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Cross-Regional Heterogeneity in Health and Economic Outcomes during the COVID-19 Pandemic: An Analysis of Japan*

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Abstract

Health and macroeconomic outcomes varied substantially across prefectures in Japan during the COVID-19 crisis. Using an estimated macro-epidemiological model as well as the idea of revealed preference, we compute the marginal rate of substitution (MRS) and the conditional trade-off curve between health and economic outcomes in each prefecture. We find that there is a large heterogeneity in the MRS as well as the location and shape of the conditional trade-off curve.

Keywords: COVID-19, SIR model, epidemiology, value of a statistical life

JEL Codes: E17, E70, I18

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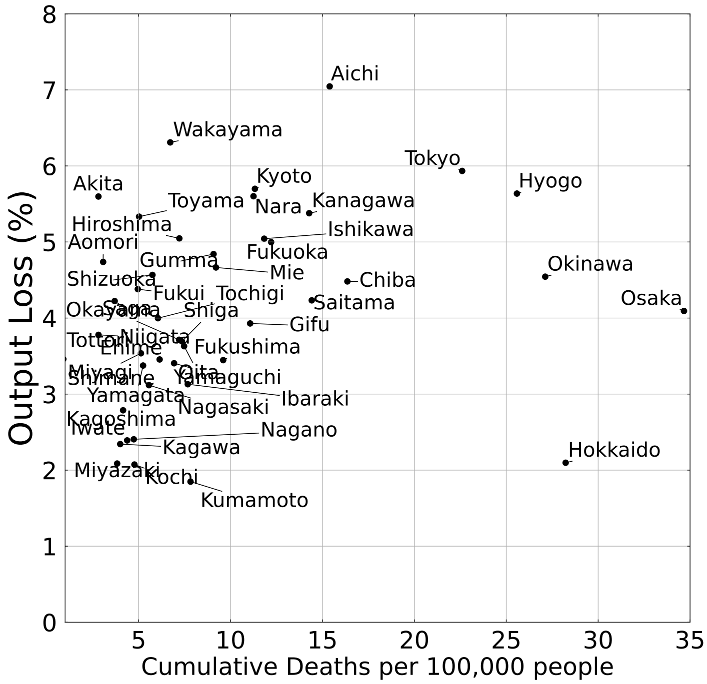
1 Introduction

Figure 1: Output loss and COVID-19 deaths: From February 2020 to December 2021



Note: The output loss is the deviation from the trend before the COVID-19 crisis.

Health and macroeconomic outcomes varied substantially across prefectures in Japan during the COVID-19 crisis, as shown in Figure 1—a scatterplot of cumulative COVID-19 deaths per 100,000 people and the average output loss from February 2020 to December 2021. Some prefectures have seen a relatively small number of COVID-19 deaths with small output loss, whereas some have seen the opposite. Some prefectures have seen a small number of COVID-19 deaths with large output loss, whereas some have seen the opposite.

In this paper, we seek to understand the sources of the heterogeneity across prefectures using an estimated macro-epidemiological model as well as the idea of revealed preferences. Using the method described in Fujii and Nakata (2021), we compute the conditional trade-off curve between COVID-19 death and output loss for each prefecture using time-series data on infection and economic activity. The conditional trade-off curve represents the "constraint."[1] We then invoke the idea of revealed preference to compute the marginal rate of substitution

[1]Our conditional trade-off curve captures various prefecture-specific factors that can be broadly described as "technology, policy, and luck." They include medical capacity/flexibility, vaccination policy, non-pharmaceutical interventions (NPIs), behavioral norms and culture. They also include demographic characteristics such as the proportion of elderlies and economic structures (e.g. the proportion of contact-intensive workers and easiness of teleworking).

(MRS) between COVID-19 death and output from each prefecture's realized outcome. This MRS can be interpreted as providing some information about how a prefecture weighed the value of reducing COVID-19 deaths against the value of reducing output.[2]

We find that (i) there is a large heterogeneity in the location and the shape of the conditional trade-off curves and that (ii) there is a large heterogeneity in the MRS between COVID-19 deaths and output. For example, the conditional trade-off curve for Iwate is located southwest of that for Tokyo in the deaths-output loss plane, and the MRS in Iwate (about 25 billion yen) is much higher than that of Tokyo (about 0.44 billion yen).

We also examine what factors are related to the MRS. We find the MRS is strongly correlated with (i) output loss per COVID-19 death, (ii) proportion of the elderly, (iii) GDP per capita, while it is weakly correlated with (i) population density.

1.1 Related Literature

Our work is closely related to Fujii et al. (2022). Fujii et al. (2022) develop the revealed-preference approach based on an estimated epi-macro model and use the approach to better understand cross-country heterogeneity in health and macroeconomic outcomes during the COVID-19 pandemic. We use the same approach to highlight the potential role of preference in generating heterogeneity in health and macroeconomic outcomes across prefectures in Japan.

Our work provides a novel contribution to a body of work analyzing the joint dynamics of infection and economic activity during the COVID-19 pandemic using epi-macro models. Examples include Acemoglu et al. (2021), Alvarez et al. (2021), Atkeson (2022), Atkeson et al. (2020), Bognanni et al. (2020), Eichenbaum et al. (2021), Farboodi et al. (2020), Jones et al. (2021), and Kaplan et al. (2020), among many others. Our work is unique because we combine a revealed preference approach and an estimated epi-macro model to quantify the marginal rate of substitution between COVID-19 death and economic activity. In particular, our approach can be seen as the converse of optimal policy exercises in which the weight of disutility from COVID-19 death—relative to output loss—is assumed in the objective function of the optimal control problem.

Various authors use epi-macro models estimated or calibrated with Japanese data to better understand the trade-off (or lack thereof) between health and economic outcomes.

[2]Our measure of MRS likely captures various factors that go beyond a country's willingness to pay to save lives from COVID-19 infection. Those factors include, but are not limited to, desire to avoid loss of work hours due to required quarantine period after infection, desire to avoid social stigma associated with COVID-19 in certain societies, desire to avoid tragedy associated with dying from COVID-19 such as not being able to spend the last moment of one's life with loved ones, and fear of the unknown, among many others. As with any model-based analysis, misspecification of our model also affects our calculation.

Examples include Fujii and Nakata (2021), Fukao and Shioji (2022), Hamano et al. (2020), Hoshi et al. (2021), Kubota (2021), Kobayashi and Nutahara (2021), Hosono (2021), Shibata and Kosaka (2021). Like these authors, we use epi-macro models to better understand the Japanese experience during the COVID-19 pandemic. Our contribution is to use the revealed preference approach to highlight the role of preference in explaining health and economic outcomes in Japan.

2 Framework

In this section, we describe our model, data, and procedure to trace out the conditional trade-off curve for each prefecture. Since the model and the conceptual framework are the same as in those in Fujii et al. (2022), our description will be concise. We refer interested readers to Fujii et al. (2022) for details. Our model is parsimonious, yet contains what we believe are minimal factors necessary to decompose health and regional economic outcomes into a constraint and preferences. And, estimation of our model requires readily available prefecture-level data only.

