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Abstract

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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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July 5, 2023

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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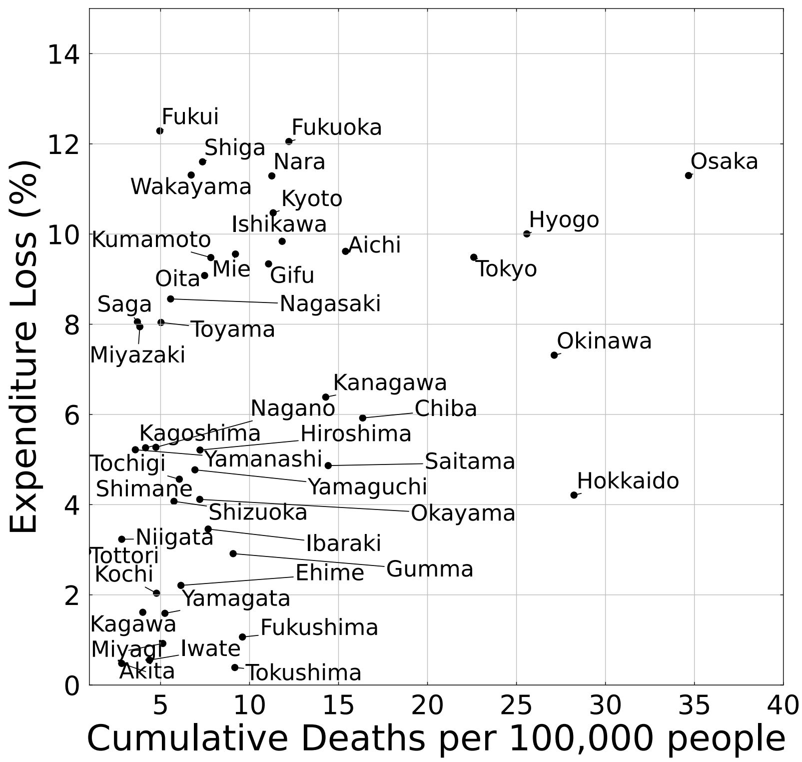
1 Introduction

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



Note: The expenditure 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 ??—a scatterplot of cumulative COVID-19 deaths per 100,000 people and the average expenditure loss from February 2020 to December 2021. Some prefectures have seen a relatively small number of COVID-19 deaths with small expenditure loss, whereas some have seen the opposite. Some prefectures have seen a small number of COVID-19 deaths with large expenditure 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 ?, we compute the conditional trade-off curve between COVID-19 death and expenditure loss for each prefecture using time-series data on infection and economic activity. The conditional trade-off curve represents the "constraint."[1] We then

[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-

invoke the idea of revealed preference to compute the marginal rate of substitution (MRS) between COVID-19 death and expenditure 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 expenditure.[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 expenditure. For example, the conditional trade-off curve for Tottori is located southwest of that for Tokyo in the deaths-expenditure loss plane, and the MRS in Tottori (about 14.7 billion yen) is much higher than that of Tokyo (about 0.79 billion yen).

We also examine what factors are related to the MRS. We find the MRS is positively correlated with (i) expenditure loss per COVID-19 death, (ii) average age, (iii) aging rate, while it is negatively correlated with population density.

1.1 Related Literature

Our work is closely related to **?**. **?** 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 **?**, **?**, **?**, **?**, **?**, **?**, **?**, **?**, and **?**, 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 expenditure 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 between health and economic outcomes. Examples include **?**, **?**, **?**, **?**, **?**, **?**, **?**, **?**. Like these authors, we use epi-macro models to better understand the

intensive workers and easiness of teleworking).

[2]Our measure of MRS likely captures various factors that go beyond a prefecture'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.

Japanese experience during the COVID-19 pandemic.

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 **?**, our description will be concise. We refer interested readers to **?** 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. 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. The number of susceptible, infectious, and recovered people in prefecture j at time t are denoted by $S_{j,t}$, $I_{j,t}$, and $R_{j,t}$ respectively. The number of cumulative deaths is denoted by $D_{j,t}$. The laws of motion are given by the following system of equations

$$S_{j,t+1} = S_{j,t} - \underbrace{\frac{\beta_{j,t}(1-h_j\alpha_{j,t})^k}{POP_j} I_{j,t} S_{j,t}}_{N_{j,t}} - V_{j,t} \tag{1}$$

$$I_{j,t+1} = I_{j,t} + \underbrace{\frac{\beta_{j,t}(1-h_j\alpha_{j,t})^k}{POP_j} I_{j,t} S_{j,t}}_{N_{j,t}} - N_{j,t}^{IR} - N_{j,t}^{ID} \tag{2}$$

$$R_{j,t+1} = R_{j,t} + N_{j,t}^{IR} + V_{j,t} \tag{3}$$

$$D_{j,t+1} = D_{j,t} + N_{j,t}^{ID} \tag{4}$$

$$N_{j,t}^{IR} = \gamma I_{j,t} \tag{5}$$

$$N_{j,t}^{ID} = \delta_{j,t} I_{j,t} \tag{6}$$

The flow variables $N_{j,t}$, $N_{j,t}^{IR}$, and $N_{j,t}^{ID}$ are the number of the newly infected, newly recovered, and new deaths from COVID-19 between time t and time $t+1$ in prefecture j, respectively. $V_{j,t}$ is the number of newly vaccinated people from time t to time $t+1$. The common 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 by prefecture, which is denoted by $\delta_{j,t}$. The path of $\delta_{j,t}$ will be estimated from data. The total population in prefecture j is denoted by POP_j.

