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Understanding Cross-Country Heterogeneity in Health and Economic Outcomes during the COVID-19 Pandemic: A Revealed-Preference Approach*

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June 30, 2022

Abstract

There is a large heterogeneity in health and macroeconomic outcomes across countries during the COVID-19 pandemic. We present a novel framework to understand the source of this heterogeneity, combining an estimated macro-epidemiological model and the idea of revealed preference. Our framework allows us to decompose the difference in health and macroeconomic outcomes across countries into two components: preference and constraint. We find that there is a large heterogeneity in both components across countries and that some countries such as Japan or Australia are willing to accept a large output loss to reduce the number of COVID-19 deaths.

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

JEL Codes: E17, E70, I18

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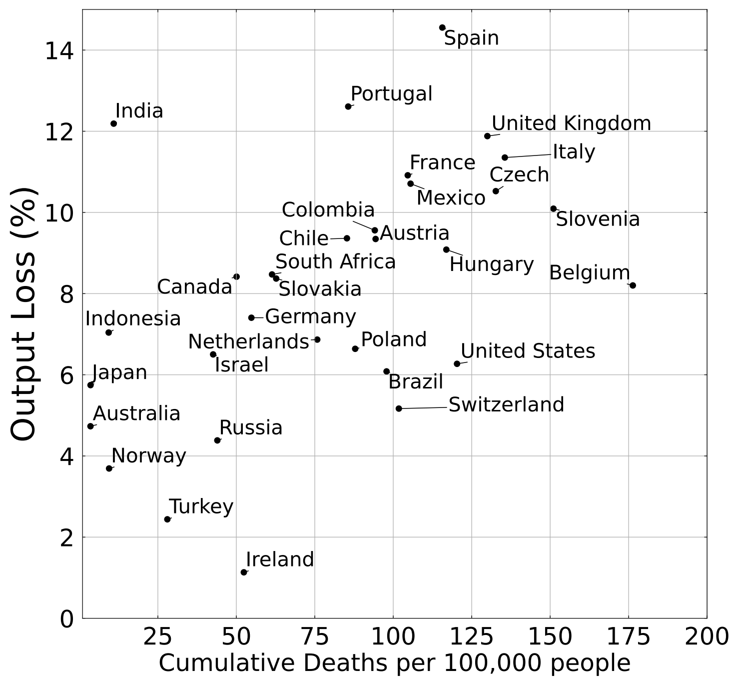
1 Introduction

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



Source: OECD Main Economic Indicators Publication

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

The COVID-19 pandemic has posed the world a question that has not been asked for many decades: How should a society balance infection control and economic activity during a pandemic? Different countries have struggled with this question differently, and we have witnessed a diverse set of health and macroeconomic outcomes across countries during the COVID-19 pandemic. As shown in Figure 1, there are countries that have seen large output loss and many deaths, while there are countries that have seen small output loss and few deaths. There are countries with large output loss and few deaths, yet there are countries with small output loss and many deaths.

To shed light on the sources of the observed heterogeneity in health and macroeconomic outcomes, we present a novel framework to decompose the difference in those outcomes into two components: preference and constraint. In particular, we estimate a macro-SIR model with each country's time-series data on output, infection, and death, and compute the set of possible pairs of COVID-19 deaths and output loss through counterfactual simulations. We call this set the "conditional" trade-off curve between COVID-19 deaths and output. This curve tells us how many COVID-19 deaths could have been avoided (or how many more

COVID-19 deaths would need to be accepted) if a country had reduced economic activities more (or had not suppressed economic activity by less) than it did, holding constant all other factors—medical and economic policies, country-specific transmission and mortality rates, etc. In our revealed-preference approach, our conditional trade-off curve represents a "constraint."

Our conditional trade-off curve is intended to capture various country-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—such as whether "hugs and kisses" or "handshaking and bows" are more common way of greeting friends and families. They also include people's health conditions—such as the proportion of people with high BMIs and the proportion of elderlies, economic policies including fiscal and monetary policies to support households and businesses during lockdowns, economic structures—such as proportion of contact-intensive workers and easiness of teleworking, and luck, etc.