2.1 Model

We employ a standard SIRD model, but allow for time-varying transmission and mortality rates to describe the observed evolution of infection in each prefecture. The model is formulated in discrete time at a weekly frequency. Let subscript t denote time period, S_t, I_t, and R_t be the number of susceptible, infectious, and recovered people, respectively. D_t denotes the number of cumulative deaths. The laws of motion are given by the following system of equations

$$S_{t+1} = S_t - \underbrace{\frac{\beta_t(1-h\alpha_t)^k}{POP} I_t S_t}_{N_t} - V_t \tag{1}$$

$$I_{t+1} = I_t + \underbrace{\frac{\beta_t(1-h\alpha_t)^k}{POP} I_t S_t}_{N_t} - N_t^{IR} - N_t^{ID} \tag{2}$$

$$R_{t+1} = R_t + N_t^{IR} + V_t \tag{3}$$

$$D_{t+1} = D_t + N_t^{ID} \tag{4}$$

$$N_t^{IR} = \gamma I_t \tag{5}$$

$$N_t^{ID} = \delta_t I_t \tag{6}$$

The flow variables N_t, N_t^{IR}, and N_t^{ID} are the number of the newly infected, newly recovered, and new deaths from COVID-19 between time t and time $t+1$, respectively. V_t is the number of newly vaccinated people from time t to time $t+1$. The parameter γ denotes recovery rate, and it is assumed to be $\gamma = 7/18$, which implies that the average duration of infection is 18 days. We allow for a time-varying mortality rate, which is denoted by δ_t. The path of δ_t will be estimated from data. The total population in the prefecture is denoted by POP.

The number of newly infected people N_t is proportional to the product $I_t S_t$ normalized by POP. The time-varying parameter β_t captures the "output-adjusted" or "raw" transmission rate that would prevail in the absence of any decline in economic activity. The term α_t denotes output loss in percentage, and $(1 - h\alpha_t)$ is a proxy for people's mobility. The elasticity of output loss to mobility is denoted by h. A high value of h means that the infection rate can be reduced a lot without reducing output that much. We can reduce the number of new infection at time t by lowering mobility, but it comes at a cost of larger output loss. This relationship between infection and output leads to the trade-off each prefecture faces. Throughout this paper, we assume quadratic matching of the susceptible and the infected, and set $k = 2$. As shown in Fujii et al. (2022), the value of k changes each state's MRS uniformly, and does not alter the ranking of MRS.

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

$$Y_t = (1 - \alpha_t)\bar{Y}_t \tag{7}$$

where Y_t is output at time t. The second component $\bar{Y}_t$ is the reference level of output that would have prevailed if no one restrained his or her economic activities at time t. Please see the Appendix of Asai et al. (2022) for how to construct $\bar{Y}_t$ for each prefecture.

2.2 Data and Estimation

All the following analyses are conducted prefecture by prefecture. We set the start of the model as the first week of February 2020. The time window of analysis to be 99 weeks ($T = 99$) , implying that our sample end at the end of 2021. In Section 3.5, we will discuss results based on alternative sample preiods. The number of new positive PCR test cases N_t and the number of deaths due to COVID-19 N_t^{ID} are retrieved from the database of the Ministry of Health, Labour and Welfare (MHLW) in Japan.[3]

Set the initial condition as $S_0 = 0.9999 * POP$, $I_0 = 0.0001 * POP$, $R_0 = 0$, and $D_0 = 0$.

[3] The path of vaccinated population V_t is computed as follows. Let E_1 and E_2 be the efficacy of first and second shots of vaccine. With $V_{1,t}$ and $V_{2,t}$ be the number of first and second shots of vaccines respectively, we compute

$$V_t = E_1 V_{t,1} + (E_2 - E_1)\, V_{2,t}$$

With these initial values and N_t, N_t^{ID} and V_t, we can recover the paths of variables S_t, I_t, R_t and D_t. We can then back out the time-varying parameters $\tilde{\beta}_t$ and δ_t.

A measure of prefecture-level monthly GDP is constructed based on the methodology developed in **?**. We assume the same GDP value for weeks in the same month and construct the path of Y_t. [4] The estimation of h is elaborated in the Appendix A.

2.3 Tracing Out the Conditional Trade-Off Curves

For each prefecture, we first calculate δ_t, β_t and h as described above. Then, we consider a hypothetical path of output loss α_t^c by multiplying α_t with a time-invariant constant, ranging from 0.1 to 5.0.

$$\alpha_t^c = c\alpha_t \text{ for } \forall t \text{ and } c \in C = \{0.1, 0.11, ..., 5.0\}$$

It means that the hypothetical output loss is smaller by 50 percent for every period if $c = 0.5$. It is important to note that the shape of the original α_t is preserved for the hypothetical paths. Due to the nonlinearity of the epidemiological model, there exists a benefit of the front-loading of infection control. Holding the time-series average output loss constant, we can reduce the number of cumulative deaths by imposing a stronger restriction (larger α_t) in the early phase of pandemic. Our counterfactual exercise takes this type of decision (the timing and stringency of NPIs) as given, and considers multiplicative perturbations of the observed α_t. For each hypothetical path α_t^c, we compute the paths of new infections and cumulative deaths using the estimated β_t, δ_t and h. For each scaler c, we obtain a pair of average output loss and cumulative deaths $\{(\overline{\alpha}^c, D_T^c)\}_{c\in C}$ where $\overline{\alpha}^c = \frac{\sum_{t\in\{1,2,...,T\}} \alpha_t^c}{T}$.

3 Results

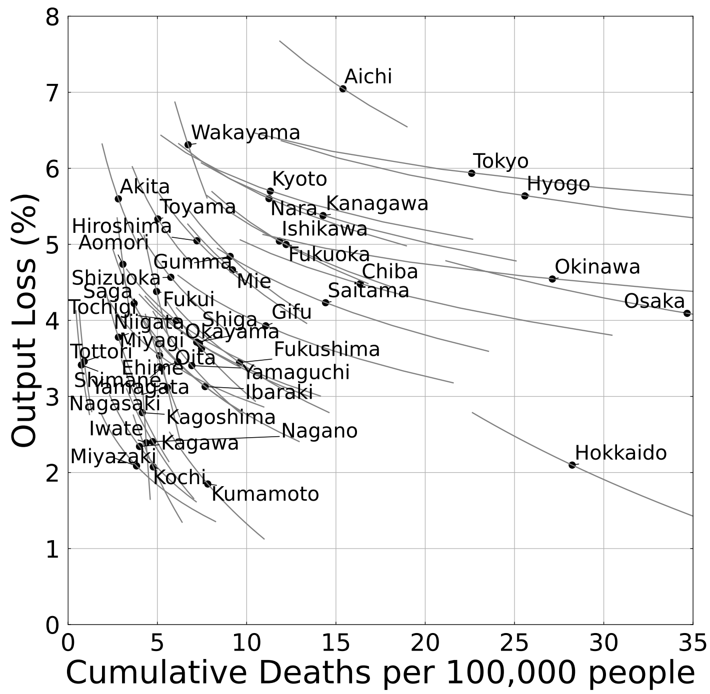
3.1 The Conditional Trade-Off Curves

Figure 2 shows the estimated conditional trade-off curves between output loss and COVID-19 deaths for each prefecture. In this figure, we overlay the scatterplot shown in Figure 1 with the conditional trade-off curves derived from the counterfactual simulations described in Section 2.3. We can confirm a large heterogeneity in the location and shape of these curves. The trade-off curves of prefectures that exhibit a larger output loss and higher number of deaths such as Osaka or Okinawa locate in the upper-right part of the figure. Yet, many curves cross each other due to the difference in shape. Wakayama and Nara are

