real GDP computed by the Japan Center for Economic Research.[6]

We assume the following initial conditions: $S_0 = 125.7M$, $I_0 = 1$, $R_0 = 0$, and $D_0 = 0$. Throughout the analysis, we assume that γ_t is constant at 7/10. This value of γ_t implied the average duration of 10 days for recovery. $V_t = 0$ for all t up to today.

3.1 Finding S_t, I_t, R_t, and D_t

Given S_0 and the paths of V_t and N_t, we can recover the path of S_t using equation (1). Given I_0 and the paths of N_t^{ID} and γ_t, we can recover the path of I_t using equation (2). Given R_0 and the path of I_t, we can recover the path of R_t using equation (3). Given D_0 and the path of N_t^{ID}, we can recover the path of D_t using equation (4).[7]

3.2 Finding δ_t, β_t, $\tilde{\beta}_t$, and α_t

Once we recover the path of D_t, we can recover the path of the death rate (δ_t) using equation (6). Once we recover the paths of I_t and S_t, we can use equation (8) to recover the path of $\tilde{\beta}_t$.

We make an assumption about the path of $\bar{Y}_t$, which is described in detail in Appendix A. Our assumed path grows very slowly over time and is essentially flat. Using the assumed path of $\bar{Y}_t$, we can recover the path of α_t using equation (7). Because of the essential flatness of $\bar{Y}_t$, fluctuation of α_t largely inherits that of Y_t.[8]

We obtain an estimate of h by regressing the Google mobility index (M_t) on α_t.[9] As

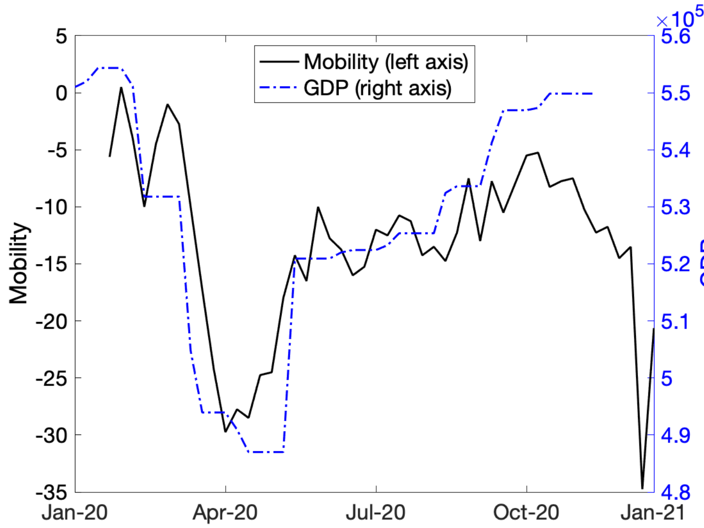
[6]The monthly real GDP from the Japan Center of Economic Research can be accessed here: `https://www.jcer.or.jp/en/economic-forecast/monthly-gdp`. We assume the same GDP values for all weeks in the same month. If a week spans over two different months, its weekly GDP is prorated using two values.

[7]See Fernández-Villaverde and Jones (2020) for a similar identification strategy.

[8]The most recent monthly GDP available from the Japan Center for Economic Research is for November 2020. We compute the path of output for December 2020 and the first two weeks of January using the mobility index during these periods and the correlation between the mobility index and GDP from September 2020 to November 2020.

[9]Google's COVID-19 Community Mobility Reports provide mobility indices across different categories of places at a daily frequency. We pick the following four categories as we think they compose a good

Figure 2: Mobility and output



Source: Japan Center for Economic Research and Google.

shown in Figure 2, the correlation between M_t and Y_t is high, and thus the correlation between M_t and α_t is also high because $\bar{Y}_t$ is essentially flat. Given the path of α_t and the estimated h, we can recover the path of β_t using equation (9).

Figures 3 and 4 show the identified paths of time-varying parameters and model variables, respectively.

4 Conditional projections of Covid-19

We use our model to compute projections of Covid-19 conditional on various paths of output. In computing these conditional projections, we make the following assumptions regarding the evolution of time-varying parameters.[10]

We assume that the death rate (δ_t) and the output-adjusted infection rate (β_t) will be constant at their average values over the most recent three months.

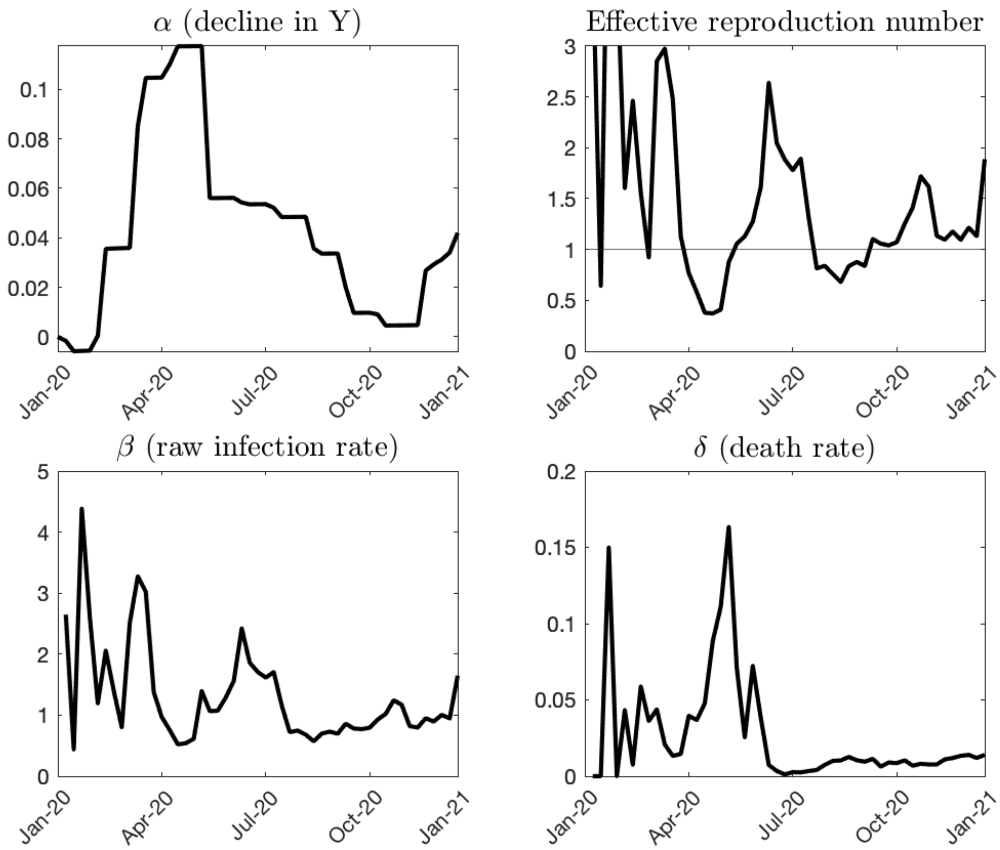
We assume that the vaccine distribution begins in the first week of March 2021.[11] The number of vaccine shots administered will increase from zero in the last week of February 2021 to 2.52M in the last week of March 2021. Thereafter, 2.52M vaccine shots will be

measure of mobility which affects the overall infection rate: parks, transit stations, retail and recreation, and workplaces. For each week, we compute the average of the median values of those four series to construct M_t. We use median values to eliminate the irregularity of holidays.

[10]The results shown in this section and the section that follows were generated on on January 15th, 2021, using the data through January 10th, 2021.

[11]Our starting-date assumption is consistent with the statement made by Prime Minister Suga during a press conference earlier this month.