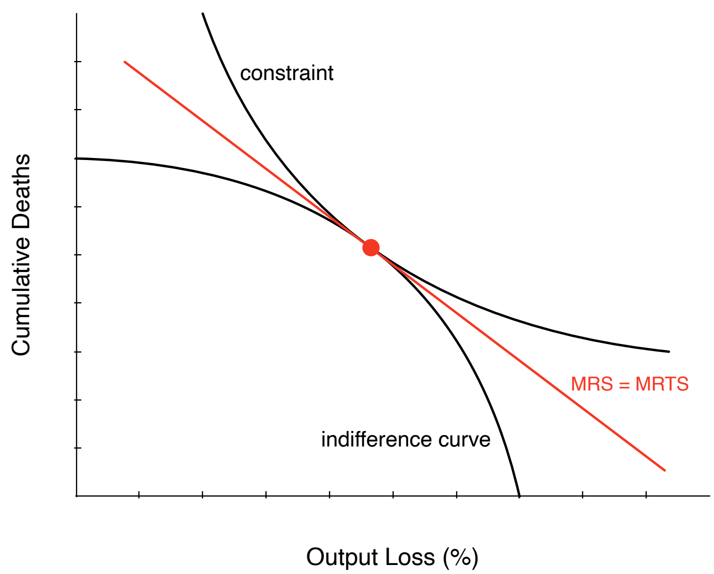
We then compute the marginal rate of substitution (MRS) between COVID-19 deaths and output loss at their realized pair using the optimality condition which equalizes MRS and marginal rate of technical substitution (MRTS) as depicted in Figure 2. In the figure, the red dot is the actualized pair of output loss and cumulative deaths, and the associated conditional trade-off curve from counterfactual simulations is illustrated as a constraint. Although we do not observed the indifference curve, we can infer the MRS by computing the slope of the tangent at the red dot (MRTS). This MRS can be interpreted—subject to various caveats described later on—as providing some information about how a country weighed the value of reducing COVID-19 deaths against the value of reducing output. Depending on the context, our MRS can be rephrased as the willingness to pay or shadow price of reducing a COVID-19 death. It is also related to, but not identical to, the concept of the value of statistical life studied in other strands of economic literature.

We find that (i) there is a large cross-country heterogeneity in the location and the shape of the conditional trade-off curve and that (ii) there is a large cross-country heterogeneity in the MRS between COVID-19 deaths and output. For example, the conditional trade-off curve for Japan is located south (or west) of that for the U.S. or U.K.; the MRS in Japan (about 13.6 million dollars) is much higher than those of the U.S. and U.K. (about 1 million or 0.5 million dollars).[1]

Our primary aim is to provide a novel framework to investigate questions of first-order

[1] These two types of heterogeneity—preference and constraint—exist across regions within a country. In Beppu et al. (2022), we apply the framework in this paper to state-level data in Japan and find large heterogeneity in both dimensions.

Figure 2: Optimality condition



importance under any pandemics. What is the right balance between controlling infection and maintaining human activities? What outcomes the government should aim to achieve? Why is there a large heterogeneity across countries or regions within a country? Having a framework to think about these questions is useful because, with so many lives and jobs at stake and little time for decision-making, it might be sometime challenging to discuss these big-picture questions from holistic perspectives in the middle of any pandemic.

We do not intend to provide a metric to rank the performance of countries during the COVID-19 pandemic. In particular, we caution our readers not to interpret our measure of MRS as the value of statistical life in a traditional way. 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 reputational loss associated with COVID-19 in certain societies where getting infected with COVID-19 led to ostracization, [2] 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.[3]

Beyond our primary aim of presenting a framework to think about the policy question of first-order importance, our analysis may be of interest to readers in the following two

[2] In some cities in Japan, there were reports of discrimination against those who got infected during the early phase of the pandemic. See also Delgado Narro (2021) for the social stigma of COVID-19 infection in Japan.

[3] As with any model-based analysis, misspecification of our model also affects our calculation.

ways. First, our MRS measure may help predict economic activity in the future. All else equal, a country with a higher MRS is likely to experience a more sluggish recovery from the COVID-19 crisis. For example, our quantitative result implies slower economic recovery for Japan than for the U.S. and U.K. going forward.

Second, our analysis can be used to put into perspective one's view towards how to balance infection risk and an ordinary life in a pandemic. During the COVID-19 pandemic, almost everyone in the world struggled with the question of how much sacrifice on normal ways of living one would be willing to accept in order to avoid infection risk. A better understanding of the sources of diverse health and macroeconomic outcomes across countries may be able to prepare people for facing the same question in future pandemics.

1.1 Related Literature

Our work is related to Atkeson (2020) and Fernández-Villaverde and Jones (2020) which document cross-sectional heterogeneity in health and economic outcomes during the early phase of the COVID-19 pandemic. They discuss various factors influencing the realized outcomes, such as policy and luck. We develop a novel framework to quantitatively analyze factors affecting the realized health and economic outcomes in any given country. To do so, we estimate key parameters of an epi-macro model using time-series data and conduct counterfactual simulation to compute a conditional trade-off curve in each country.

Our work is closely related to Hall et al. (2020), Acemoglu et al. (2021), Alvarez et al. (2021), Eichenbaum et al. (2021), Farboodi et al. (2020), Hamano et al. (2020), and Jones et al. (2021). These authors take a utilitarian approach. That is, they specify an objective function of the planner and analyze health and economic outcomes consistent with that specific utility function, either statically or dynamically. Our approach can be seen as the converse of these optimal policy exercises that assume a certain weight on disutility from COVID-19 death—relative to disutility from output loss—in the objective function of the planner's control problem. In contrast, we assume that the realized outcome is optimal—at least locally and in the broadest sense of the word—and reverse-engineer the marginal rate of substitution between COVID-19 death and output loss from the conditional trade-off curve computed with an estimated epi-macro model.