The time-series data of $V_{1,t}$ and $V_{2,t}$ are also retrieved from the MHLW. We assume Pfizer vaccines are used and set $E_1 = 0.625$ and $E_2 = 0.895$ based on the UK's SPI-M-O Summary on March 31st, 2021.

[4] If a week spans two months, we prorate two GDP values accordingly.

Figure 2: Conditional trade-off curves



geographically located in the same Kinki region, and their realized outcomes of output loss and COVID-19 deaths are also similar. Nonetheless, the shape of their conditional trade-off curves are quite different with the curve of Wakayama being much steeper. This highlights the relevance of our model analysis to unveil the unobserved constraint each prefecture had faced through the pandemic.

These conditional trade-off curves in Figure 2 represent constraints each prefecture had faced when balancing economic activity and health outcomes of the pandemic. In our framework, the location and shape of constrains can be different due to the difference in four parameters: i) h, the elasticity of mobility with respect to output loss, ii) $\{\alpha_t\}_{t=0}^T$, the path of economic restriction, iii) $\{\beta_t\}_{t=0}^T$, the time-varying parameter of transmission rate, and iv) $\{\delta_t\}_{t=0}^T$, the time-varying parameter of mortality rate. For instance, if a prefecture experiences higher β_t or δ_t for all periods compared to another prefecture, its trade-off curve locates northeast in the figure. Due to the nonlinearity of the dynamics, the paths of α_t and β_t play an important role even when the time-series average is held constant. A larger α_t or smaller β_t in the early phase of pandemic benefits the society by shifting the trade-off curve down.

Figure 3: Histograms of estimated parameters

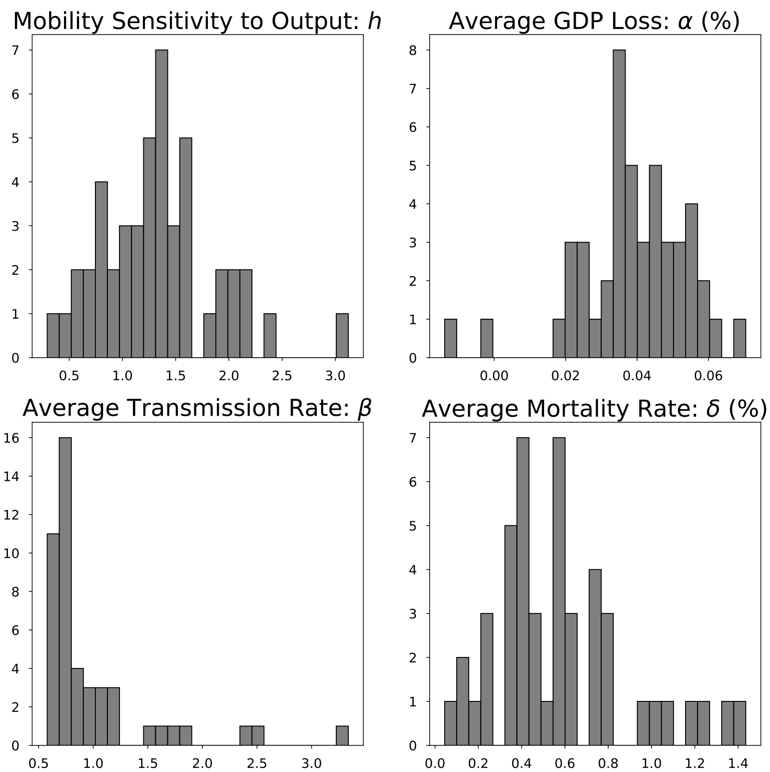
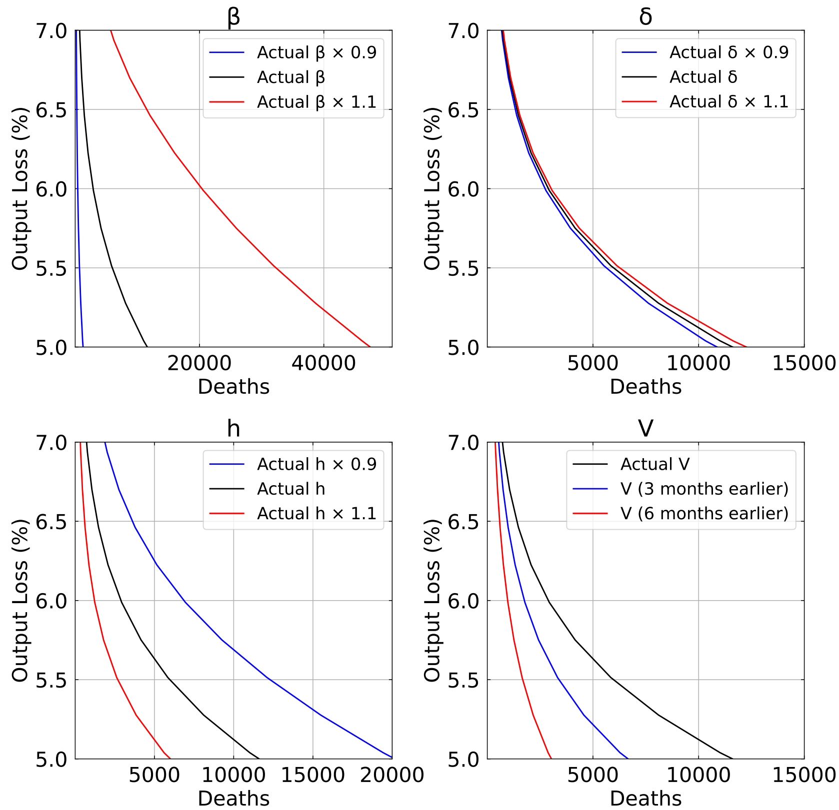


Figure 3 shows the histograms of estimated h, average α_t, β_t and δ_t. The differences in these parameters are the source of the cross-regional heterogeneity of the trade-off curves. The estimated elasticity of mobility with respect to output loss is concentrated around 1.5 but some prefectures exhibit h larger than 3 or less than 0.5. The distribution of the average transmission rate β_t is skewed to the left around 0.7, yet some prefectures experienced a large transmission rate with average β_t being over two. The average mortality rate also varies across prefectures ranging from 0.05 to 1.4.