The number of newly infected people $N_{j,t}$ is proportional to the product $I_{j,t}S_{j,t}$ normalized by POP_j. The time-varying parameter $\beta_{j,t}$ captures the "expenditure-adjusted" or "raw" transmission rate that would prevail in the absence of any decline in economic activity. The term $\alpha_{j,t}$ denotes expenditure loss in percentage, and $(1 - h_j\alpha_{j,t})$ is a proxy for people's mobility. The elasticity of expenditure loss to mobility is denoted by h_j, which is estimated for each prefecture separately. A high value of h_j means that the infection rate can be reduced a lot without reducing expenditure much. We can reduce the number of new infection at time t by lowering mobility, but it comes at a cost of larger expenditure loss. This relationship between infection and expenditure 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 **?**, the value of k changes each state's MRS uniformly, and does not alter the ranking of MRS.

Note that SIR models would not be able to capture multiple waves of infection observed in data if it featured a constant transmission rate, as discussed by **?** and **?**, among many others. Our model allows time-variation in the transmission rate—beta has a time subscript—which enables us to perfectly fit any path of infection by construction.

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

$$Y_{j,t} = (1 - \alpha_{j,t})\bar{Y}_{j,t} \tag{7}$$

where $Y_{j,t}$ is expenditure in prefecture j at time t. The second component $\bar{Y}_{j,t}$ is the reference level of expenditure that would have prevailed if no one restrained his or her economic activities at time t. Please see the Appendix of **?** for how to construct $\bar{Y}_{j,t}$ for each prefecture.

2.2 Data and Estimation

All of 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 Appendix **??**, we present our estimation results based on alternative sample periods. The number of new positive PCR test cases $N_{j,t}$ and the number of deaths due to COVID-19 $N^{ID}_{j,t}$ in prefecture j are retrieved from the database of the Ministry of Health, Labour and Welfare (MHLW) in Japan.[3]

Set the initial condition as $S_{j,0} = 0.9999 * POP_j$, $I_{j,0} = 0.0001 * POP_j$, $R_{j,0} = 0$, and

[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,

$D_{j,0} = 0$ for all j. With these initial values and $N_{j,t}$, $N_{j,t}^{ID}$ and $V_{j,t}$, we can recover the paths of variables $S_{j,t}$, $I_{j,t}$, $R_{j,t}$ and $D_{j,t}$. Using the data of $\alpha_{j,t}$ and estimated value of h_j, we can then back out the time-varying parameters $\beta_{j,t}$ and $\delta_{j,t}$.

We use Regional Domestic Expenditure Index (RDEI) provided by the Cabinet Office of Japan to proxy prefecture-level monthly expenditure $Y_{j,t}$. RDEI is constructed by aggregating four different expenditure indices at monthly frequency for each prefecture: (i) consumption, (ii) private housing, (iii), private investment, and (iv) public investment. Expenditure measures may be more appropriate than output measures to gauge economic activity within each prefecture since it is less affected by external factors from both international and inter-prefectural trade. We assume the same expenditure value for weeks in the same month and construct the path of $Y_{j,t}$. [4] The estimation of h_j is elaborated in the Appendix **??**.

2.3 Tracing Out the Conditional Trade-Off Curves

For each prefecture, we first calculate $\delta_{j,t}$, $\beta_{j,t}$ and h_j as described above. Then, we consider a hypothetical path of expenditure loss $\alpha_{j,t}^c$ by multiplying $\alpha_{j,t}$ with a time-invariant constant, ranging from 0.1 to 5.0.

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

It means that the hypothetical expenditure loss is smaller by 50 percent for every period if $c = 0.5$. It is important to note that the shape of the original $\alpha_{j,t}$ 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 expenditure loss constant, we can reduce the number of cumulative deaths by imposing a stronger restriction (larger $\alpha_{j,t}$) 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 $\alpha_{j,t}$. For each hypothetical path $\alpha_{j,t}^c$, we compute the paths of new infections and cumulative deaths using the estimated $\beta_{j,t}$, $\delta_{j,t}$ and h_j. For each scaler c, we obtain a pair of average expenditure loss and cumulative deaths $\{(\overline{\alpha}_j^c, D_{j,T}^c)\}_{c\in C}$ where $\overline{\alpha}_j^c = \frac{\sum_{t\in\{1,2,...,T\}} \alpha_{j,t}^c}{T}$.

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we compute

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

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 expenditure values accordingly.