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. In addition to the aforementioned papers analyzing optimal control policies in epi-macro models, many papers—including Atkeson (2022), Atkeson et al. (2020), Bognanni et al. (2020), Fujii and Nakata (2021), Kaplan et al. (2020), and Kubota (2021)—use epi-macro models to analyze the joint dynamics of infection and economy and effective policies during a pandemic. Our work is unique because we combine the revealed preference approach with an estimated epi-macro model to understand the source of heterogeneity in health and economic outcomes across countries.

This paper is organized as follows. Section 2 describes our framework and explains how to derive conditional trade-off curves using time-series data. Section 3 presents the main results on cross-country heterogeneity in health and economic outcomes. Section 4 concludes.

2 Theoretical Framework

This section describes our framework to understand the cross-country heterogeneity in health and economic outcomes. Our model is based on the one considered in Fujii and Nakata (2021). We abstract from explicit dynamic optimization problems of individuals, as in Acemoglu et al. (2021), Alvarez et al. (2021), Atkeson (2022), and Farboodi et al. (2020). Our parsimonious model requires readily available country-level time-series data only, but captures essential ingredients to decompose the heterogeneous outcomes of health and economic activity into preference and constraint.

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. 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

$$S_{t+1} = S_t - N_t - V_t \tag{1}$$

$$I_{t+1} = I_t + N_t - N_t^{IR} - N_t^{ID} \tag{2}$$

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

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

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

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

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 $t+1$.[4] 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.[5] 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 is denoted by POP. Since we do not consider birth and other sources of deaths, the total population is preserved at any time t

$$S_t + I_t + R_t + D_t = POP \text{ for any } t$$

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 and α_t is output loss. The first component of the right-hand side, $(1 - \alpha_t)$, captures the reduction in output per person due to social-distancing—be it voluntary or government-imposed—or other measures aimed at reducing the risk of infection. The second component $\bar{Y}_t$ is the trend of output that would have prevailed if no one restrained his or her economic activities at time t. See Footnote 9 in the next subsection for the details no how to construct $\bar{Y}_t$.

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

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

where

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

We denote the transmission rate by $\tilde{\beta}_t$, which is comprised of two parts. The first term β_t denotes the "output-adjusted" or "raw" transmission rate that would prevail in the absence of any decline in economic activity. The second term $(1 - h\alpha_t)^k$ captures the effect of a decline in economic activity on the transmission rate. It is helpful to think of $(1 - h\alpha_t)$ as a proxy of people's mobility. A lower mobility rate by infection control leads to a larger output loss. The parameter h captures the elasticity of mobility with respect to output loss. A high value of h means that the infection rate can be reduced a lot without reducing output that much. Throughout this paper, we assume quadratic matching of the susceptible and

[4] As we will discuss shortly, we assume that an individual becomes fully vaccinated after she receives her second shot of vaccine.

[5] Eichenbaum et al. (2021) use the same value.

the infected, and set $k = 2$.[6] In Appendix, we provide a sensitivity analysis of our estimated MRS with respect to k. The value of k changes each country's MRS uniformly, and does not alter the ranking of MRS.

2.2 Data and Estimation

All the following analyses are conducted country by country. We set the start of the model to the first week of February 2020 and the time window of analysis to 48 weeks ($T = 48$), focusing on what happened in 2020. In the Appendix, we present results based on longer samples. 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 Our World in Data, which compiles Johns Hopkins University CSSE COVID-19 Data. 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

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

The time-series data of $V_{1,t}$ and $V_{2,t}$ are also retrieved from Our World in Data. 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.[7] Set the initial condition as $S_0 = POP$, $I_0 = 0$, $R_0 = 0$, and $D_0 = 0$. 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.

Monthly GDP data for each country are obtained from the OECD main economic indicator database. We assume the same GDP value for weeks in the same month and construct the path of Y_t. [8] From the past data of Y_t, we extrapolate the reference output level $\hat{Y}_t$. Using the series of Y_t and $\hat{Y}_t$, the path of output loss α_t is recovered. [9]

[6] See Alvarez et al. (2021) and Farboodi et al. (2020) for similar matching functions.

[7] SPI-M-O stands for the Scientific Pandemic Influenza Group on Modelling, Operational sub-group. The report "SPI-M-O: Summary of further modelling of easing restrictions – Roadmap Step 2" is available here.