Figure 4: Comparative statics of structural parameters



To illustrate the effect of those parameter values on the shape and location of trade-off curves, we examine the comparative statics of each parameter for Tokyo. Figure 4 displays the counterfactual trade-off curves when we change one of the structural parameters. In all four panels, black lines are the trade-off curves from our baseline specification. The top-left panel shows trade-off curve for different paths of transmission rate β_t holding other parameters constant. For each scenario, we multiply our estimated β_t by a constant preserving the shape of the path. We confirm that the curve shifts to the right as β_t becomes larger. The top-right panel presents a similar analysis for the path of mortality rate δ_t. As δ_t becomes larger, the curve shifts to the right, but the effect is not as large as that of β_t. Since an increase in δ_t does not cause an exponential growth of infection like an increase in β_t, the effect of different values of δ_t on the trade-off curve is milder.

The bottom-left panel considers the effect of changing the elasticity of output loss on mobility h. As h becomes larger, the trade-off curve moves to the southwest with a greater concavity. This is welfare-enhancing since we can achieve both lower number of deaths and smaller output loss. A larger value of h means that a reduction in output by a lockdown is very effective to reduce infection. The bottom-right panel shows the counterfactual situations where vaccine distribution started earlier than the actual. An earlier rollout of vaccines moves the trade-off curve to the left as we can expect.

3.2 MRS

Table 1: MRS (in billion yen)

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Iwate	24.77	Kagawa	2.33	Okayama	1.16
Shimane	12.99	Yamaguchi	2.27	Ishikawa	1.05
Aomori	12.95	Hiroshima	2.00	Fukuoka	0.81
Tottori	12.49	Oita	2.00	Hokkaido	0.77
Fukui	8.20	Gumma	1.86	Gifu	0.75
Nagasaki	6.57	Kumamoto	1.83	Kyoto	0.62
Niigata	5.52	Mie	1.76	Nara	0.53
Yamagata	5.14	Tokushima	1.74	Kanagawa	0.52
Wakayama	4.93	Ehime	1.66	Saitama	0.52
Akita	4.65	Tochigi	1.56	Tokyo	0.44
Kochi	3.56	Miyazaki	1.54	Chiba	0.4
Kagoshima	3.35	Aichi	1.54	Osaka	0.34
Saga	3.29	Ibaraki	1.51	Hyogo	0.27
Toyama	3.17	Shiga	1.33	Okinawa	0.13
Nagano	3.11	Miyagi	1.32		
Shizuoka	2.44	Fukushima	1.28		

Table 1 summarizes the MRS between output loss and COVID-19 deaths across prefectures.[5] These numbers can be interpreted as willingness to pay to reduce a COVID-19 death in each prefecture. Like the cross-country heterogeneity of MRS studied in Fujii et al. (2022), there exists a considerable heterogeneity in MRS across regions within Japan as well. Some prefectures such as Iwate and Shimane exhibit a large MRS (24.77 and 12.99, respectively) while other prefectures like Okinawa and Hyogo exhibit a very small MRS (0.13 and 0.27, respectively). In general, rural areas show a higher MRS than urban areas.

As illustrated in Figure 8 in the Appendix, the optimality condition implies the equality between the marginal rate of technical substitution (MRTS) of the constraint and the MRS of the preferences. Given the same conditional trade-off curve, people in a prefecture with high MRS choose a point in the upper-left part of the curve, implying that they are willing to sacrifice a larger output loss to reduce COVID-19 deaths.

[5]The numbers in the table correspond to the slope of the tangent line through each dot in Figure 2, but are translated into billion yen/death.