Figure 3: History of time-varying parameters



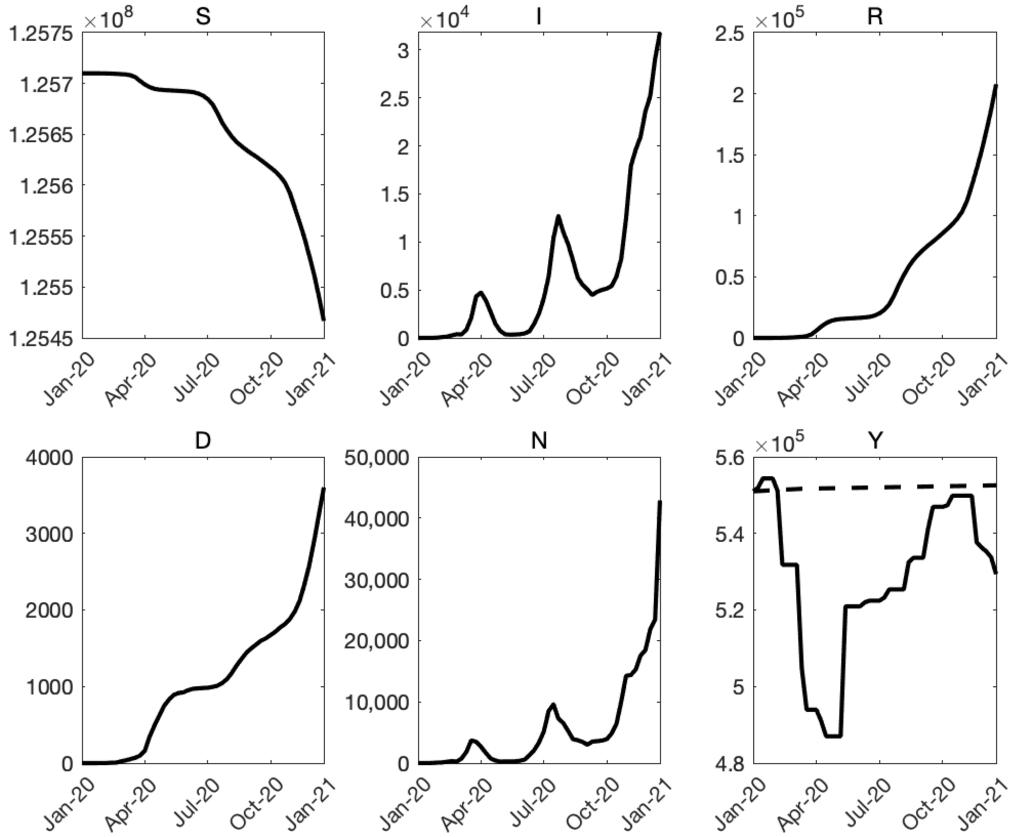
Source: Authors' calculation.

administered per week over the projection horizon. We explain how we arrived at this assumed path in detail in Appendix B.

We assume that a person receives the second vaccine shot 28 days after the first vaccine shot. For simplicity, we assume that a person remains susceptible between the first and second shots and that 80 percent of persons who have received two vaccine shots will obtain full immunity. With these simplifying assumptions, we obtain our baseline projection of V_t that increases from zero in the last week of March 2021 to 1.01M ($\approx 0.8 * 2.52M/2$) in the last week of April 2021. Thereafter, V_t will remain 1.01M for our projection horizon.

The assumption that the second shot is administered 28 days after the first shot makes V_t path conservative because the time between the first and second shots is expected to be 21 days for some types of vaccines. The simplification that a person remains susceptible between the first and second shots also makes our V_t path conservative because some fractions of persons obtain immunity after the first shot, alebit for an unknown duration. Our assumption that 80 percent of persons who receive two shots will obtain full immunity

Figure 4: History of Covid-19 and output



Source: Authors' calculation, Japan Center for Economic Research, Ministry of Health, Labor, and Welfare.

Note: In the bottom-right panel, the dashed line shows the reference level of output.

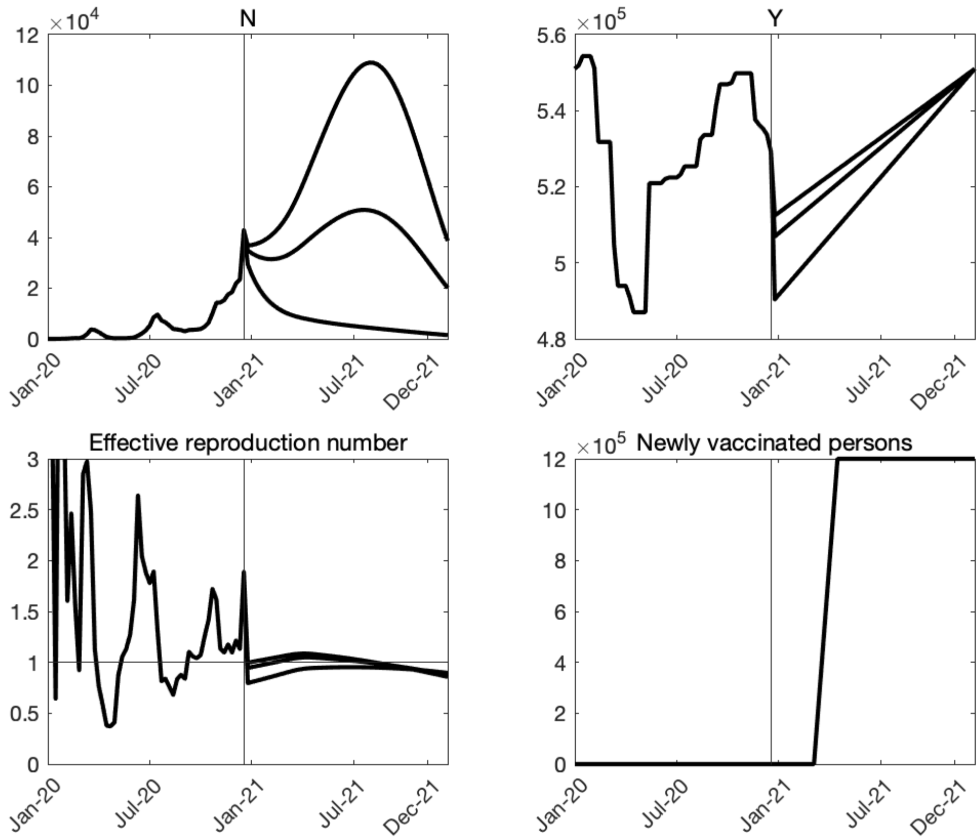
also makes our V_t path conservative based on our reading of clinical evidence.

In our projection, we use the estimate of h based on the regression of the mobility index on output loss using the final three months of data in which GDP is available—from September 2020 to November 2020 at the time of this writing. The value of h obtained in this way is 4.1, nontrivially higher than the value of h based on the entire sample, which is 2.3. We believe that the higher value of h obtained in the recent sample reflects the increased ability of the economy to perform efficiently even under various social distancing measures and is more informative of how the economy will perform going forward. Our judgment is informed by abundant anecdotal stories suggesting higher teleworkability for office workers, more restaurants expanding their takeout services, and, more generally, a larger share of households and businesses getting used to "new normal" in the recent months than in the early stage of the Covid-19 crisis.

We condition our projection on various simple paths of α_t. In particular, we consider a set of linearly declining paths whose initial value (the first week in the projection) is positive and whose last value (the last week of our 12-month projection) is zero.

Figure 5 shows our projection of Covid-19, conditional on three alternative paths α_t. The average output losses over the next 12 months associated with these paths are 1.6%, 2%, and 3%.