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

[9] Let Y_t be the GDP observed at time t and $\hat{Y}_t$ be the reference GDP at time t. The reference level GDP is constructed as

$$\hat{Y}_t = \hat{\beta}_0 + \hat{\beta}_1 t$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are the estimates from the following OLS:

$$Y_t = \beta_0 + \beta_1 t + \varepsilon_t$$

where $t = \{\text{Jan 2016, Feb 2016, ..., Nov 2019, Dec 2019}\}$. The series of output loss, α_t, is then computed as

$$\alpha_t = 1 - \frac{Y_t}{\hat{Y}_t}.$$

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 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

$$m_t = h_0 + h_1 \alpha_t + \epsilon_t^h \text{ for } t \in [1, 48]$$

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

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

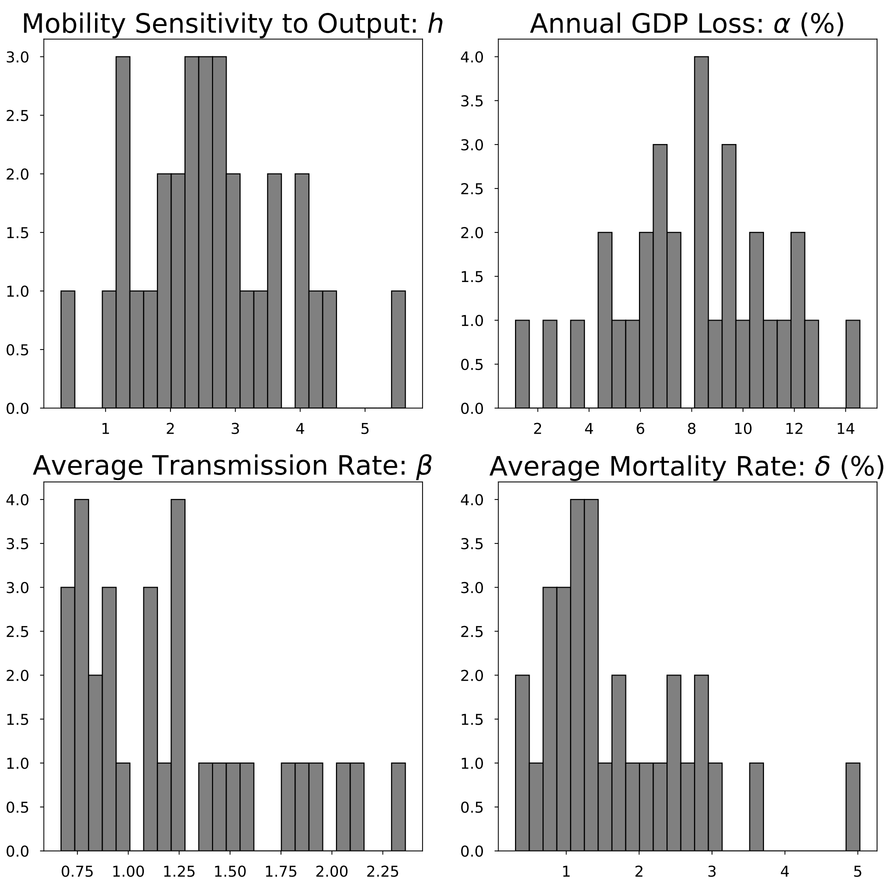
Figure 3 shows the histograms of estimated h, average α_t, β_t and δ_t, which reveal the cross-country heterogeneity in many dimensions.

2.3 Tracing Out the Conditional Trade-Off Curves

The realized points in Figure 1 represents heterogeneity in economic loss and number of deaths. An interesting question is what outcome policymakers would have gotten if they have chosen different NPIs, either severe or loose one. To provide an answer to this question, we conduct the following counterfactual experiment. For each country, 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.

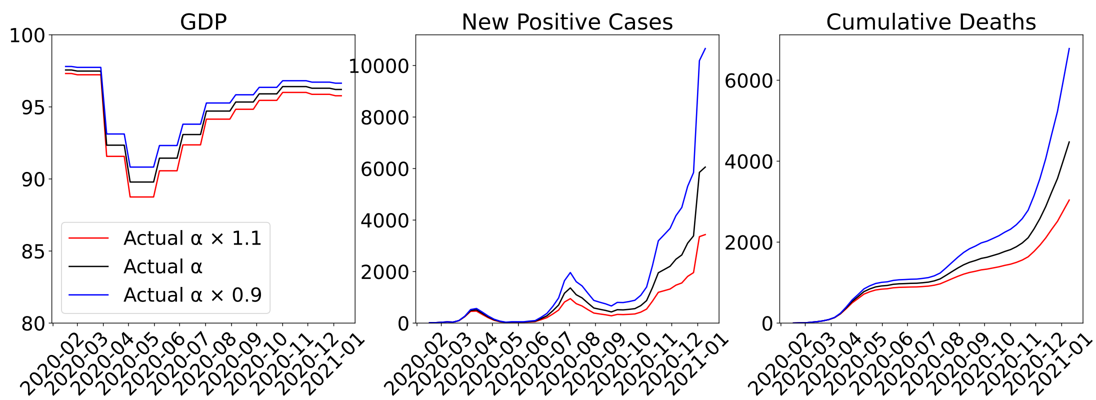
$$\alpha_t^c = c\alpha_t \text{ for } \forall t \text{ and } c \in C = \{0.1, 0.11, ..., 5.0\}$$

Figure 3: Histograms of estimated parameters



It means that the hypothetical output loss is smaller by 50 percent for every period if $c = 0.5$. The left panel of Figure 4 shows the path of α_t^c when the multiplier c is 0.9, 1.0, and 1.1. 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. The middle and right panels of Figure 4 show those counterfactual paths of N_t and D_t. Accelerating economic activity by a bit in every period (blue line) leads to a larger cumulative deaths, and vice versa.