Figure 5: MRS vs. other variables

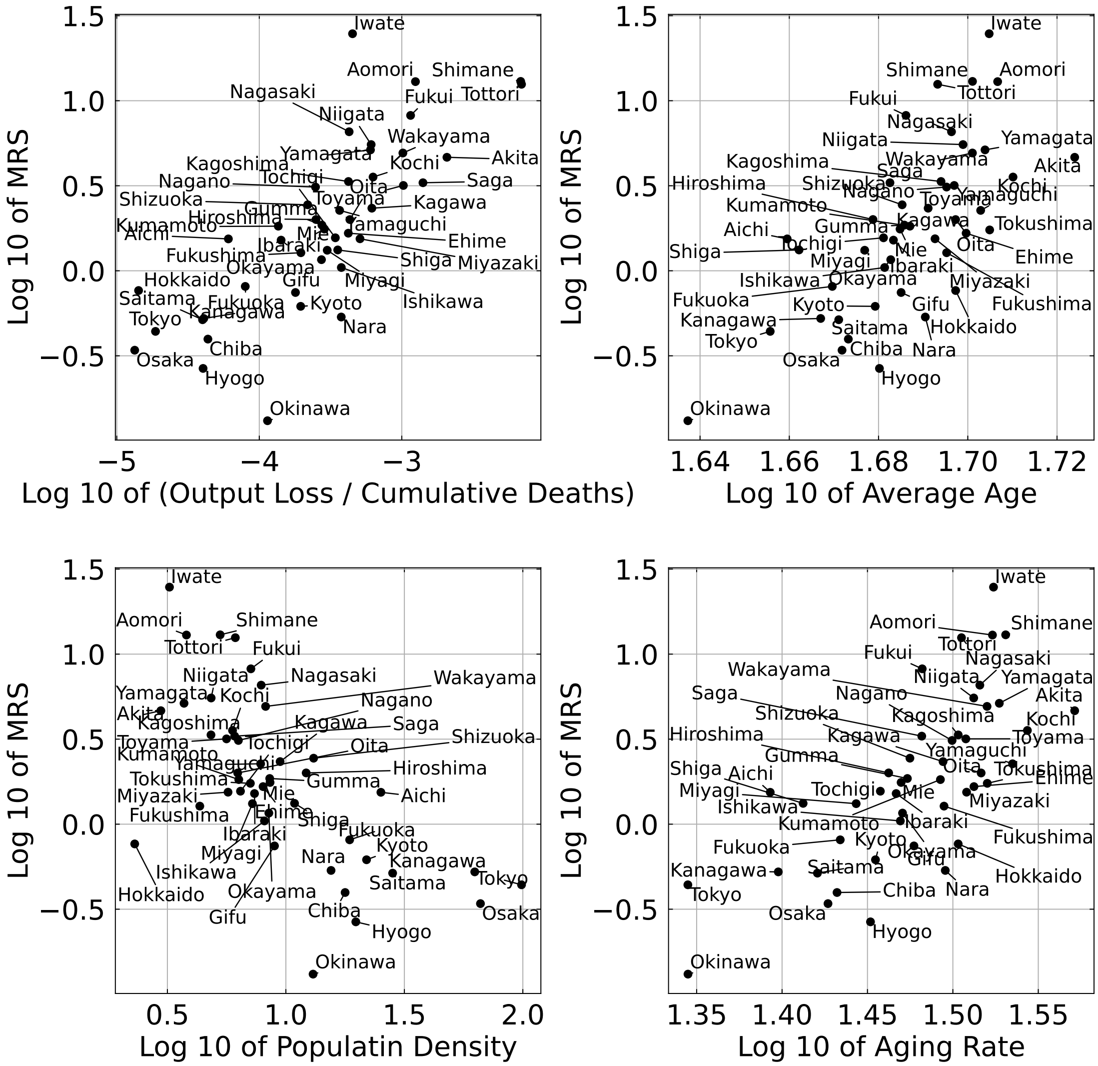


Figure 5 presents the scatterplots of the MRS and other variables. The top-left panel examines the relationship between the MRS and output loss/deaths across prefectures. We observe a positive correlation, but the relationship is not perfect. Our model analysis reveals the heterogeneity of preferences, which cannot be inferred by just looking at the ratio between output loss and cumulative deaths. The bottom-left panel analyzes the relationship with population density. Densely populated areas such as Tokyo or Osaka exhibit lower MRS. The top-right panel illustrates a positive relationship between the MRS and the average age. Prefectures with higher average age, which tend to be rural areas, exhibit higher MRS. This relationship holds when we use another measure of age, aging rate (the ratio of the elderly over total population), as shown in the bottom-right panel.

Why rural areas exhibit larger MRS? Demographic structure is a potential candidate to explain the correlation. Since the mortality rate of COVID-19 is much higher for the elderly, prefectures with a higher aging rate may fear the risk of infection more and accept a larger output loss to reduce the number of casualties. Another potential reason is the culture of peer pressure and social ostracism. As studied in Delgado Narro (2021), stigma of being infected may be an important factor for many people to refrain from going out. There is a growing body of anecdotal evidence on social ostracism of COVID-19 in Japan.[6] Fear of being ostracized from the community might have contributed to a large output loss in some rural prefectures even when there were few or no positive cases.[7]

3.3 Hypothetical Exercises

Our framework allows us to decompose a realized outcome of output loss and COVID-19 deaths into a constraint and preferences. Using this framework, we can answer a variety of counterfactual questions to shed light on the source of cross-regional heterogeneity in health and economic outcomes.

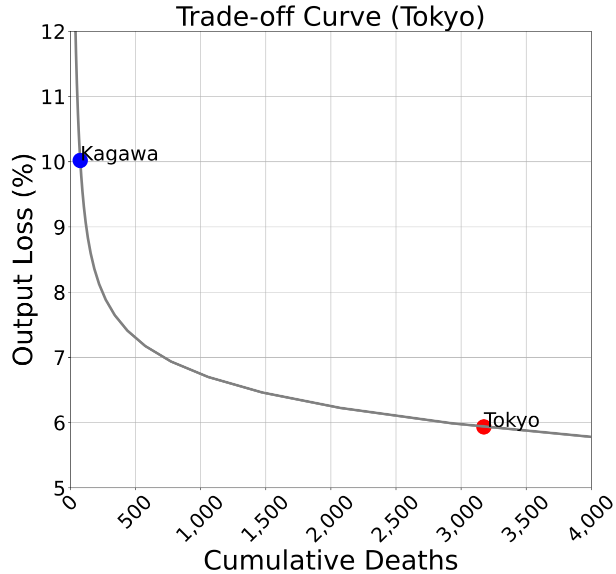
The following type of questions can isolate the role of preference heterogeneity in generating the outcome heterogeneity: What outcome would people or policymakers in Tokyo have chosen if their MRS had been the same as that of people or policymakers in Kagawa?[8] Us-

[6]For example, see the article by Manabe in Tokyo Keizai on April 19th, 2020, the Mainichi Shimbun on December 30th, 2020, and the Asahi Shimbun on February 19th, 2021.

[7]Our casual observation is that heterogeneity in preference have manifested itself in the heterogeneity in the words and deeds of local policymakers. For instance, Johnston (2021) and Namima (2021) report that the Governor of Shimane prefecture threatened to cancel participation in the Tokyo Olympic torch relay and related events even when the number of new cases was very low at that time. On the other hand, the Governor of Osaka repeatedly emphasized the need to increase medical capacity and maintain a certain level of economic activity throughout the COVID-19 pandemic. For example, the article of the Mainichi Shimbun on February 5th, 2021 reports that the Governor of Osaka set loose benchmarks to lift the state of emergency to accelerate economic activity despite some warnings from health experts.

[8]An alternative way of stating the same question is, if people in Kagawa faced the trade-off curve of

Figure 6: Conditional trade-off curve of Tokyo with the MRS of Kagawa



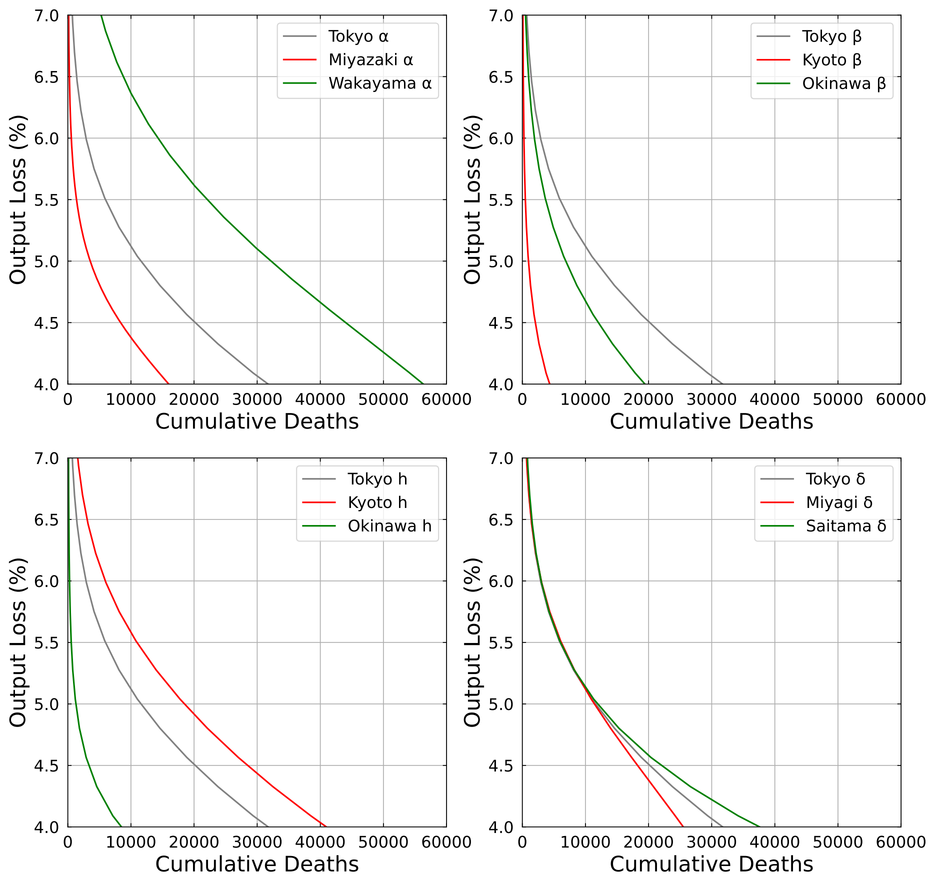
ing the estimated MRS and assuming a linear indifference curve,[9] the point on the trade-off curve of Tokyo where the slope of the tangent equals to the MRS of Kagawa gives the answer to this question. Figure 6 depicts the estimated conditional trade-off curve of Tokyo. The red dot is the realized outcome of Tokyo, whereas the blue dot would be the answer to the aforementioned hypothetical question. Outcome would be a substantially smaller number of deaths (around 100) and a greater output loss (around 10%), reflecting a larger estimate of MRS (2.33) in Kagawa than in Tokyo (0.44).