Figure 5: Conditional projections of Covid-19

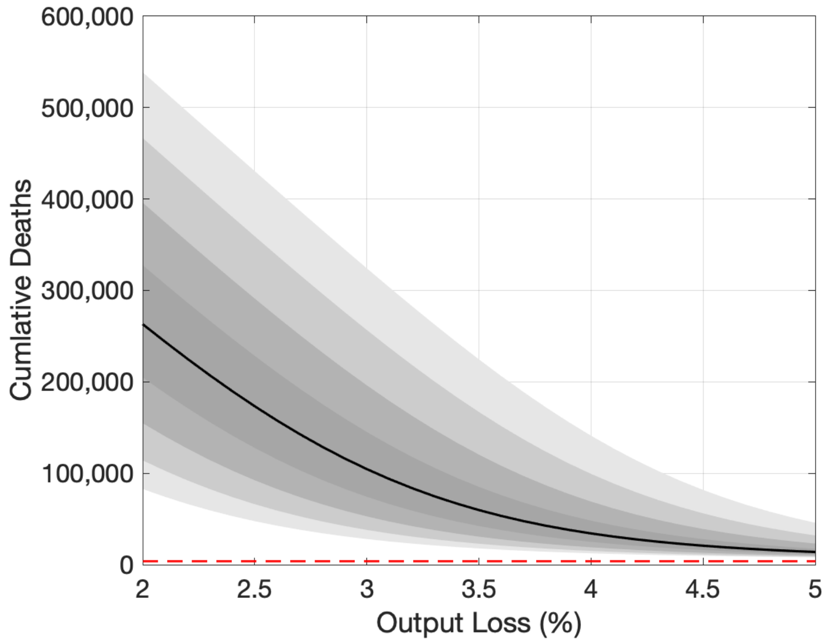


Source: Authors' calculation.

5 Relationship between Covid-19 and the economy

5.1 Baseline Case

Figure 6: Projected relationship between Covid-19 and output



Source: Authors' calculation.

Note: The vertical axis shows the number of cumulative deaths by the end of the next 12 months. The horizontal dashed line indicates the total number of Covid-19 deaths during 2020.

Figure 6 shows the set of pairs of cumulative deaths by the end of the next 12 months and the average output loss over the next 12 months associated with various linearly-declining paths of α_t. As a reference, output loss in 2020 was 4.3 percent. Recent projections for the growth rate of GDP in Japan by IMF, OECD, and World Bank are 2.3 percent, 2.3 percent, and 2.5 percent, respectively. Output loss in 2021 consistent with these projections is about 2 percent.[12]

According to Figure 6, our model predicts 6,700, 10,500, and 24,000 deaths by the end of the next 12 months if the average output loss over the next 12 months is 3%, 2.5%, and 2%, respectively.

Our trade-off curve is concave, reflecting the explosive dynamics inherent in the SIRD model as well as our nonlinear specification of the matching function. One key implication of this concavity is that we can save more lives by reducing output by one unit when the

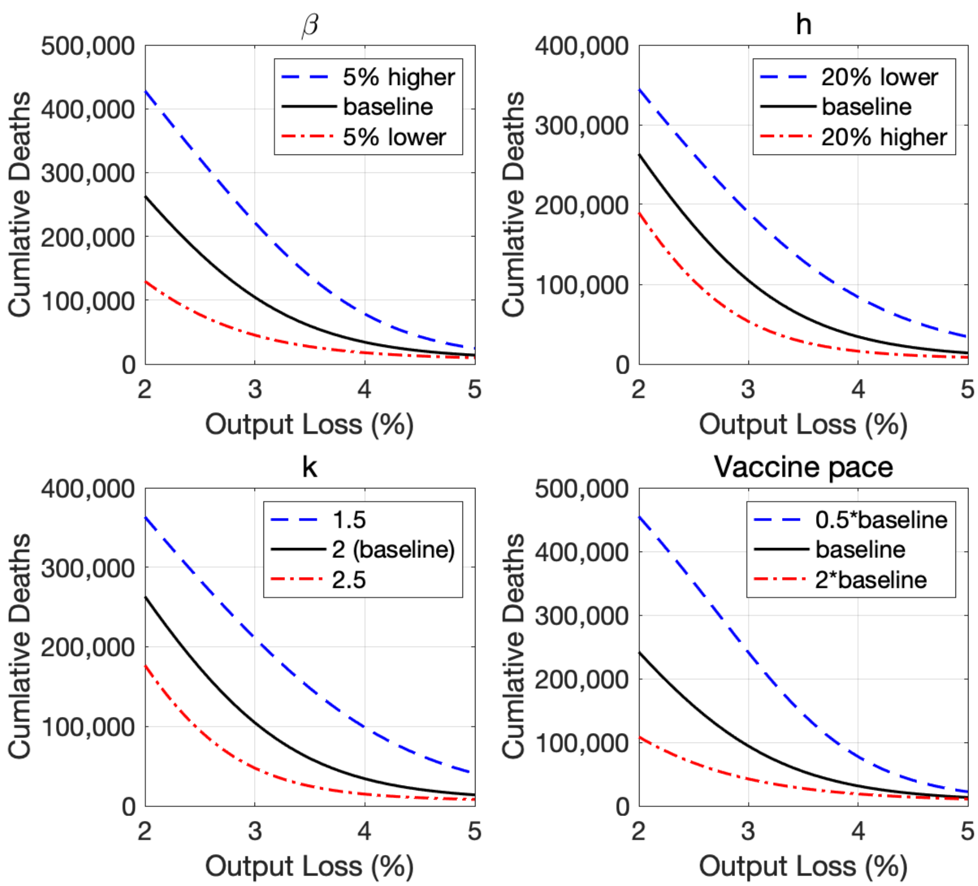
[12] The most recent projections by OECD, IMF, and Word Bank are published in October 2020, December 2020, and January 2020, respectively.

output loss is expected to be smaller than when it is expected to be larger. In other words, there is a diminishing return to scale to reducing output.

5.2 Sensitivity analysis

Figure 7 shows how sensitive our trade-off curve is to deviations from our baseline specifications.

Figure 7: Projected relationship between Covid-19 and output:
Sensitivity Analysis



Source: Authors' calculation.
Note: The vertical axis shows the number of cumulative deaths by the end of the next 12 months.

The top-left panel of Figure 7 shows how the trade-off curve depends on the assumed path of the raw infection rate. The panel shows that a small increase in the raw infection rate increases the number of cumulative deaths by tens of thousands if output loss is expected to be small.

The top-right panel demonstrates the importance of improving teleworkability, promoting flexible work arrangement, or encouraging households and businesses to substitute their economic activities in contact-intensive sectors with those in less contact-intensive sectors. When new monthly GDP data becomes available, we will update our projection of h by re-estimating this parameter using the most recent three months.

The bottom-left panel demonstrates how sensitive our projection is to the specification of the matching function for new infections. In the baseline projection, we assume a quadratic function for how α affects the infection rate—recall $(1 - h\alpha_t)^2$ in equation (9). The panel considers two alternative functions—$(1 - h\alpha_t)^{1.5}$ and $(1 - h\alpha_t)^{2.5}$.

The bottom-right panel demonstrates the benefit of distributing vaccines at a faster pace. One key feature of the panel is that the benefit of distributing vaccines at a pace faster than in the baseline scenario is larger when the output loss is expected to be smaller. When the output loss is expected to be large, the disease is contained pretty well anyway so that the marginal value of a faster vaccine distribution is smaller.

These analyses demonstrate the quantitative importance of the government to shift the trade-off curve down. Short-run lockdown policies are sometimes necaessary to contain the spread fo the disease but reduce output. Better health policies and better individual habits contain the spread of the disease without necessarily reducing output.