Figure 4: Paths of GDP, new positive cases, and new deaths in Japan



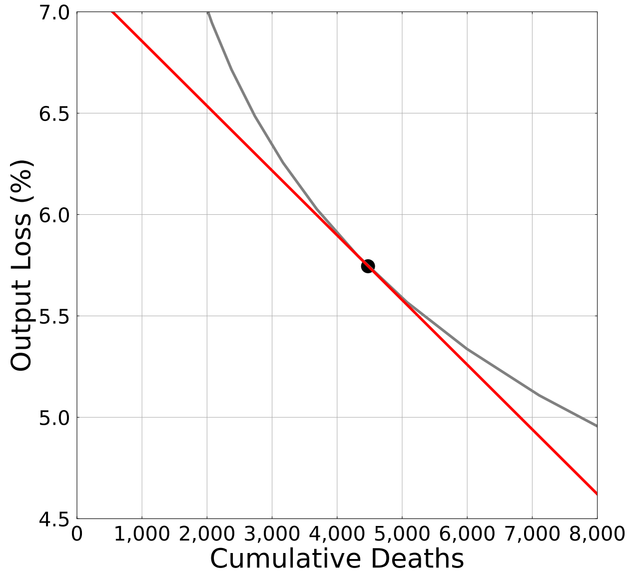
For each scaler c, we obtain a pair of average output loss and cumulative deaths $\{(\overline{\alpha}^c, D_T^c)\}_{c \in C}$ where

$$\overline{\alpha}^c = \frac{\sum_{t \in \{1,2,\ldots,T\}} \alpha_t^c}{T}$$

It is important to note that we preserve the shape of the original α_t for the hypothetical paths in this counterfactual simulation. 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 path of α_t.

Figure 5 plots the pair of $\bar{\alpha}^c$ and D_T^c for each c. This is the trade-off curve between COVID-19 deaths and output loss conditional on the actual paths of transmission rate, mortality rate, and other parameters. We call this curve as a conditional trade-off curve to underscore the importance of the conditioning factors behind the calculation. The black dot indicates the realized point, which is the pair of economic loss and cumulative deaths from the first week of February 2020 to the end of 2020. The red line indicates the tangent line of the tradeoff curve at the realized point. The slope of this tangent line is the marginal rate

Figure 5: Conditional trade-off curve in Japan



of substitution (MRS) between COVID-19 deaths and output loss. Figure 2 the slope. Our model analysis elucidates the trade-off curve, a constraint, from observed data. This MRS can also be interpreted as the willingness to pay or shadow price of reducing a COVID-19 death. A steeper red tangent line implies that people or policymakers in the country is willing to accept a larger output loss to reduce COVID-19 deaths.

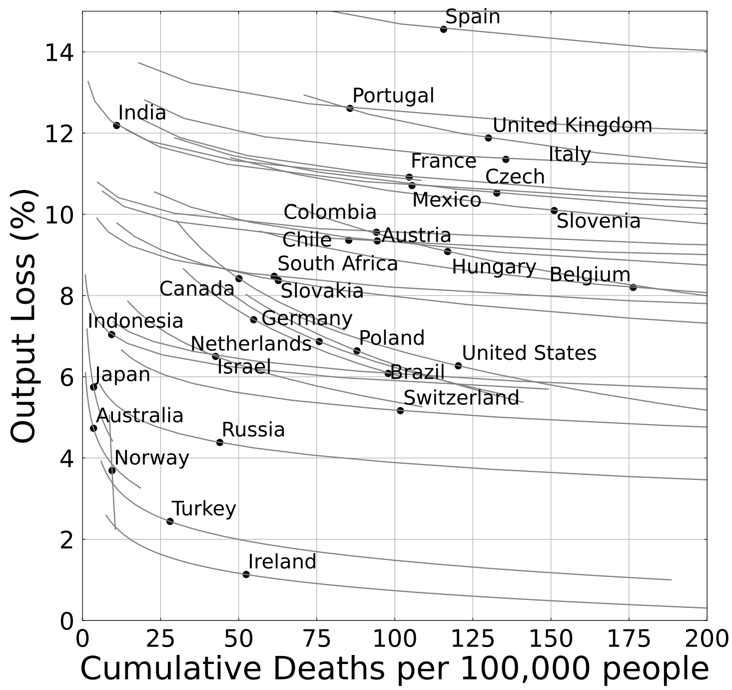
3 Results

3.1 The Conditional Trade-Off Curves

Figure 6 displays the estimated conditional trade-off curves between output loss and COVID-19 deaths for each country.[10] The scatterplot is the same as Figure 1, and we overlay the tradeoff curves derived from the counterfactual simulations described in Section 2.3. According to the figure, there is a large heterogeneity in the location and shape of these curves. In general, the trade-off curves of countries that exhibit a larger output loss and higher number of deaths such as Spain or the U.K. locate in the upper-right part of the figure. Yet, many curves cross each other due to the difference in shape. Also, the slope of the tangent line to the curve at the realized pair, which corresponds to the measure of

[10]There are several countries whose estimated value of h is negative implying that a lower mobility rate leads to a larger output. We drop those countries from our analysis since we cannot draw sensible conditional trade-off curves with negative h.