We can also ask the question of which factors are responsible for the difference in the location and shape of the conditional trade-off curves across two regions. In Figure 7, we investigate the effect of swapping a structural parameter on the trade-off curve of Tokyo with those of another other regions. In the top-left panel, the gray line is the original trade-off curve of Tokyo. The green curve is derived by using Wakayama's realized path of $\{\alpha_t\}$, and other parameters of Tokyo. If the path of output in Tokyo had been the same as that in Wakayama, its trade-off curve would have shifted to the right, leading to more deaths conditional on the same output loss. Notice that the shape of α_t, the timing and stringency of NPIs, is different in the counterfactual experiment. On the other hand, if the path of α_t in Tokyo had been the same as that of Miyazaki's, the trade-off curve would have shifted to

Tokyo, what outcome would they have chosen?

[9]The linear case is an extreme case where the MRS is constant along the indifference curve. With a concave indifference curve, the magnitude of our counterfactual change would be smaller. Hence, we can interpret the result in this subsection as an upper bound of the effect of swapping "preference" between two regions.

Figure 7: Hypothetical trade-off curves in Tokyo



the left.

The bottom-left panel illustrates the hypothetical trade-off curves of Tokyo when swapping the value of h, the sensitivity of output loss to mobility. If Tokyo had the same h as Kyoto, the curve would shift to the right since the estimated h is smaller for Kyoto, and the opposite is true for using Okinawa's h. In the top-right panel, the path of transmission rate β_t is swapped with that of Kyoto and Okinawa. In both cases, the Tokyo's trade-off curve shifts to the left leading to a better outcome since Tokyo experienced relatively high values of β_t. Lastly, the bottom-right panel shows the result of swapping the path of mortality rate δ_t.

3.4 Results based on other sample periods

In Appendix C, we compute conditional trade-off curves and the MRS for three alternative sample periods. All three alternative samples start in February 2020, as in our baseline sample period. We consider three end dates: March 2021, June 2021, and September 2022.

As in the baseline analysis, we find a large heterogeneity in the location and shape of the conditional trade-off curve and a large heterogeneity in the MRS. The most interesting result is that the MRS is declining over time for most prefectures. This pattern likely reflects the fact that our MRS measure captures factors beyond what a standard value of statistical life aims to capture, including fear of the unknown and fear of social ostracism and that, as the information about the virus became more available over time, the unknown has become less unknown, and social ostracism has come less of an issue in many regions in Japan.

4 Conclusion

Health and macroeconomic outcomes varied substantially across prefectures in Japan during the COVID-19 crisis, just as they did across countries. Using an estimated macro-epidemiological model, we derive the conditional trade-off curve between COVID-19 deaths and output loss in each prefecture, which represents the constraint each prefecture faced during the pandemic. Invoking the idea of revealed preference, we compute the marginal rate of substitution (MRS) at the realized outcome, which represents the preferences of people in the prefecture. We find that there is a large heterogeneity in the MRS as well as the location and shape of the trade-off curve.

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Appendix

A Estimation of the elasticity of output to mobility h

The sensitivity of economic activity to mobility, h, is estimated by regressing GDP loss on the Google mobility index as in Fujii and Nakata (2021). The Google COVID-19 Community Mobility Reports provide movement trends for each prefecture across six categories of places: retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. For our analysis, we compute the average of the weekly median values of four series: retail and recreation, parks, workplaces, and transit stations, which is denoted as M_t. Since the Google mobility data are expressed as a percentage change compared to the baseline period Jan 3rd - Feb 6th of 2020, we convert the mobility series by

$$m_t = 1 + \frac{M_t}{100}$$

Here, $m_t = 1$ implies that mobility at t is the same as a median value of mobility between January 3rd to February 6th in 2020. We then run the following regression

$$m_t = h_0 + h_1 \alpha_t + \epsilon_t^h \text{ for } t \in [1, T]$$

to obtain the estimates $\hat{h}_0$ and $\hat{h}_1$. In the above equation, h_0 corresponds to the mobility level where there is no output loss. We normalize the elasticity h_1 by h_0 since we formulate our mobility as $(1 - h\alpha_t)$ and $h\alpha_t$ is the deviation from a normalized level of one. Thus, we obtain our estimate of h as