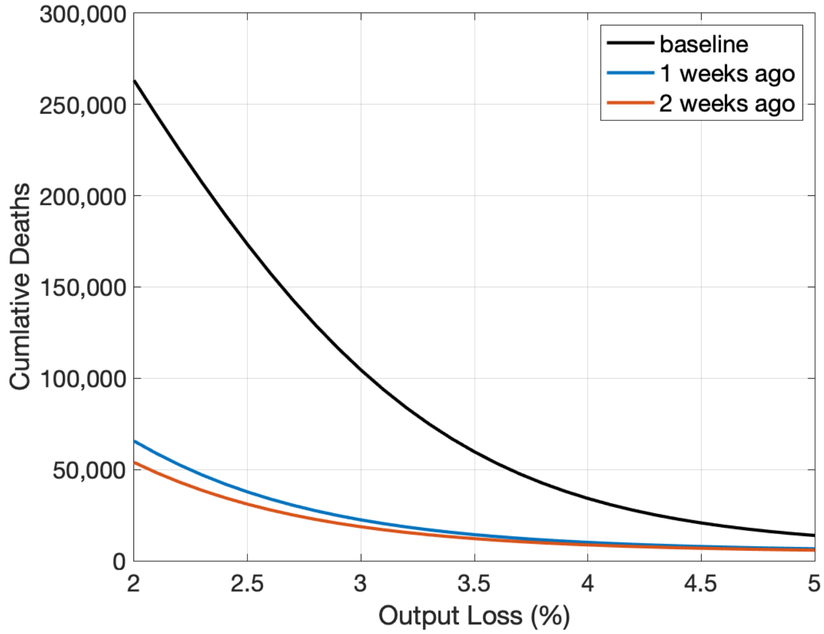
5.3 Evolution of the relationship

The projection of Covid-19 depends on the initial condition as well as the projected paths of the raw infection rate and the death rate, which in turn depend on the recent realizations of them, as we use the average value over the past three months for projection. As a result, the projected trade-off varies over time. To illustrate this point, Figure 8 compares the baseline trade-off curve shown earlier with two trade-off curves computed one and two weeks earlier using the data available up to that point. Because the number of new infections was lower one and two weeks ago than now, the projected numbers of cumulative deaths were lower for any given level of output loss back then.

5.4 Relationship between Covid-19 and output in 2020

Figure 9 shows the relationship between the number of deaths and the average output loss in 2020, based on counterfactual simulations of Covid-19—computed conditional on various counterfactual paths of α_t. In this exercise, our counterfactual simulation starts from the first week of April 2020 when the Japanese government declared the state of

Figure 8: Projected relationship between Covid-19 and output:
January 10th, 2021
versus
January 3rd, 2021 and December 27th, 2020



Source: Authors' calculation. The vertical axis shows the number of cumulative deaths by the end of the next 12 months.
Note: The vertical axis shows the number of cumulative deaths by the end of the next 12 months.

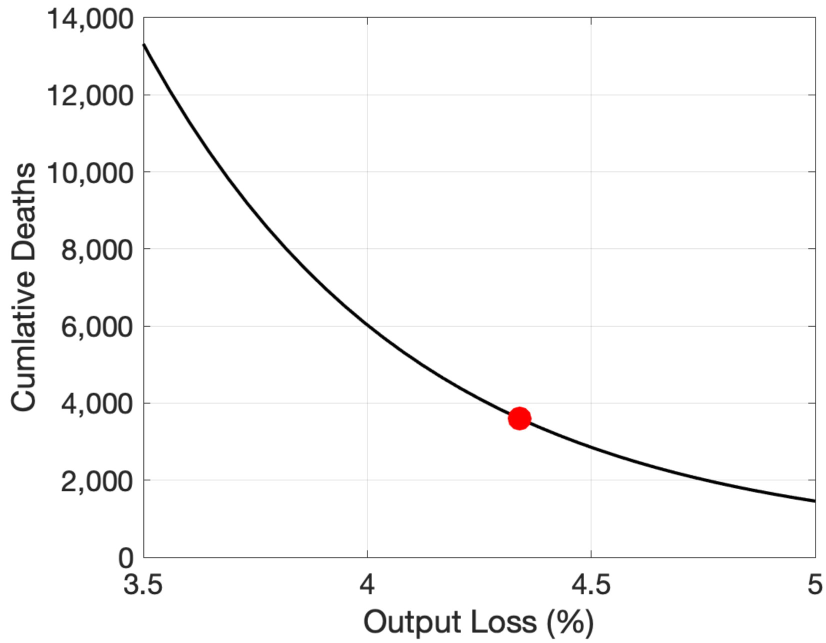
emergency for the first time.[13] We find that, if the average economic decline had been 4% and 5%, instead of the actual 4.3%, the number of deaths in 2020 would have been about 10,500 and 540, respectively, instead of 3,598.

The slope of the trade-off curve at the realized pair of deaths and output loss—shown by the red circle—can be seen as capturing the value of statistical life, albeit with many caveats. The implied value of statistical life based on the slope of the curve in this figure is 102 years. In a future work, we plan to apply our methodology to other countries and explore cross-country heterogeneity in the implied value of statistical life based on realized health and economic outcomes in 2020.[14]

[13] In this exercise, we consider alternative paths of the economy in which the path of α_t is multiplied by a constant for any time t after the first week of April until the last week of December 2020.

[14] See Hall, Jones, and Klenow (2020) for discussion of the value of statistical life in the context of Covid-19.

Figure 9: Relationship between Covid-19 and output in 2020



Source: Authors' calculation.

Note: The vertical axis shows the number of cumulative deaths by the end of 2020. The red filled circle indicated the realized pair of death and average output loss in 2020.

5.5 Discussion

There are many factors absent in our analysis but that would be of utmost importance if this type of analysis were to be used to inform the decisions of policymakers and public. Here, we discuss two such factors—hospital capacity and suicides.[15]

We abstract from a potential increase in the death rate due to hospital congestion. Not only do overcrowded hospitals contribute to an increase in the death rate among Covid-19 patients, they also increase the death rate from other diseases by constraining the supply of medical resources. Taking this consideration into account would increase the overall deaths associated with Covid-19—both direct and indirect—particularly when output loss is small and the number of Covid-19 cases is large.

We also abstract from a potential increase in the number of suicides associated with a prolonged economic distress. According to Chen, Choi, and Sawada (2009), the number of suicides per capita is more responsive to the unemployment rate in Japan than in other OECD countries. The average unemployment rate in the first eleven months of 2020 is 2.8 percent, up from 2.4 percent in 2019. The number of suicides in the first eleven months of 2020 is 19,225—up from 18,675 in the first 11 months of 2019—reversing the

[15] We plan to incorporate these factors into our analysis.

decade-long downward trend for the first time.[16] Some private-sector analysts expect the unemployment rate to edge up in 2021, which could push up the number of suicides further.

6 A real-time assessment of our model's forecasting performance

If a model were to be a useful guidepost for policy, it is important to know how reliable the model is in predicting the future. In this subsection, we examine a quasi-real-time forecasting performance of our model since the first week of September 2020.

For each week from the first week of September 2020 to the last week of December 2020, we compute the number of new infections and new Covid-19 deaths over the next week and the next four weeks, applying the same forecasting procedure we describe using the data available up to that point. In particular, at each point in time, we compute the projected paths of raw infection and death rates from their three-month averages and estimate h by regressing the mobility index on α. We evaluate our model's forecasts conditional on the realized path of α_t, as our paper focuses on conditional projections of Covid-19.

Our exercise is not fully real-time for two reasons. First, the monthly GDP data produced by the Japan Center for Economic Research is revised every month, but we abstract from that historical revision in this exercise. Second, we assume that the weekly GDP data—which is computed from the monthly GDP data become available after six weeks. In practice, the discrepancy between the week in which conditional projections are prepared and the week for which the most recent GDP is available depend on which week of the month the projection is made. For example, if one is preparing projections in the final week of December 2020, the most recent monthly GDP is from October 2020. Thus, we need to nowcast seven weeks of GDP.[17] However, if one is preparing projections in the second week of January, the monthly GDP for November 2020 is available, and that one needs to nowcast only five weeks of GDP.