3 Results

3.1 The Conditional Trade-Off Curves

Figure 2: Conditional trade-off curves

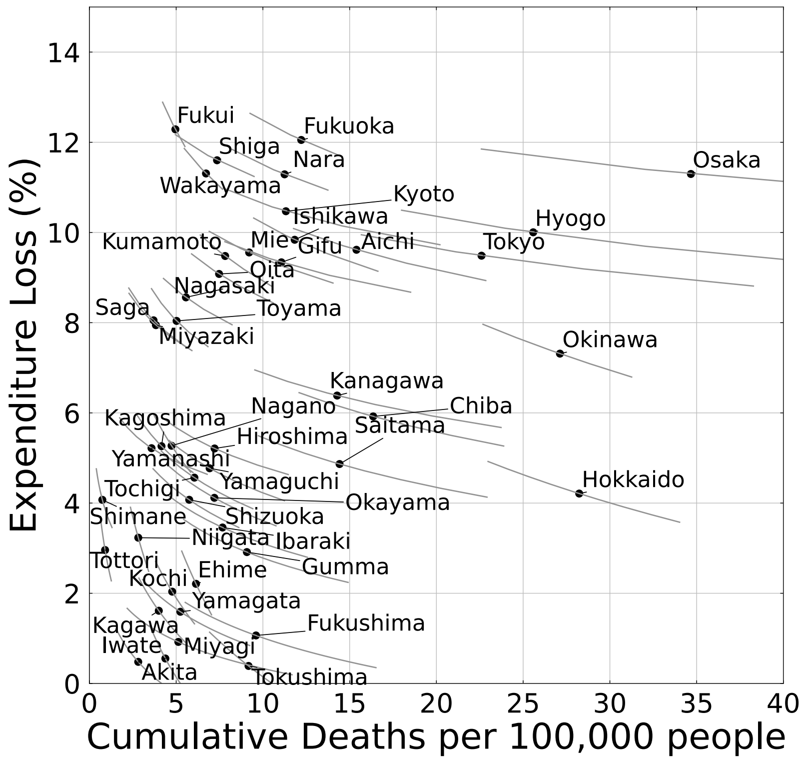


Figure ?? shows the estimated conditional trade-off curves between expenditure loss and COVID-19 deaths for each prefecture. In this figure, we overlay the scatterplot shown in Figure ?? with the conditional trade-off curves derived from the counterfactual simulations described in Section ??. We can confirm a large heterogeneity in the location and shape of these curves. The trade-off curves of prefectures that exhibit a larger expenditure loss and higher number of deaths such as Osaka or Hyogo locate in the upper-right part of the figure. Yet, many curves cross each other due to the difference in shape. Miyagi and Akita are geographically located in the same Tohoku region, and their realized outcomes of expenditure loss and COVID-19 deaths are also similar. Nonetheless, the shape of their conditional trade-off curves are quite different with the curve of Akita 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 ?? 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_j, the elasticity of mobility with respect to expenditure loss, ii) $\{\alpha_{j,t}\}_{t=0}^{T}$, the path of economic restriction, iii) $\{\beta_{j,t}\}_{t=0}^{T}$, the time-varying parameter of transmission rate, and iv) $\{\delta_{j,t}\}_{t=0}^{T}$, the time-varying parameter of mortality rate. For instance, if prefecture j experiences higher $\beta_{j,t}$ or $\delta_{j,t}$ 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 $\alpha_{j,t}$ and $\beta_{j,t}$ play an important role even when the time-series average is held constant. A larger $\alpha_{j,t}$ or smaller $\beta_{j,t}$ in the early phase of pandemic benefits the society by shifting the trade-off curve down.

Figure 3: Histograms of estimated parameters

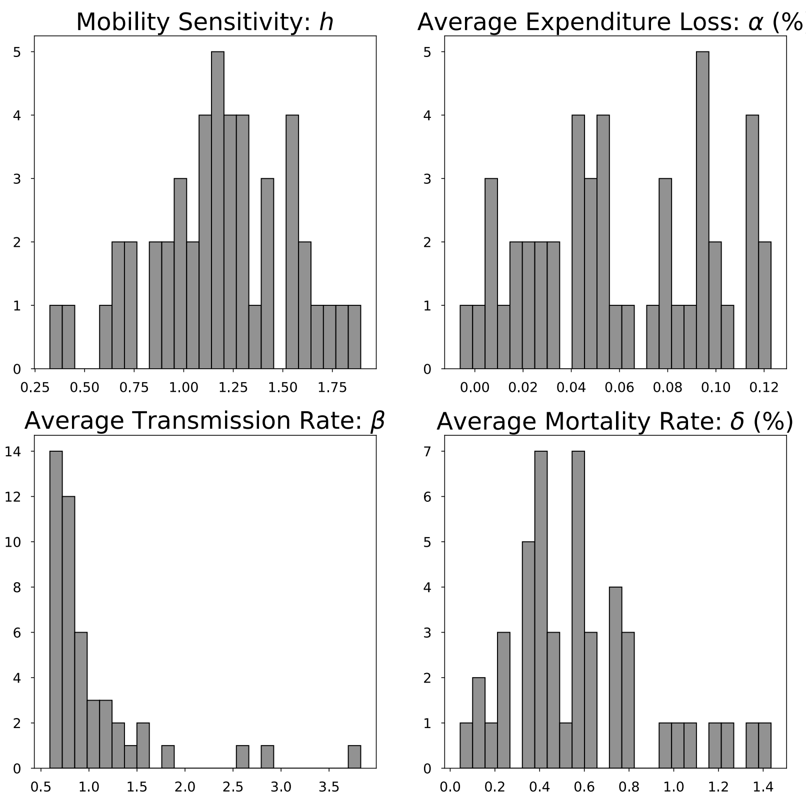
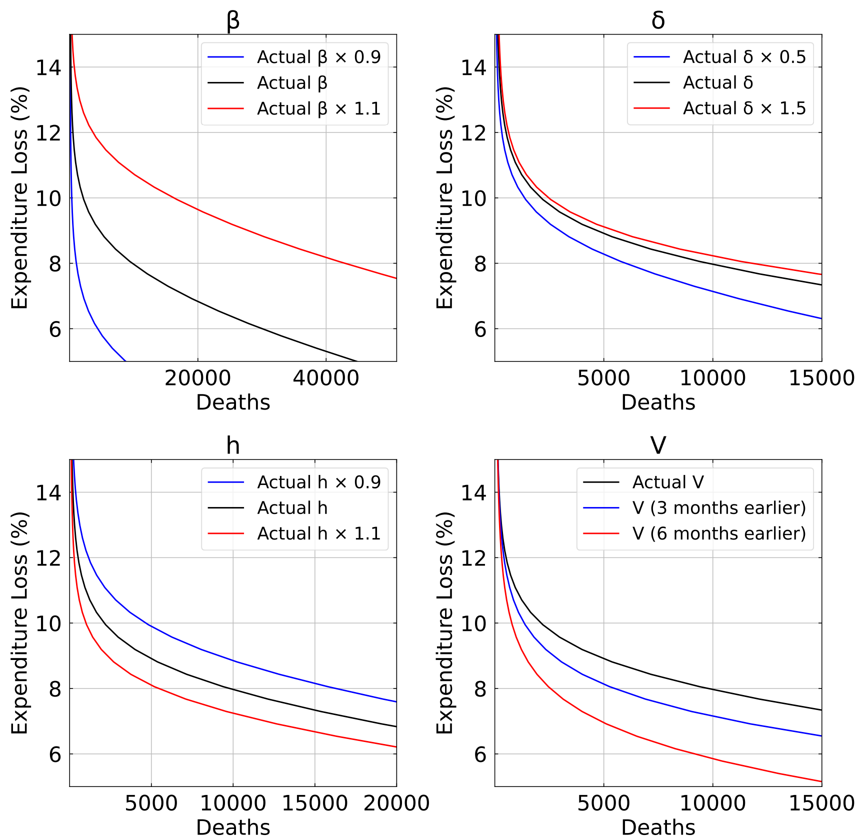