Figure 6: Conditional trade-off curves



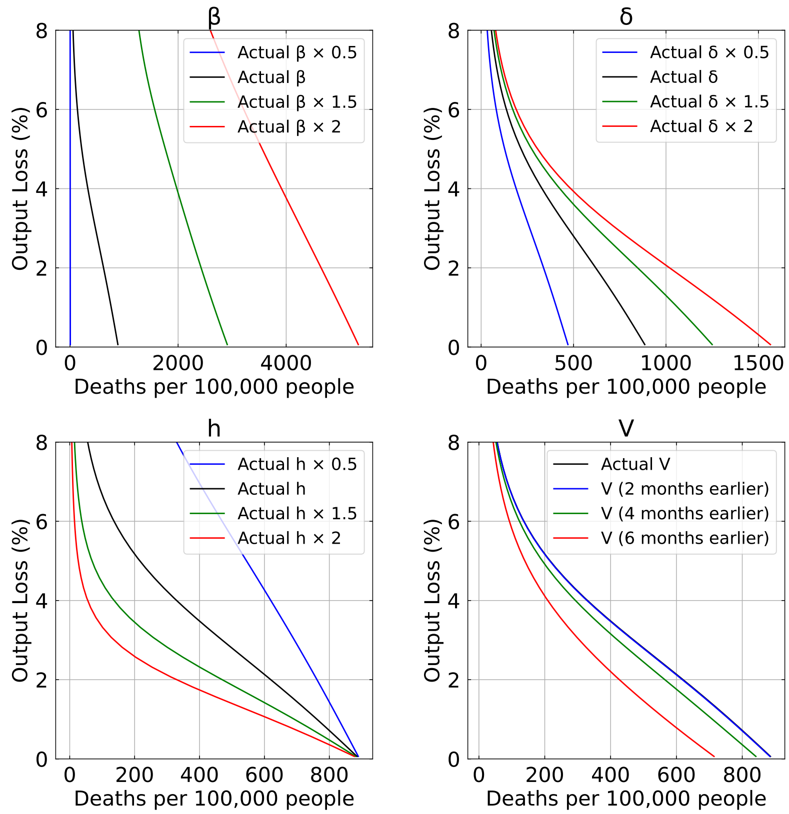
willingness to pay to reduce a COVID-19 death, differs across countries.

These conditional trade-off curves in Figure 6 can be interpreted as representing the constraint each country had faced when balancing economic activity and health outcomes of the pandemic.[11] 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 country experiences higher β_t or δ_t for all periods compared to another country, 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.

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 the United States. Figure 7 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

[11] Of course, there was a large degree of uncertainty about various factors affecting the conditional trade-off curve, and many policy decisions were made under imperfect information.

Figure 7: Comparative statics of structural parameters for the U.S.



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.

Figure 8 displays the estimated values of h with a 90% confidence interval for each coun-

Figure 8: Cross-country comparison of h (elasticity of mobility w.r.t output loss)