$$h = \frac{\hat{h}_1}{\hat{h}_0}$$

Figure 8: Optimality condition

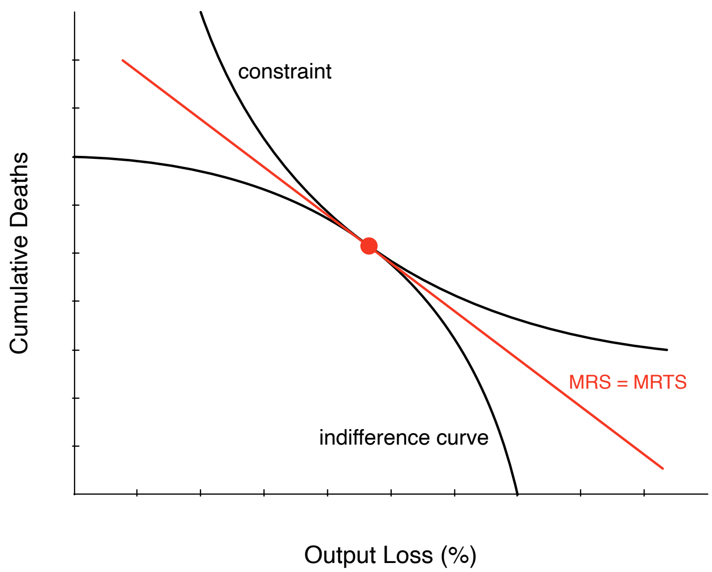


Figure 9: End of sample period: December 2020

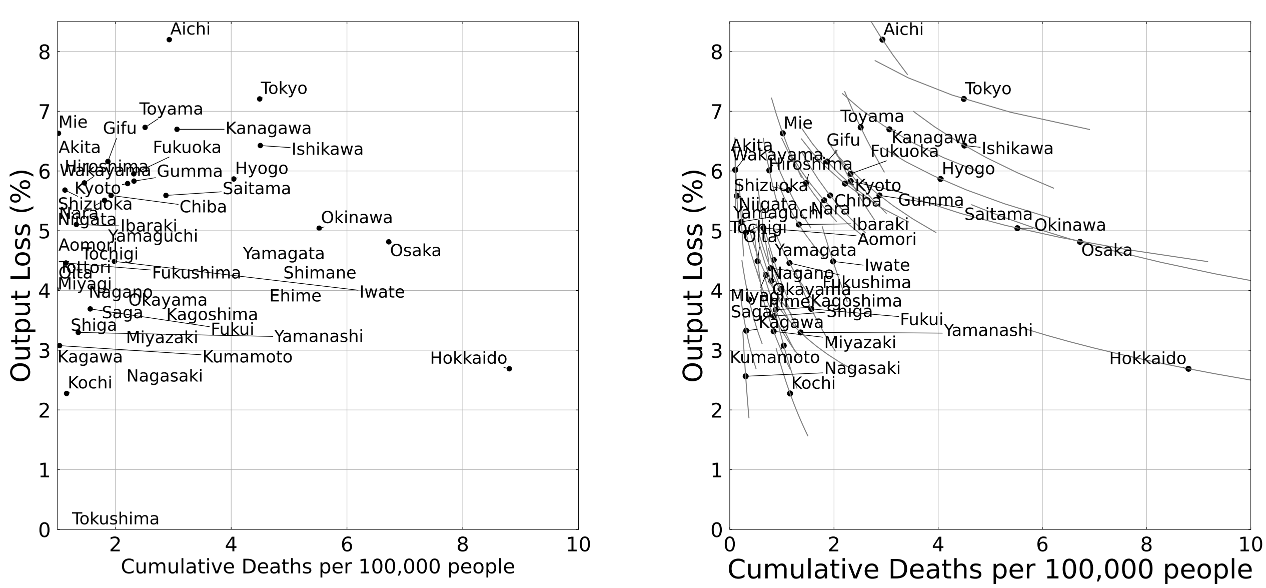


Figure 10: End of sample period: March 2021

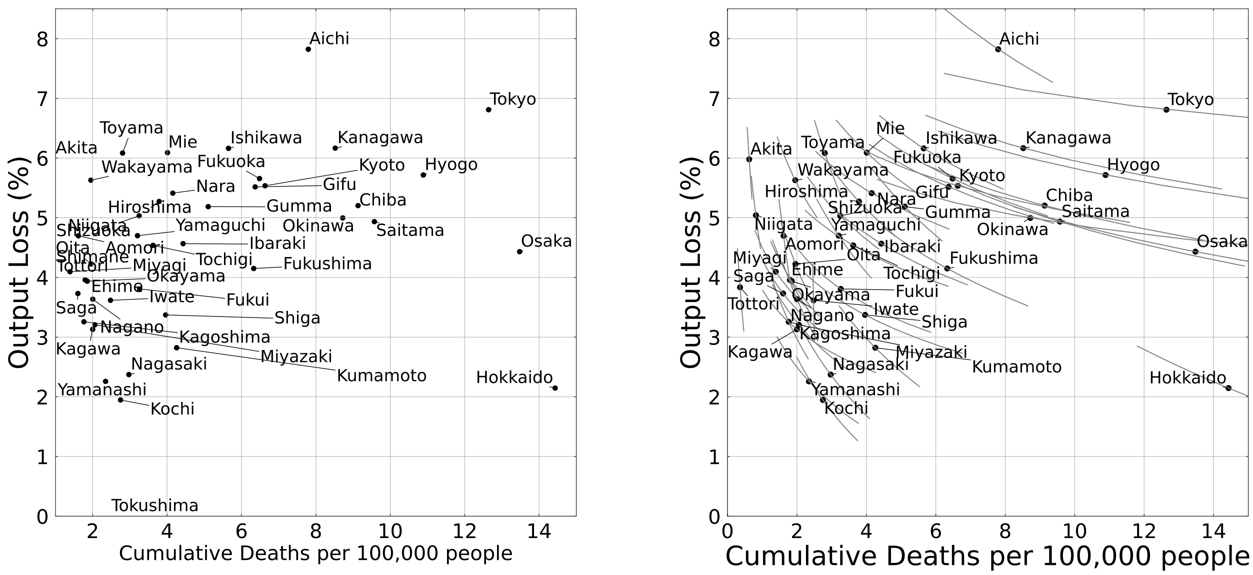


Figure 11: End of sample period: June 2021

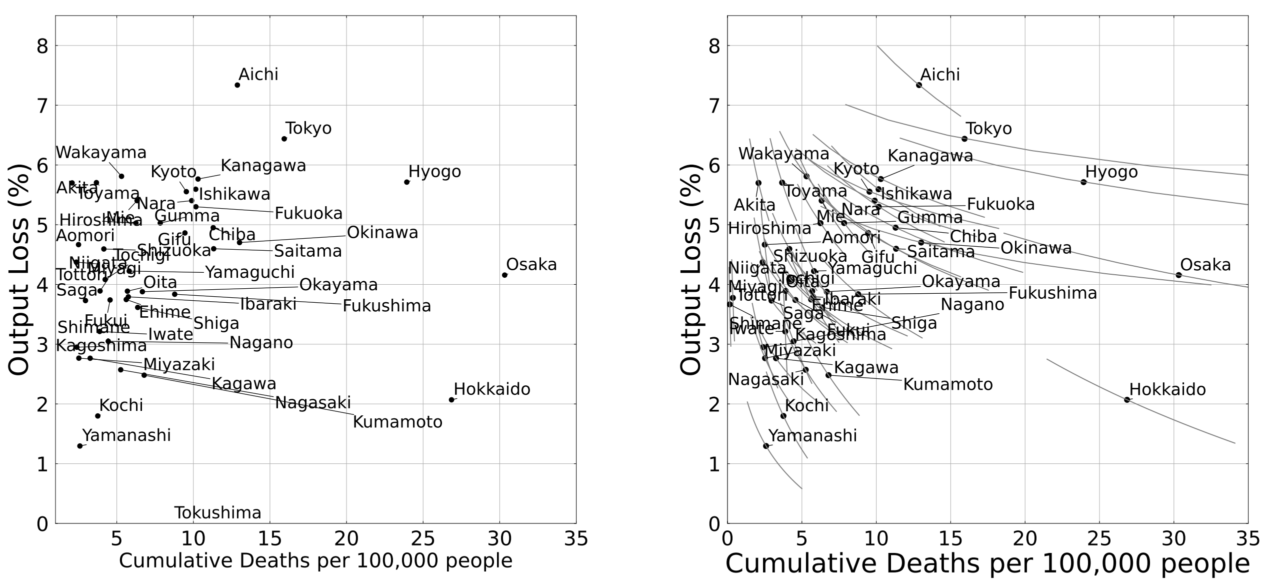
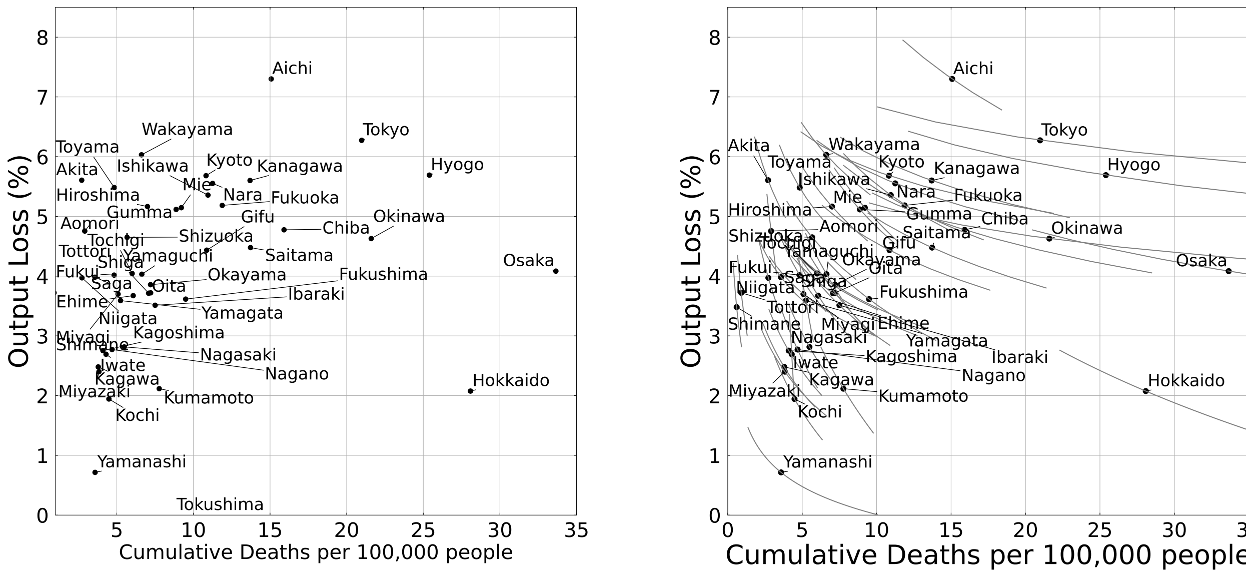