Figure **??** shows the histograms of estimated h_j, average $\alpha_{j,t}$, $\beta_{j,t}$ and $\delta_{j,t}$. The differences in these parameters are the source of the cross-regional heterogeneity of the trade-off curves. The estimated elasticity of mobility with respect to expenditure loss is concentrated around 1.2 but some prefectures exhibit h_j larger than 1.7 or less than 0.5. The distribution of the average transmission rate $\beta_{j,t}$ is skewed to the left around 0.7, yet some prefectures experienced a large transmission rate with average $\beta_{j,t}$ 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 **??** 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 expenditure loss on mobility h. As h becomes larger, the trade-off curve moves to the southwest. This is welfare-enhancing since we can achieve both lower number of deaths and smaller expenditure loss. A larger value of h means that a reduction in expenditure 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
Tottori	14.67	Shizuoka	2.17	Fukuoka	1.2
Shimane	10.61	Miyazaki	2.14	Gumma	1.19
Niigata	9.77	Tochigi	2.14	Aichi	1.11
Aomori	8.95	Yamanashi	1.85	Fukushima	1.02
Fukui	5.93	Yamaguchi	1.80	Kyoto	0.87
Ehime	5.61	Kumamoto	1.79	Gifu	0.83
Iwate	4.79	Nagasaki	1.77	Hokkaido	0.82
Nagano	4.31	Oita	1.77	Tokyo	0.79
Kochi	4.03	Okayama	1.71	Nara	0.78
Kagawa	4.01	Yamagata	1.69	Okinawa	0.76
Toyama	3.21	Shiga	1.58	Kanagawa	0.66
Wakayama	2.73	Mie	1.47	Chiba	0.62
Akita	2.71	Hiroshima	1.43	Saitama	0.62
Saga	2.55	Ibaraki	1.41	Hyogo	0.38
Kagoshima	2.44	Ishikawa	1.37	Osaka	0.31
Tokushima	2.43	Miyagi	1.26		

Table **??** summarizes the MRS between expenditure 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 **?**, there exists a considerable heterogeneity in MRS across regions within Japan as well. Some prefectures such as Tottori and Shimane exhibit a large MRS (14.67 and 10.61, respectively) while other prefectures like Osaka and Hyogo exhibit a very small MRS (0.31 and 0.38, respectively). In general, rural areas show a higher MRS than urban areas.

As illustrated in Figure **??** 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 expenditure 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 **??**, but are translated into billion yen/death.

Figure 5: MRS vs. other variables

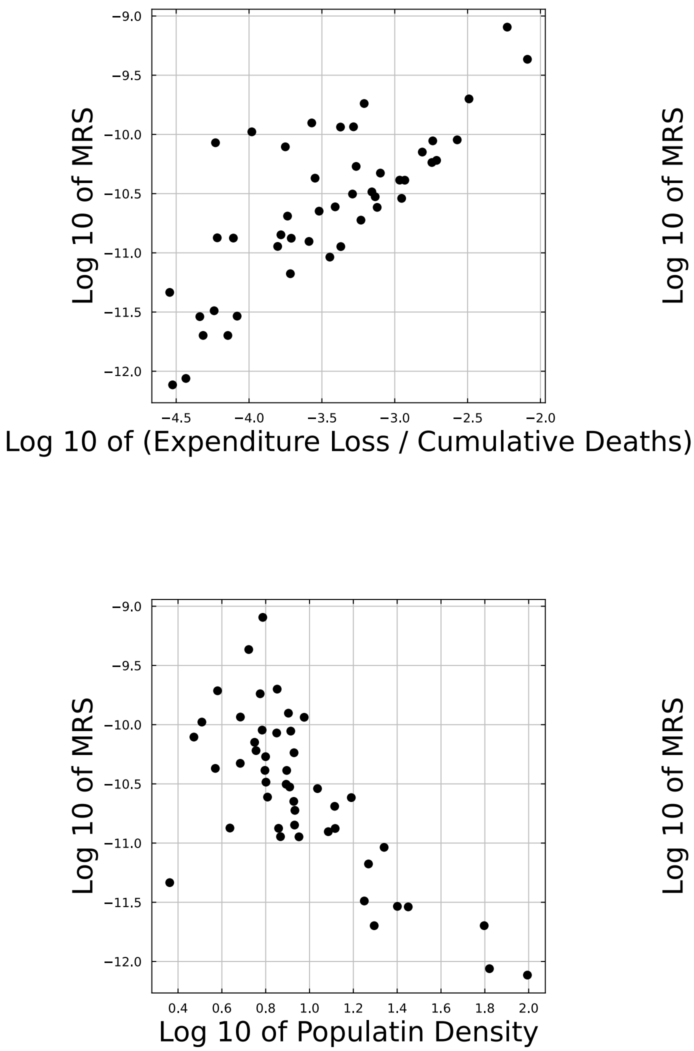


Figure **??** presents the scatterplots of the MRS and other variables. The top-left panel examines the relationship between the MRS and expenditure loss/deaths across prefectures. We observe a positive correlation, but the relationship is not perfect. Our model analysis reveals the heterogeneity of preferences, which cannot be inferred by just looking at the ratio between expenditure 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 expenditure loss to reduce the number of casualties. Another potential reason is the culture of peer pressure and social ostracism. As studied in **?**, 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 expenditure 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 expenditure 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.