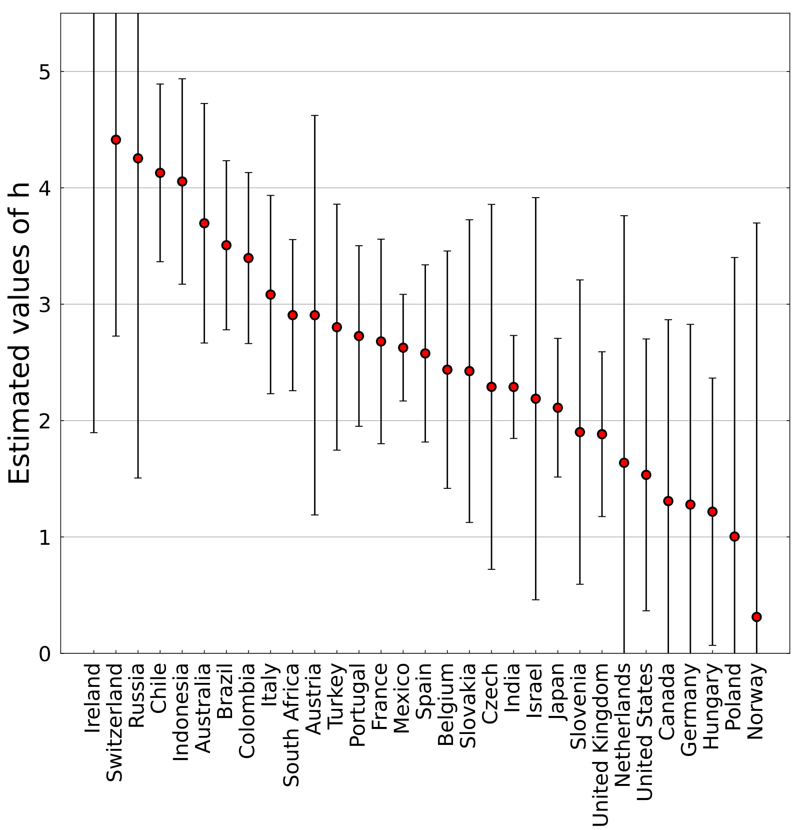


Table 1: MRS from monthly GDP data (in million USD of 2015)

Country	MRS	Country	MRS	Country	MRS
Norway	105.54	Poland	0.44	Czech	0.14
Japan	13.61	Austria	0.37	Italy	0.14
Australia	13.23	Turkey	0.32	Russia	0.13
Canada	2.19	France	0.27	India	0.1
Germany	1.70	Belgium	0.26	Chile	0.07
Netherlands	1.45	Hungary	0.26	Mexico	0.05
Israel	1.08	Spain	0.24	South Africa	0.05
United States	1.01	Slovakia	0.23	Brazil	0.04
Ireland	0.90	Indonesia	0.20	Colombia	0.03
United Kingdom	0.54	Slovenia	0.18		
Switzerland	0.49	Portugal	0.16		

Table 2: Distribution of MRS (in million USD of 2015)

Mean	Variance	50%	5%	95%
4.69	361.01	0.26	0.05	13.42

try.[12] There seems to be no systematic relationship between the value of h and characteristics of the country such as region or size.[13]

3.2 MRS

Table 1 summarizes the MRS between output loss and COVID-19 deaths for each country. Roughly speaking, these numbers can be interpreted as willingness to pay to reduce a COVID-19 death in each country. It is clear that there exists a considerable heterogeneity in MRS across countries. Some countries such as Japan and Australia exhibit a large MRS (13.61 and 13.23, respectively) while other countries like Colombia and Brazil exhibit a very small MRS (0.03 and 0.04, respectively).[14] The mean of MRS is 4.69 while the variance is 361.01. Since we translate the output loss into the constant USD, low-income countries show a lower MRS. Nonetheless, we still observe a large degree of heterogeneity even when adjusting these numbers by GDP per capita. See Appendix D for more details. Japan accepts a large economic loss to reduce COVID-19 deaths by government's non-pharmaceutical

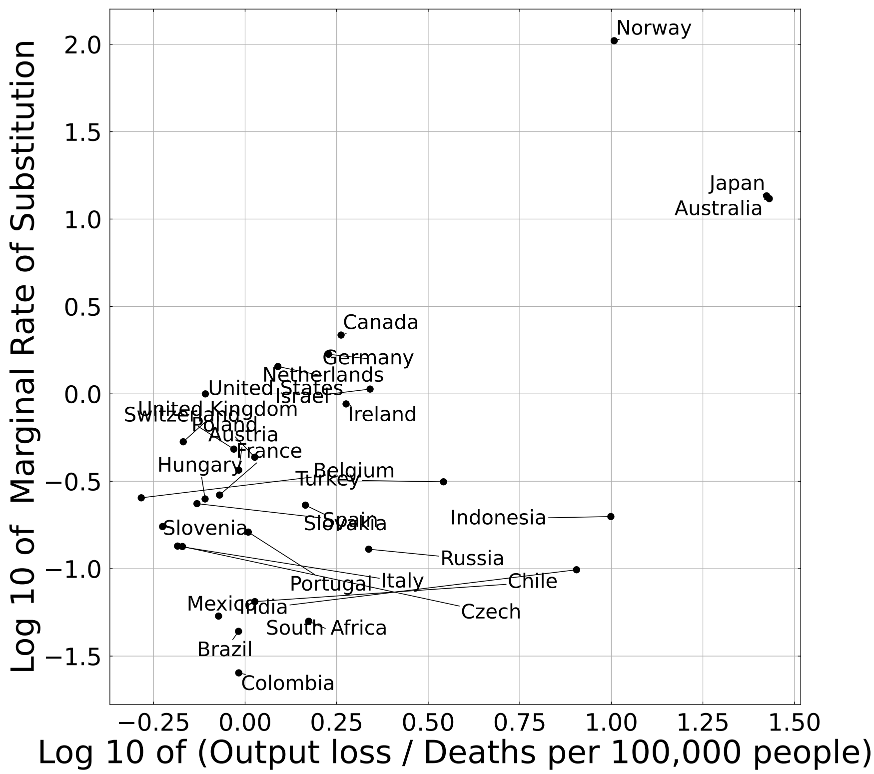
[12] We use the confidence interval of $\hat{h}_1$ normalized by $\hat{h}_0$ as described in 2.2.