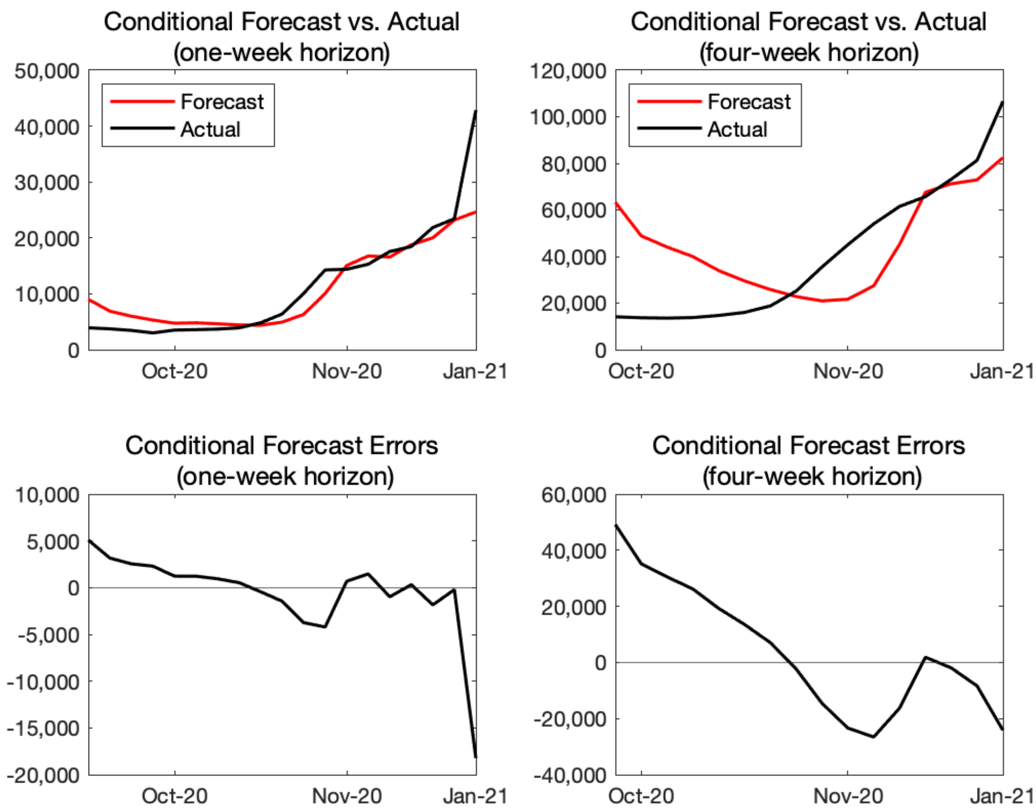
Top two panels in Figure 10 shows actual and forecasted outcomes for the number of new infections for one- and four-week horizons, whereas bottom two panels shows their differences—forecast errors. For the one-week projection, our model tracks the overall contour but it often misses actual outcomes by large amount. For example, our model (conditionally) predicted about 25,000 new cases in the first week of January, 2021, which

[16] Source: `https://www.npa.go.jp/publications/statistics/safetylife/jisatsu.html`.

[17] See Section 3 for how we nowcast Y_t.

is substantially smaller than about 43,000 we observed. For the four-week projection, our model systematically over predicted the number of new infections for October and November of 2020, but underpredicted it thereafter.

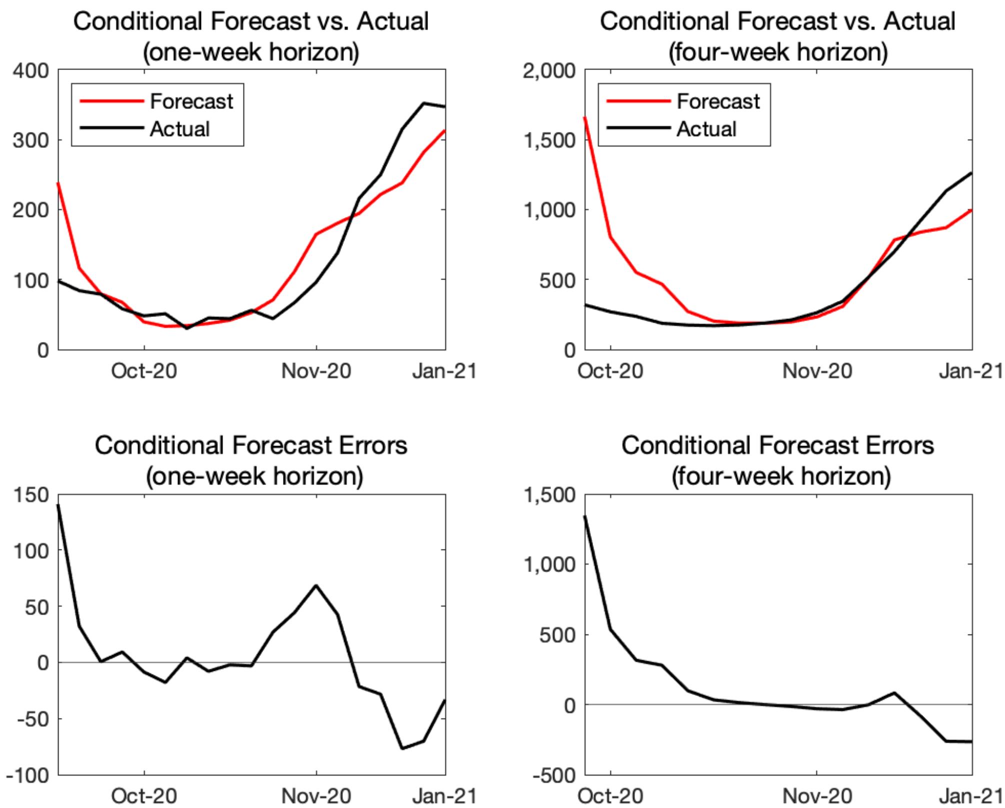
Figure 10: Real-time forecast evaluation:
New infections



Source: Authors' calculation.

Top two panels in Figure 11 shows actual and forecasted outcomes for the number of new Covid-19 deaths for one- and four-week horizons, whereas bottom two panels shows their forecast errors. For both one- and four-week horizons, our model have underpredicted the new Covid-19 deaths in the recent few weeks.

Figure 11: Real-time forecast evaluation:
New Covid-19 deaths



Source: Authors' calculation.

7 Analysis of Covid-19 and output in Tokyo

In this section, we use our model to examine the economic consequences of alternative criteria for ending the state of emergency currently in place in Tokyo.[18]

The Japanese government declared the state of emergency in Tokyo and several other sub-regions of Japan on January 7th, 2021, in an attempt to slow the spread of Covid-19. Since then, Governor of Tokyo has asked individuals to stay at home after 8pm, restaurants to close their doors by 8pm, and offices to reduce the number of workers going to the office by 70 percent, etc. Some officials have suggested that they would like to maintain the state of emergency until the number of new infections is down to around 500 per day in Tokyo. In the week ending in January 10th, 2021, the average number of new daily infections was 1,668.

[18]The results shown in this section were generated on January 15th, 2021, using the data through January 10th, 2021.

We use our model to examine the consequences of adopting alternative stopping criteria for the state of emergency in Tokyo. We recalibrate our model using the numbers of new infections, new deaths, and the mobility index in Tokyo. Because GDP data is not available at a regional level, we assume that GDP in Tokyo is proportional to GDP in Japan. It is possible to use various official and non-official statistics to estimate monthly GDP in Tokyo, but such an exercise is currently outside the scope of our analysis.

We consider three scenarios. In the first scenario, the economic activity during the state of emergency is such that the number of new daily cases reaches 500 in the eighth week. We refer to this scenario as the baseline scenario. In the second and third scenarios, the number of new daily cases reaches 500 in the fourth and twelfth week, respectively. We refer to these two scenarios as rapid- and gradual-decline scenarios. These scenarios are implemented by adjusting the level of α during the state of the emergency.