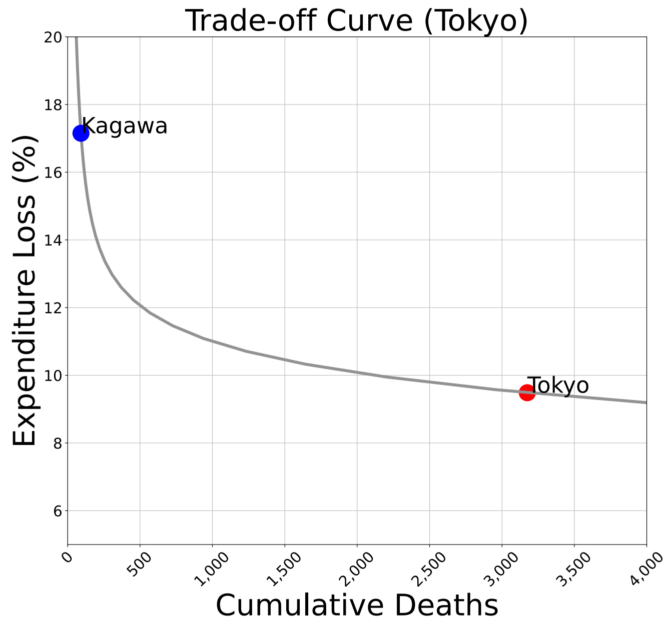
The following type of questions can isolate the role of preference heterogeneity in generating the outcome heterogeneity: What outcome would people or policymakers in Tokyo have chosen if their MRS had been the same as that of people or policymakers in Kagawa?[8] Us-

[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, **?** and **?** 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



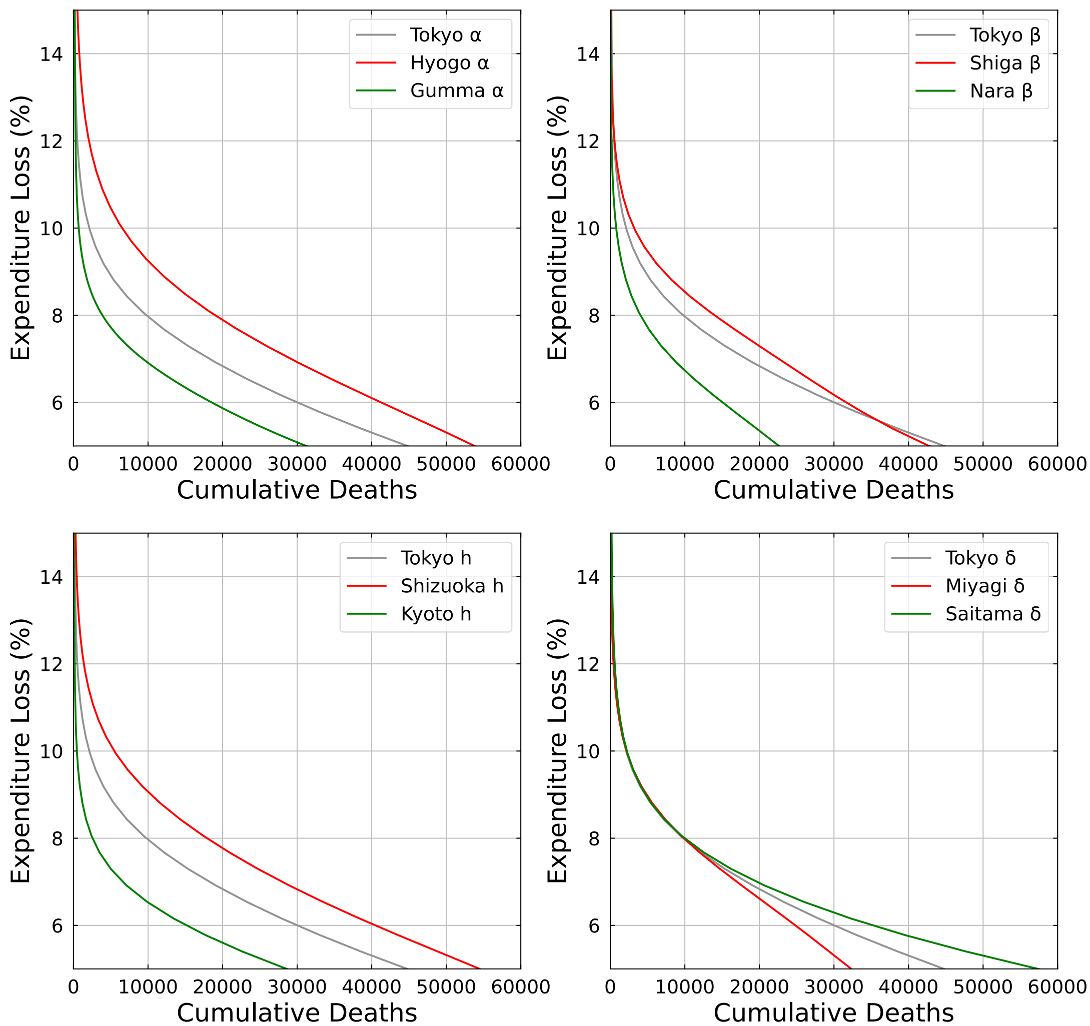
ing the estimated MRS and assuming a linear indifference curve,[9] the point on the trade-off curve of Tokyo where the slope of the tangent equals to the MRS of Kagawa gives the answer to this question. Figure **??** depicts the estimated conditional trade-off curve of Tokyo. The red dot is the realized 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 expenditure loss (around 17%), reflecting a larger estimate of MRS (4.01) in Kagawa than in Tokyo (0.79).

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 **??**, 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 Gunma's realized path of $\alpha_{j,t}$, and other parameters of Tokyo. If the path of expenditure in Tokyo had been the same as that in Kumamoto, its trade-off curve would have shifted to the left, leading to fewer deaths conditional on the same expenditure loss. If we replace the path of $\alpha_{j,t}$ with that of Hyogo, the trade-off curve shifts to the right. Notice that the shape of $\alpha_{j,t}$, the timing and stringency of NPIs, is different in the counterfactual experiment.