Figure 12: End of sample period: September 2021



B Optimality Condition

C Sensitivity of MRS with different sample periods

Table 2: MRS (in 100 million yen) by December 2020

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Akita	319.50	Okayama	8.68	Hiroshima	5.13
Niigata	63.33	Nagano	8.28	Fukuoka	3.68
Yamaguchi	57.56	Ehime	8.14	Gifu	3.34
Nagasaki	36.57	Kochi	7.75	Chiba	3.12
Tokushima	35.94	Fukui	7.27	Yamanashi	3.08
Oita	23.38	Shizuoka	7.20	Kyoto	2.46
Aomori	20.24	Toyama	7.11	Nara	2.31
Tochigi	16.63	Shiga	7.08	Tokyo	1.94
Kagawa	15.33	Kagoshima	7.03	Saitama	1.87
Wakayama	13.48	Miyazaki	6.94	Kanagawa	1.82
Saga	12.21	Miyagi	6.44	Ishikawa	1.81
Kumamoto	10.04	Gumma	6.34	Hyogo	1.35
Mie	9.84	Aichi	6.23	Osaka	0.99
Yamagata	9.58	Fukushima	6.10	Hokkaido	0.56
Iwate	9.04	Ibaraki	5.52	Okinawa	0.53

Table 3: MRS (in 100 million yen) by March 2021

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Iwate	116.75	Kochi	3.30	Ishikawa	1.69
Akita	38.12	Hiroshima	3.10	Shiga	1.55
Tottori	30.14	Shizuoka	3.08	Fukushima	1.50
Niigata	20.49	Saga	3.07	Fukuoka	1.17
Aomori	19.31	Gumma	3.00	Gifu	1.10
Toyama	8.56	Yamanashi	2.97	Nara	1.03
Tokushima	7.73	Nagasaki	2.97	Hokkaido	1.01
Oita	6.54	Mie	2.84	Kyoto	0.78
Nagano	6.33	Miyazaki	2.67	Kanagawa	0.68
Kagoshima	5.12	Kumamoto	2.38	Saitama	0.61
Wakayama	4.91	Aichi	2.34	Tokyo	0.58
Ehime	4.72	Kagawa	2.17	Osaka	0.57
Yamaguchi	4.35	Fukui	2.07	Chiba	0.57
Okayama	4.31	Ibaraki	1.80	Hyogo	0.50
Miyagi	4.04	Tochigi	1.75	Okinawa	0.34

Table 4: MRS (in 100 million yen) by June 2021

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Shimane	59.63	Ehime	2.31	Okayama	1.1
Tottori	36.10	Hiroshima	2.21	Ishikawa	1.03
Iwate	31.14	Gumma	2.00	Gifu	0.83
Aomori	11.66	Kagawa	2.00	Fukuoka	0.83
Niigata	6.24	Tochigi	1.89	Kanagawa	0.63
Akita	5.47	Nagasaki	1.87	Saitama	0.59
Toyama	4.68	Kumamoto	1.85	Hokkaido	0.58
Kagoshima	4.07	Ibaraki	1.84	Kyoto	0.57
Nagano	3.75	Fukui	1.81	Tokyo	0.54
Yamaguchi	3.17	Saga	1.72	Chiba	0.52
Shizuoka	2.91	Wakayama	1.71	Nara	0.43
Mie	2.67	Miyagi	1.56	Osaka	0.29
Miyazaki	2.66	Aichi	1.51	Okinawa	0.25
Kochi	2.63	Tokushima	1.43	Hyogo	0.22
Yamanashi	2.42	Shiga	1.23		
Oita	2.33	Fukushima	1.21		

Table 5: MRS (in 100 million yen) by September 2021

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Iwate	27.38	Ehime	2.34	Shiga	1.26
Shimane	15.57	Shizuoka	2.25	Ishikawa	1.18
Aomori	13.20	Mie	2.13	Okayama	1.13
Tottori	12.17	Oita	2.03	Gifu	0.81
Yamagata	9.05	Gumma	2.00	Fukuoka	0.8
Niigata	5.61	Hiroshima	1.99	Hokkaido	0.63
Akita	4.01	Miyazaki	1.91	Kyoto	0.55
Nagano	3.70	Saga	1.87	Saitama	0.55
Yamaguchi	3.12	Ibaraki	1.75	Kanagawa	0.54
Fukui	3.06	Tokushima	1.69	Tokyo	0.45
Toyama	2.99	Wakayama	1.66	Nara	0.44
Kagawa	2.65	Aichi	1.49	Chiba	0.4
Kochi	2.58	Tochigi	1.46	Osaka	0.3
Kagoshima	2.43	Miyagi	1.37	Hyogo	0.24
Kumamoto	2.42	Yamanashi	1.36	Okinawa	0.16
Nagasaki	2.39	Fukushima	1.28		