We assume that, once the emergency period ends, α declines to 1.4%—the average level from September 2020 to November 2020. We also assume that, if the number of new daily cases increases to 2,000 after the end of the current emergency period, there will be another emergency declaration, which would be in place until the same stopping criterion is met. This assumption is motivated by our observation that the hospital capacity seems to become an pressing concern around this threshold. It would be useful to examine the benefit of expanding the hospital capicity and increasing the threshold for the second mergency declaration.

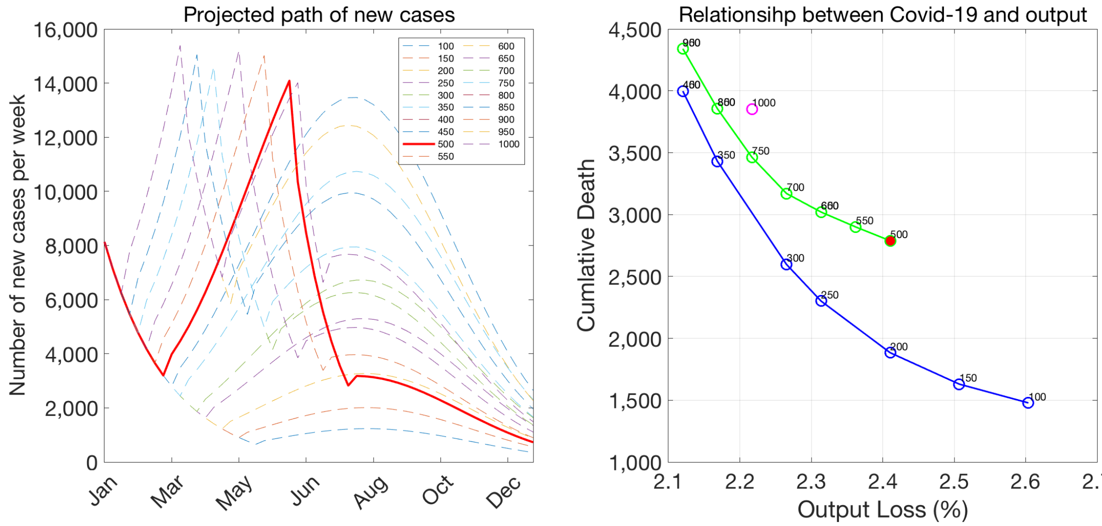
Finally, we assume that the pace of vaccination distribution in Tokyo is such that $V_t = 101,000$ from the first week of March.[19]

The left panel of Figure 12 shows the paths of new infections under the baseline scenario with alternative criteria for ending the state of emergency. The solid red line shows the path when the stopping criterion is 500 per day (or 3,500 per week), whereas other thin dashed lines shows the paths under alternative criteria. One important feature of this panel is that, if the stopping criterion is sufficiently high and the current emergency period is sufficiently short-lived, there will be a second emergency declaration down the road. Otherwise, vaccines will arrive on time to avoid the second emergency declaration. The stopping criterion of 500 is slightly above the threshold value: it leads to another emergency declaration in early June.

The right panel of Figure 12 show pairs of cumulative deaths and output loss associated with various stopping criteria. Note that when the stopping criterion leads to another

[19]The assumption of 101,000 per week in Tokyo is broadly consistent with 1.01M per week in Japan in the previous few sections because population in Tokyo is roughly 10 percent of total population in Japan.

Figure 12: Alternative strategies in Tokyo:
Baseline scenario



Source: Authors' calculation.

Note: The vertical axis in the right panel shows the number of cumulative deaths by the end of the next 12 months.

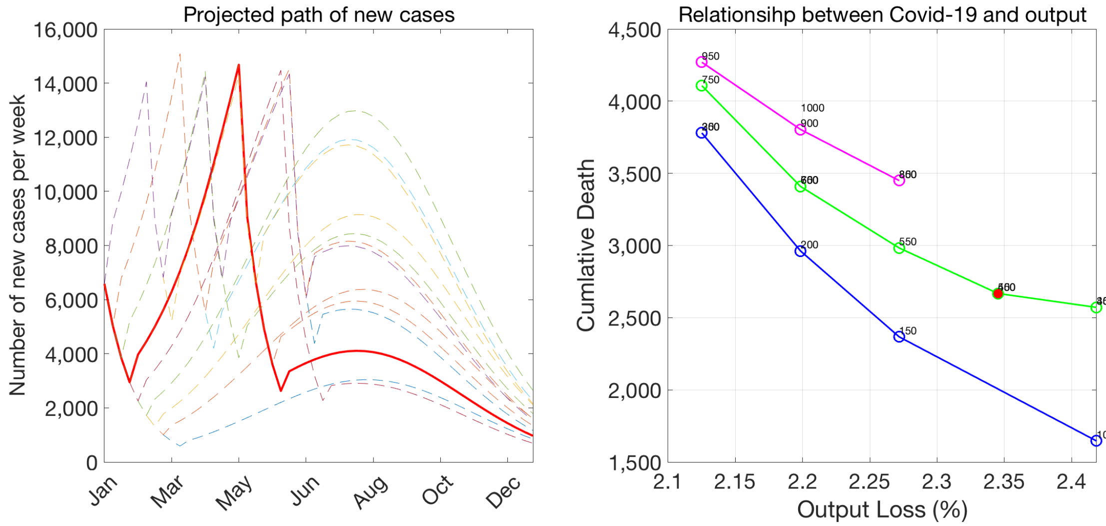
emergency declaration, the pair of deaths and output loss is interior to the trade-off frontier—shown in the blue color. If the stopping criterion is 450 or below, then the economy avoids the second emergency declaration and the pair of deaths and output loss is on the frontier curve. The virtue of avoiding the second emergency declaration in our exercise is reminiscent of the virtue of avoiding the second wave in standard SIR models. See Moll (2020) who elucidates how a loose lockdown that avoids the second wave can save more lives than a strict lockdown that leads to an eventual second wave.

Figure 13 shows the results for the rapid-decline scenario. In this scenario, the stopping criterion of 500 again leads to another emergency declaration later on, and as a result, the death-output outcome is inside the frontier of the trade-off curve. Avoiding another emergency declaration by setting the stopping criterion to, say 200, would improve both health and economics outcomes.

Figure 14 shows the results for the gradual-decline scenario. In this scenario, the pair of death and output loss associated with the stopping criterion of 500 is on the trade-off frontier because it does not lead to the second emergency declaration.

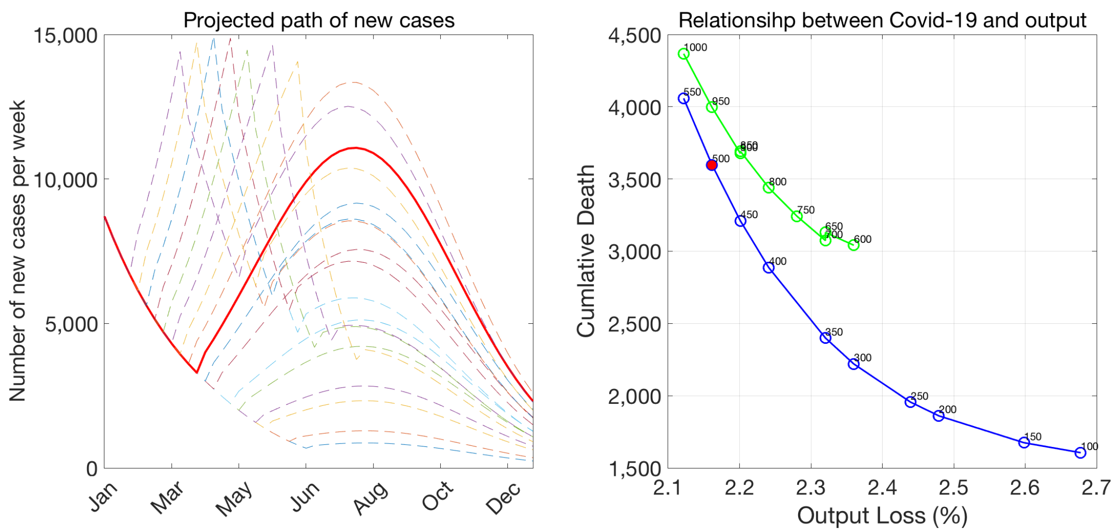
Figure 15 show all three scenarios. Several lessons emerge from the right panel. First, the first-best strategy is the strategy of a rapid decline with a low stopping criterion because the rapid-decline scenario is associated with the best trade-off frontier among other scenarios and a low stopping criterion allows the economy to be on the frontier.