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 bottom-left panel illustrates the hypothetical trade-off curves of Tokyo when swapping the value of h_j, the sensitivity of expenditure loss to mobility. If Tokyo's sensitivity h_j was the same as Kyoto's, the trade-off curve would have moved downward because Kyoto's h_j is higher. The opposite is true for Shizuoka's h_j. In the top-right panel, the path of transmission rate $\beta_{j,t}$ is swapped with that of Shiga and Nara. Shiga's transmission rate $\beta_{j,t}$ moves the trade-off curve to the right whereas Nara's $\beta_{j,t}$ moves the curve to the left. Lastly, the bottom-right panel shows the result of swapping the path of mortality rate $\delta_{j,t}$.

3.4 Results based on other sample periods

In Appendix **??**, 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 2021.

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 expenditure 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.

Appendix

A Estimation of the elasticity of expenditure to mobility h_j

The sensitivity of economic activity to mobility in prefecture j, h_j, is estimated by regressing expenditure loss on the Google mobility index as in **?**. 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 $M_{j,t}$. 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

$$m_{j,t} = 1 + \frac{M_{j,t}}{100}$$

Here, $m_{j,t} = 1$ 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

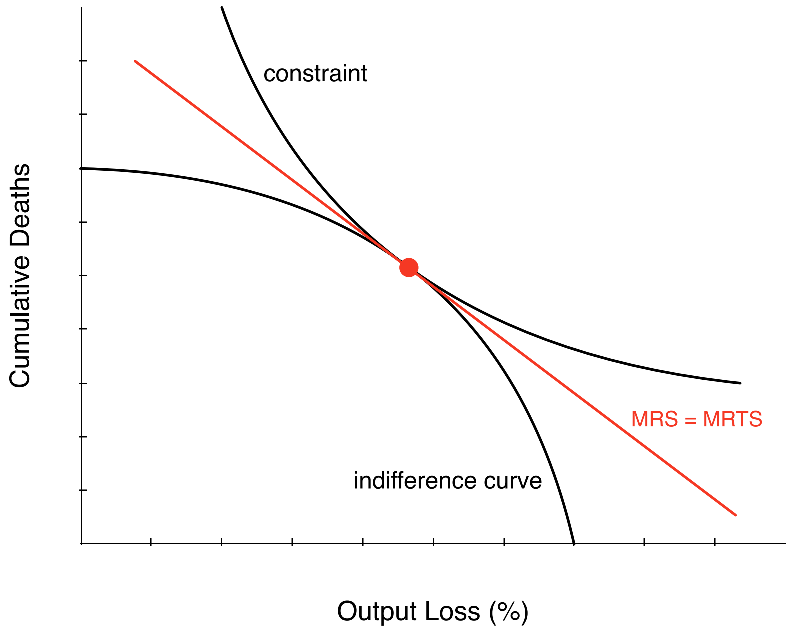
$$m_{j,t} = h_{j,0} + h_{j,1}\alpha_{j,t} + \epsilon_t^h \text{ for } t \in [1, T]$$

to obtain the estimates $\hat{h}_{j,0}$ and $\hat{h}_{j,1}$. In the above equation, $h_{j,0}$ corresponds to the mobility level where there is no expenditure loss. We normalize the elasticity $h_{j,1}$ by $h_{j,0}$ since we formulate our mobility as $(1 - h_j\alpha_{j,t})$ and $h_j\alpha_{j,t}$ is the deviation from a normalized level of one. Thus, we obtain our estimate of h_j as