Figure 13: Alternative strategies in Tokyo:
Rapid-decline scenario



Source: Authors' calculation.
Note: The vertical axis in the right panel shows the number of cumulative deaths by the end of the next 12 months.

Figure 14: Alternative strategies in Tokyo:
Gradual-decline scenario

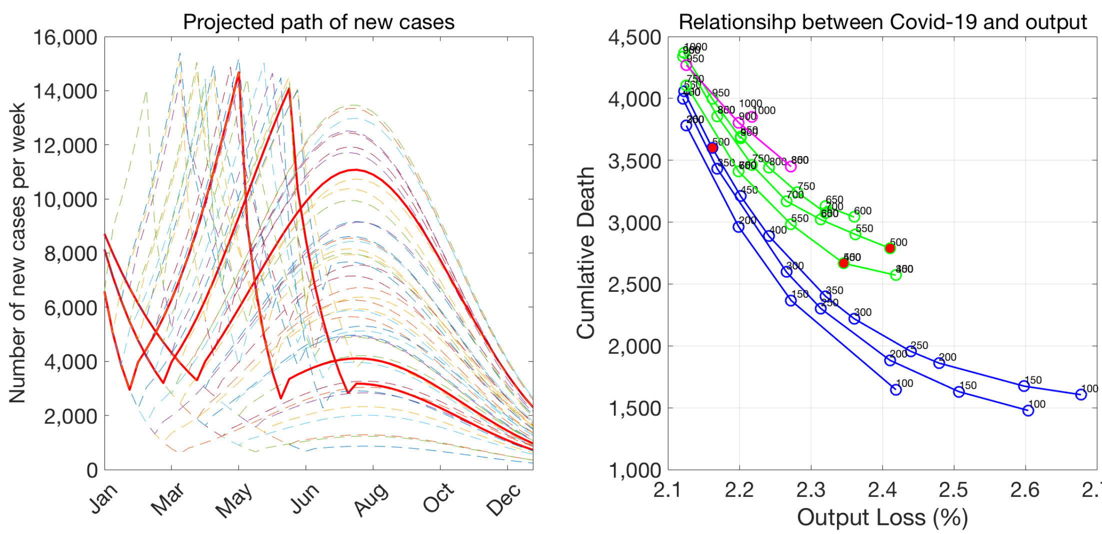


Source: Authors' calculation.
Note: The vertical axis in the right panel shows the number of cumulative deaths by the end of the next 12 months.

However, in countries like Japan in which the government lacks authorities to impose—or is hesitant to impose—strict social-distancing measures on its citizens, a rapid decline may not be possible. The second-best strategy is the strategy of a gradual decline with a moderate stopping criterion, which leads to pairs of deaths and output loss that are in the middle part of the frontier trade-off curve.

There are two types of strategies that appear inferior to the aforementioned two strategies. The first is the strategy of a rapid decline with a high stopping criterion, which puts the economy at a high risk of inducing the second emergency declaration. The second is the strategy of a gradual decline with a low stopping criterion, which are associated with pairs of deaths and output loss being in flat regions of the trade-off curve.

Figure 15: Alternative strategies in Tokyo:
All scenarios

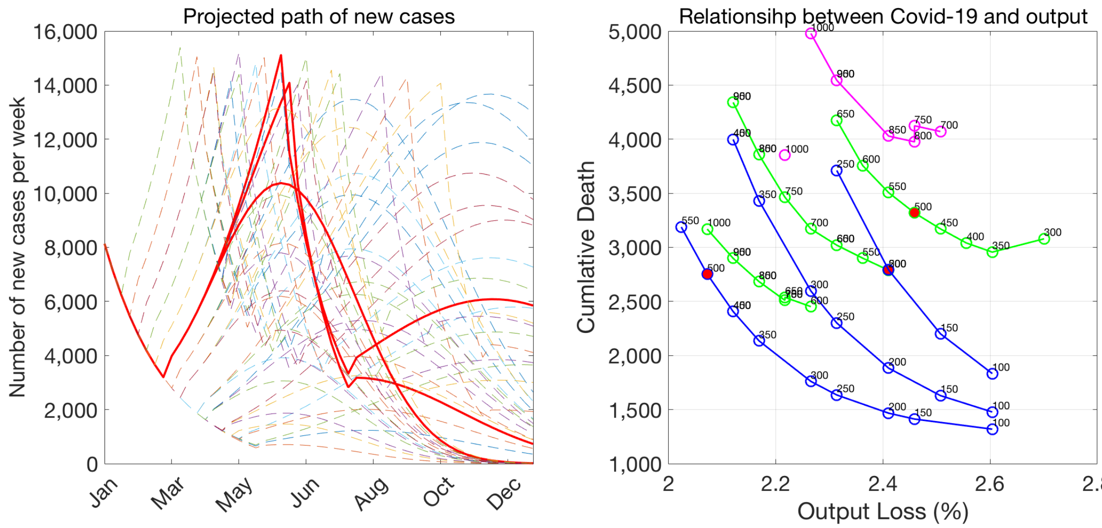


Source: Authors' calculation.
Note: The vertical axis in the right panel shows the number of cumulative deaths by the end of the next 12 months.

We end this section by examining the implications of alternative vaccine assumptions for the effectiveness of alternative stopping criteria. Figure 16 shows the evolution of Covid-19—shown in the left panel—and the trade-off curve—shown in the right panel—under the baseline scenario with the baseline and two alternative vaccine assumptions. In the first alternative vaccine assumption, the value of V_t is twice as large as that under the baseline at any t. In the second alternative vaccine assumption, the value of V_t is half of that under the baseline at any t.

Under the first alternative vaccine assumption and with the stopping criterion of 500, the number of new cases increases the emergency status is over. It peaks in early June at a level comfortably below the level that triggers the new round of the emergency period. Thus, the pair of deaths and output loss is on the frontier trade-off curve, which located is on the southwest part of the baseline frontier trade-off curve.

Figure 16: Alternative strategies in Tokyo:
Alternative vaccine assumptions



Source: Authors' calculation.

Note: The vertical axis in the right panel shows the number of cumulative deaths by the end of the next 12 months.

The frontier trade-off curve associated with the second alternative vaccine assumption is on the northeast part of the baseline frontier trade-off curve. Under this assumption and with the stopping criterion of 500, the second emergency declaration occurs. Thus, the pair of deaths and output loss associated with the stopping criterion of 500 is interior to the trade-off frontier. To be on the frontier, the stopping criterion has to be 250 or less.

Figure 16 underscores how important it is to distribute vaccines at a faster pace. Provided that the government successfully avoids the second emergency declaration, the choice of the stopping criterion is about which point to choose on a given trade-off frontier. The optimal choice depends on various factors, including model specifications, assumptions, and one's philosophy about life and death. In contrast, policies of distributing vaccines at a faster pace are desirable regardless of what these factors are, as better vaccine policies move the entire trade-off curve in the southwest direction in which the number of deaths is lower and output loss is smaller.[20]

[20]The same goes to policies of reducing β and increasing h. As we saw in the sensitivity analysis in Section 5.2, the economy can attain a lower number of deaths for any given output loss with lower β and higher h.

8 Conclusion

In this note, we used a tractable macro-SIRD model to explore the relationship between Covid-19 and the economy in Japan. We also used our model to examine the consequences of alternative stopping criteria for ending the state of emergency in Tokyo. Because our model is simple, our analysis should be seen as that of providing a back-of-the-envelope calculation. Yet, we believe that many qualitative insights from our analysis are likely to survive in alternative more-elaborate models.

We plan to update our analysis every week. Data and codes used for our analysis are available in our personal homepages. We will monitor the forecasting performance of our model and modify our model assumptions and specifications as we deem appropriate. We will keep track of any changes we make to our baseline assumptions and model specifications.

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Appendix

A Constructing the reference level of output

Our reference level of output at time t is the level of output at time t that would prevail if people did not impose any economic restraints at time t (that is, if people conducted their economic activities as if Covid-19 suddenly and magically disappeared at time t), taking as given the fact that the economy has suffered from the Covid-19 up to time t.

The reference level of output is different from the level of output consistent with pre-crisis trend (that is, the level of output that would have prevailed if there had been no Covid-19 crisis at all) because the reference level of output reflects the possibility that the Covid-19 crisis will leave permanent effects on the level of potential output. We would like our reference level of output to reflect the permanent effect of Covid-19 crisis on output because, otherwise, our alpha would be positive even at the steady state when people are not taking any social-distancing measures.

The reference level of output is different from the potential output because it reflects the cyclical position of the economy right before the Covid-19 crisis occurred. Suppose that the output gap was 5 percent right in the first quarter of 2020 and that output declines by 5 percent in the second quarter of 2020 due to social distancing measures. We would like to think that the 5% decline in output, and an associated decline in the mobility, reduced the infection rate through α_t in this example.

We construct the reference level of output in two steps.

(i) In the first step, we construct the path of potential output. We apply the Bank of Japan's estimate of the output gap in the fourth quarter of 2019 (1.2 percent) to GDP in December 2019 to construct potential GDP in December 2019.[21] For January, February, and March of 2020, we apply the expected growth rate of potential GDP computed before the Covid-19 crisis by OECD (0.63 percent, annualized) to construct the potential output for these three months.[22]

For the remaining 9 months of 2020, we let potential GDP grow at a rate of 0.21 percent (annualized) so that the average growth rate of potential GDP in 2020 is 0.35 percent, consistent with the most recent OECD estimate.[23] For 2021 and 2022, we let potential GDP grow at a rate of 0.24 percent and 0.21 percent, respectively, taking on board the December-2020 projection of OECD.

[21] The BOJ's measure of the output gap can be accessed in: `https://www.boj.or.jp/en/research/research_data/gap/index.htm/`.

[22] OECD: Economic Outlook No. 106 (November 2019).

[23] OECD: Economic Outlook No. 108 (December 2020).

Let us provide some background information on why we used two sources, the Bank of Japan and OECD, in constructing the path of potential GDP. The estimates of the output gap from these two institutions for the past three years are very similar. In particular, their estimates of the output gap for 2019 are both 1.6 percent. We apply the fourth-quarter estimate of the Bank of Japan to our monthly GDP for December 2020 to compute the starting point of our monthly potential output. We rely on the BOJ's quarterly estimate because OECD computes annual estimates only. As the fourth quarter output declined nontrivially in the fourth quarter of 2019 due to the consumption tax hike at the end of September 2019, using the fourth-quarter estimate of the output gap from the BOJ is more sensible than using the average estimate of the output gap for 2019 from OECD in constructing potential GDP in December 2019. We primarily rely on OECD in constructing the path of potential GDP from 2020 to 2022 because the Bank of Japan does not provide the growth rate of potential output.

(ii) In the second step, we add the expected cyclical component of output to the potential GDP path calculated in the first step. We take the level of the output gap in January 2020 as given and assume that the output gap will stay at that level throughout our simulation horizon.

All in all, our reference level of output grows very slowly over time and is essentially flat throughout our projection horizon.

B Distribution of vaccines

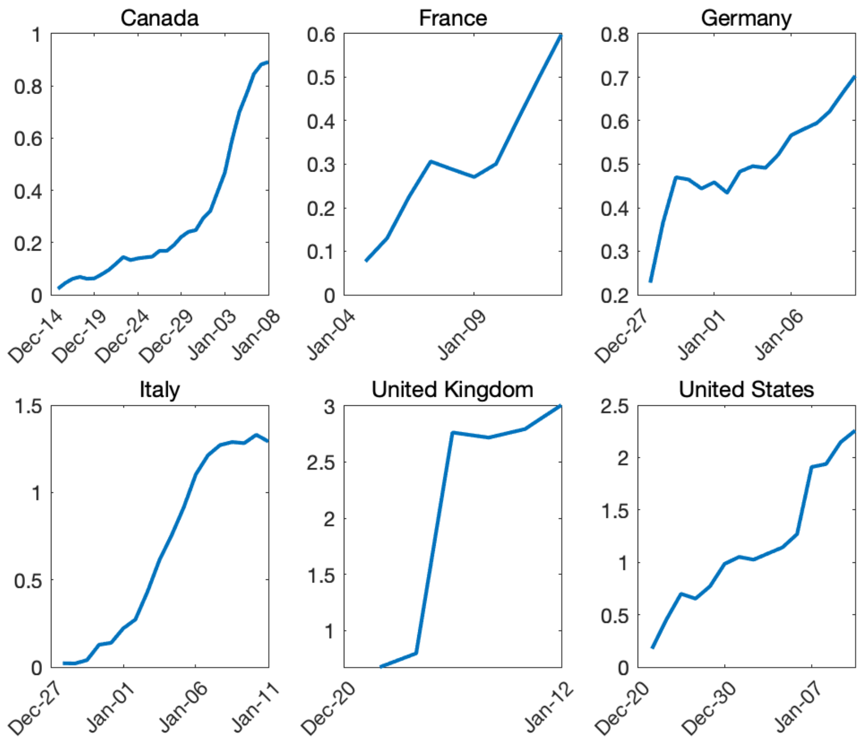
In constructing the baseline projection of V_t, we assume that the number of vaccine shots administered will increase from zero in the last week of February 2021 to 2.52M in the last week of March 2021. Thereafter, 2.52M vaccine shots will be administered per week over the projection horizon.

This assumed path of vaccine shots is informed by the evolution of the numbers of vaccine shots administered in G7 countries, except Japan (Canada, France, Germany, Italy, the United Kingdom, and the United States). Figure 17 shows the number of vaccines administered per day since the start of vaccine distribution in these six countries.

Our assumption of a linear increase in the number of vaccines administered in the first month of vaccine distribution is intended to parsimoniously capture the fact that the pace of vaccine distribution increased gradually at the initial stage of distribution in these six countries.

The value, 2.52M, is informed by the numbers of vaccines administered on January 13, 2021—the most recent observation—in these six countries. In particular, we take

Figure 17: Vaccine distribution in G7 countries



Source: Our World in Data.

the average of (i) the equally-weighted average and (ii) the population-weighted average of vaccines administered on January 13, 2021. We take this somewhat unique approach of averaging two average values because both of the two average values have their own advantages. The equally-weighted average can prevent the experience of one large country from being dominant, allowing the experience of smaller countries to be informative. The population-weighted average prevents the experience of small countries from being too influential. We then multiply the average of the two average values by 7 to translate the number into a weekly value and obtain 2.52M.

It is not clear to what extent the experiences of these countries can be informative for predicting the evolution of vaccine distribution in Japan. Our conversation with medical experts suggests that it is logistically possible to administer vaccine shots at a substantially more rapid pace than 2.52M per week. However, administrative hiccups can slow down the distribution process, and the Japanese people's well-documented aversion to new and unfamiliar vaccines may mean a substantially slower pace of vaccine distribution than in other countries.

We will closely monitor the experience of other countries as well as how the Japanese government, local governments, and medical communities prepare for the vaccine distribution. We will modify our baseline projection on vaccines distribution as we deem appropriate.