$$h_j = \frac{\hat{h}_{j,1}}{\hat{h}_{j,0}}$$

B Optimality Condition

Figure 8: Optimality condition



C Sensitivity of MRS with different sample periods

Figure 9: End of sample period: December 2020

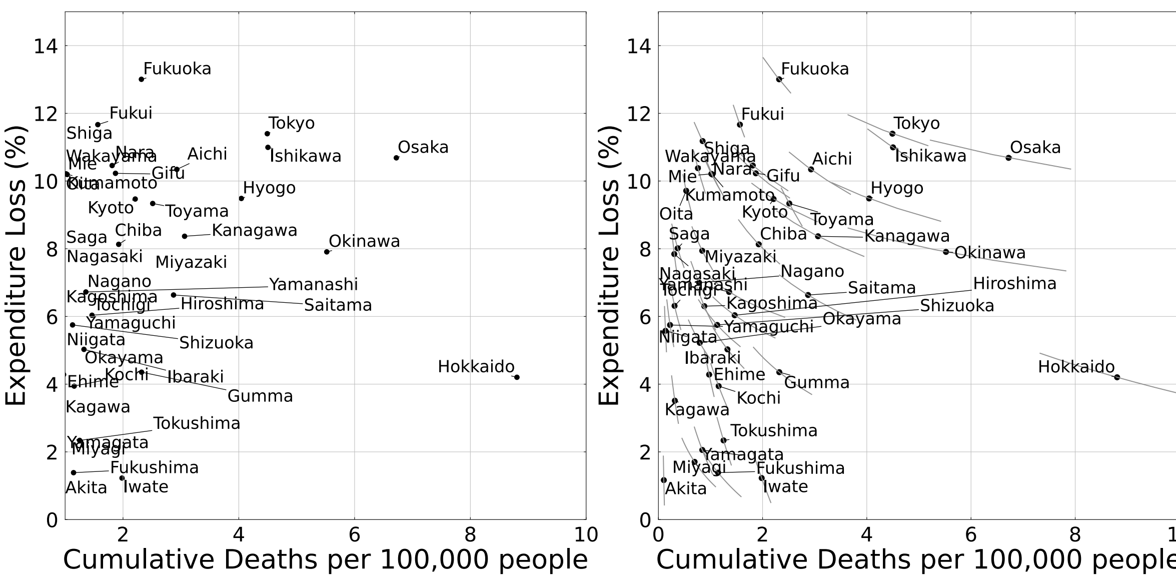


Figure 10: End of sample period: March 2021

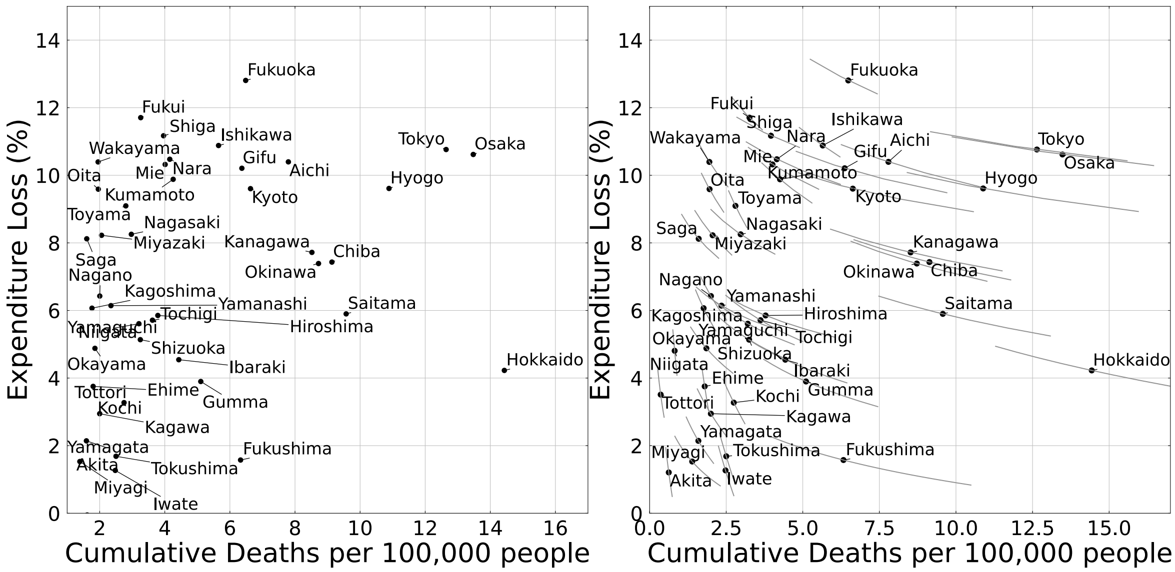


Figure 11: End of sample period: June 2021

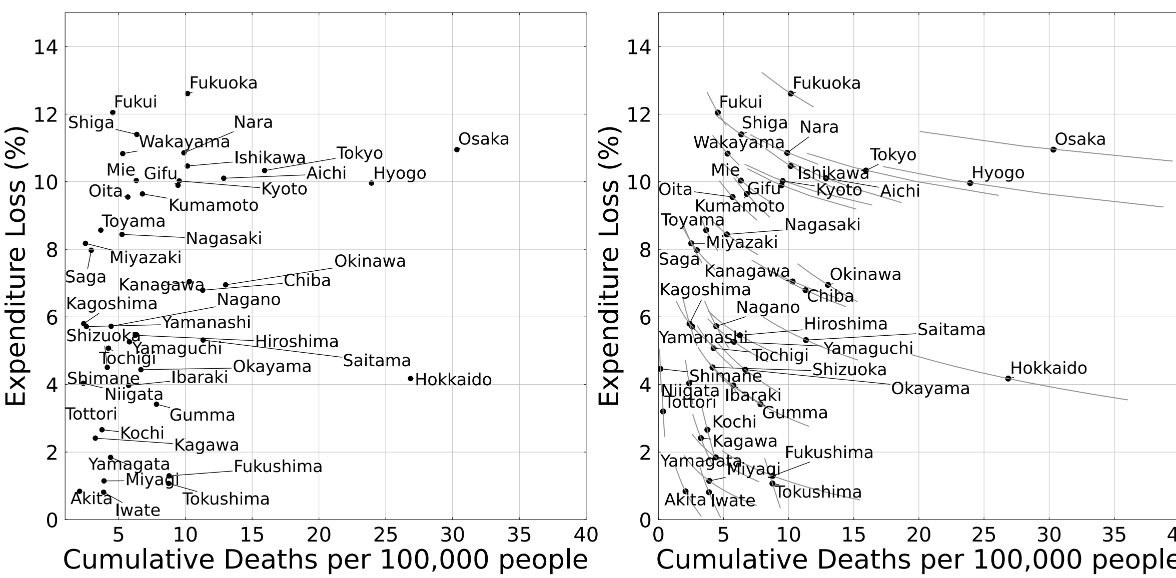


Figure 12: End of sample period: September 2021

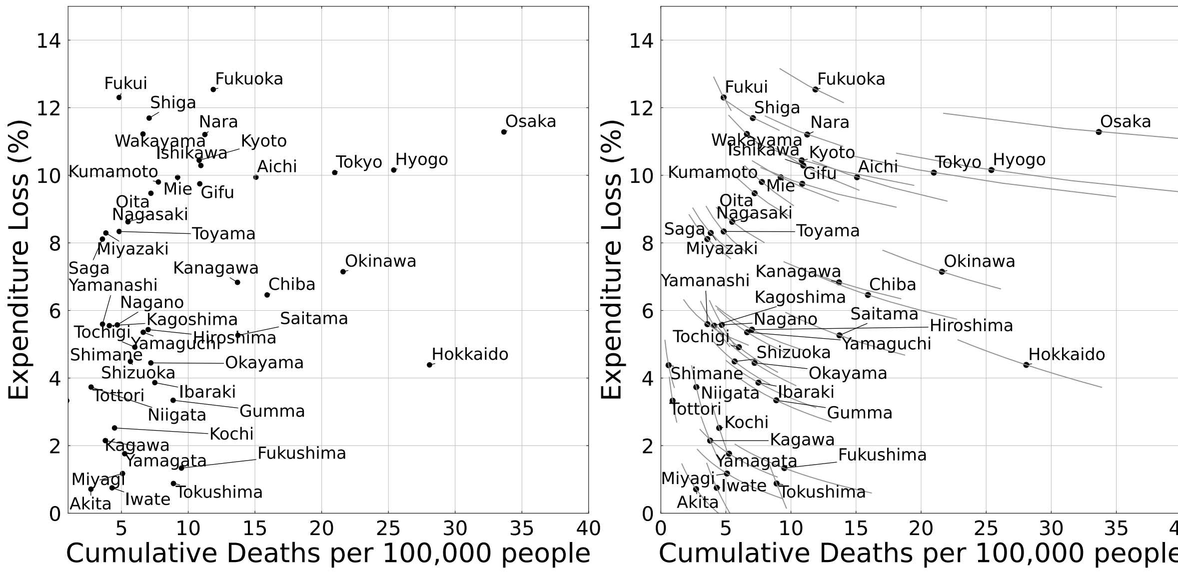


Table 2: MRS (in billion yen) by December 2020

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Akita	216.69	Kochi	12.40	Chiba	4.52
Niigata	120.92	Nagano	12.36	Gifu	4.49
Yamaguchi	40.82	Shiga	11.86	Hiroshima	4.24
Kagawa	37.99	Toyama	11.18	Tokyo	3.81
Nagasaki	37.53	Kagoshima	10.70	Ishikawa	3.8
Tochigi	27.42	Okayama	10.03	Kyoto	3.47
Oita	24.05	Kumamoto	9.67	Yamanashi	3.3
Ehime	23.23	Miyazaki	9.32	Nara	3.11
Tokushima	19.61	Miyagi	8.19	Saitama	2.54
Wakayama	19.06	Ibaraki	7.70	Kanagawa	2.52
Saga	16.58	Fukushima	6.72	Hyogo	1.96
Fukui	16.27	Shizuoka	6.70	Hokkaido	1.38
Iwate	13.78	Fukuoka	6.32	Osaka	1.2
Yamagata	12.83	Aichi	5.17	Okinawa	0.79
Mie	12.50	Gumma	4.66		

Table 3: MRS (in billion yen) by March 2021

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Niigata	43.30	Miyagi	4.60	Hiroshima	1.82
Tottori	26.67	Fukui	4.51	Aichi	1.75
Akita	26.08	Saga	4.16	Nara	1.35
Ehime	24.46	Miyazaki	4.02	Gifu	1.17
Tokushima	14.52	Ishikawa	2.96	Tokyo	1.09
Iwate	11.92	Mie	2.90	Fukushima	1.05
Toyama	9.37	Shizuoka	2.80	Kyoto	1.02
Kochi	7.12	Kumamoto	2.80	Okinawa	0.89
Oita	7.11	Tochigi	2.74	Kanagawa	0.88
Kagoshima	7.09	Yamaguchi	2.54	Hokkaido	0.81
Nagano	6.87	Nagasaki	2.35	Chiba	0.81
Kagawa	6.62	Yamanashi	2.34	Saitama	0.75
Yamagata	6.27	Shiga	2.06	Hyogo	0.71
Wakayama	5.93	Ibaraki	2.04	Osaka	0.62
Aomori	5.40	Fukuoka	1.90		
Okayama	5.00	Gumma	1.89		

Table 4: MRS (in billion yen) by June 2021

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Shimane	46.99	Saga	2.41	Fukuoka	1.26
Tottori	33.65	Yamanashi	2.39	Aichi	1.1
Niigata	11.83	Oita	2.24	Okinawa	1.0
Aomori	8.08	Wakayama	2.10	Tokyo	0.98
Tokushima	7.27	Mie	2.06	Gifu	0.83
Kochi	7.15	Kumamoto	2.00	Kanagawa	0.83
Kagoshima	5.96	Okayama	1.82	Fukushima	0.79
Kagawa	5.60	Ibaraki	1.77	Chiba	0.78
Toyama	4.97	Yamaguchi	1.70	Kyoto	0.78
Iwate	4.70	Miyagi	1.54	Saitama	0.72
Nagano	4.01	Shiga	1.46	Nara	0.59
Fukui	3.82	Yamagata	1.45	Hokkaido	0.4
Miyazaki	3.74	Nagasaki	1.43	Hyogo	0.32
Akita	3.56	Hiroshima	1.41	Osaka	0.26
Shizuoka	2.78	Ishikawa	1.33		
Tochigi	2.75	Gumma	1.26		

Table 5: MRS (in billion yen) by September 2021

Prefecture	MRS	Prefecture	MRS	Prefecture	MRS
Tottori	13.15	Shizuoka	2.18	Fukuoka	1.19
Shimane	12.48	Wakayama	2.08	Aichi	1.06
Niigata	10.14	Oita	1.86	Fukushima	0.94
Tokushima	6.99	Yamaguchi	1.79	Tokyo	0.81
Kochi	6.70	Okayama	1.76	Gifu	0.78
Kagawa	5.98	Kumamoto	1.76	Kyoto	0.78
Aomori	5.95	Yamanashi	1.75	Hokkaido	0.74
Fukui	4.98	Nagasaki	1.66	Kanagawa	0.7
Iwate	4.91	Miyagi	1.53	Saitama	0.67
Nagano	4.29	Ibaraki	1.50	Chiba	0.64
Kagoshima	3.20	Shiga	1.46	Nara	0.62
Toyama	3.13	Yamagata	1.43	Okinawa	0.61
Akita	2.91	Mie	1.42	Hyogo	0.35
Miyazaki	2.29	Hiroshima	1.40	Osaka	0.27
Saga	2.27	Ishikawa	1.39		
Tochigi	2.22	Gumma	1.28		