[13] For some countries, the estimate of h is highly sensitive to the sample period due to a high volatility of the Google mobility data.

[14] Norway exhibits a very large MRS, but it is likely to be caused by a small estimate of h as shown in Figure 8. Since we cannot reject the null hypothesis of h being zero, caution is needed when interpreting the large MRS.

interventions (NPIs) or people's voluntary reduction of mobility. Hence, its realized pair of output loss and deaths tend to appear in the lower-right corner of the constraint curve.

Figure 9: MRS vs. output loss over deaths



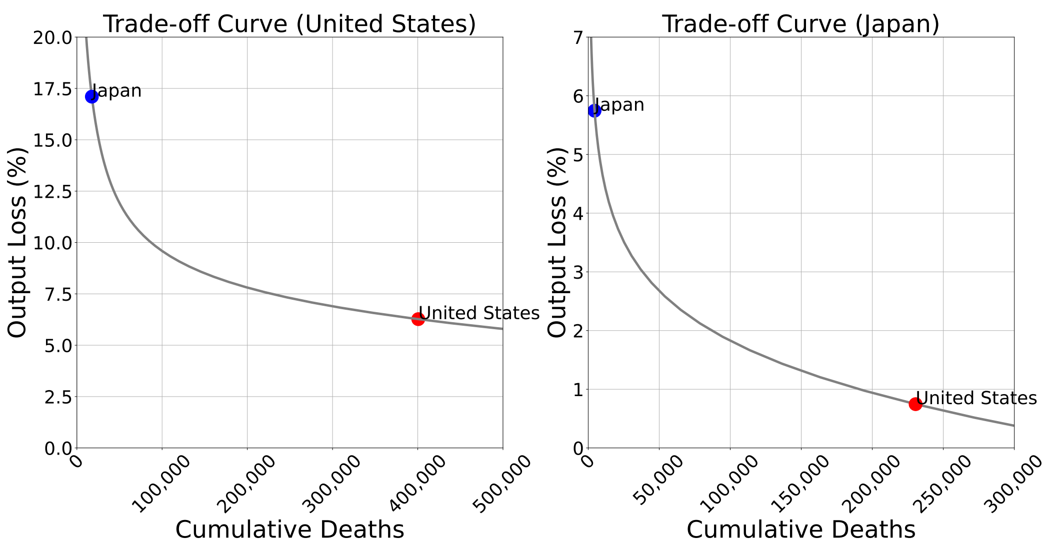
One may ask, why can't we just look at the output loss and cumulative deaths to infer the MRS? Figure 9 shows a scatterplot between the MRS and output loss/cumulative deaths across countries. If we winsorize the two outliers, Japan and Australia, correlation between these two measures are very weak. Even when those two countries are included, the correlation is not strong, indicating that our MRS estimates are something we cannot infer just by looking at output loss and deaths. Our model analysis traces out the trade-off curve passing through the realized pair of output loss and cumulative deaths for each economy as shown in Figure 6. Without a model, there is no way to compute the MRS.

3.3 The Role of the MRS

We can use our framework to better understand the sources of the outcome difference between any two countries. In this section, we present an analysis that quantifies the role of preference in generating the differences in health and economic outcomes.

In this analysis, we ask the following question: If policymakers or people in the U.S. had the same MRS as that of Japanese policymakers or people, what outcomes would have prevailed in the U.S.?[15] If we assume linearity of the indifference curve, we can answer this question by finding a point in the estimated tradeoff curve of the United States where the slope is the same as the Japanese MRS. The blue dot in the left panel of figure 10 indicates that point, whereas the red dot indicates the realized outcome in the U.S. The blue dot is associated with a larger output loss and a smaller number of COVID-19 deaths than the red dot, consistent with the aforementioned result that the MRS is higher in Japan than in the U.S. Quantitatively, this analysis shows just how important the difference in preference might be in explaining the difference in health and economic outcomes between Japan and the U.S. The output loss would have been bigger by 11 percent, and the number of deaths would have decreased by 380,000 people.

Figure 10: Conditional trade-off curves in the U.S. and Japan



The right panel of figure 10 answers the opposite question. If policymakers or people in Japan had the same MRS as that of policymakers or people in the U.S., what outcomes would have prevailed in Japan?[16] Comparison of the blue dot—the realized outcome in Japan—and the red dot—the hypothetical outcome—tells us that the number of cumulative deaths would have been substantially higher and output loss would have been substantially

[15]An alternative way of stating the same question is, of policymakers or people in Japan had faced the same conditional tradeoff as that in the U.S., how severe would they have restricted their economy and what would be the outcome for the number of COVID-19 deaths?

[16]An alternative way of stating the same question is, if policymakers or people in the U.S. had faced the same conditional tradeoff as that in Japan, how severe would they have restricted their economy and what would be the outcome for the number of COVID-19 deaths?

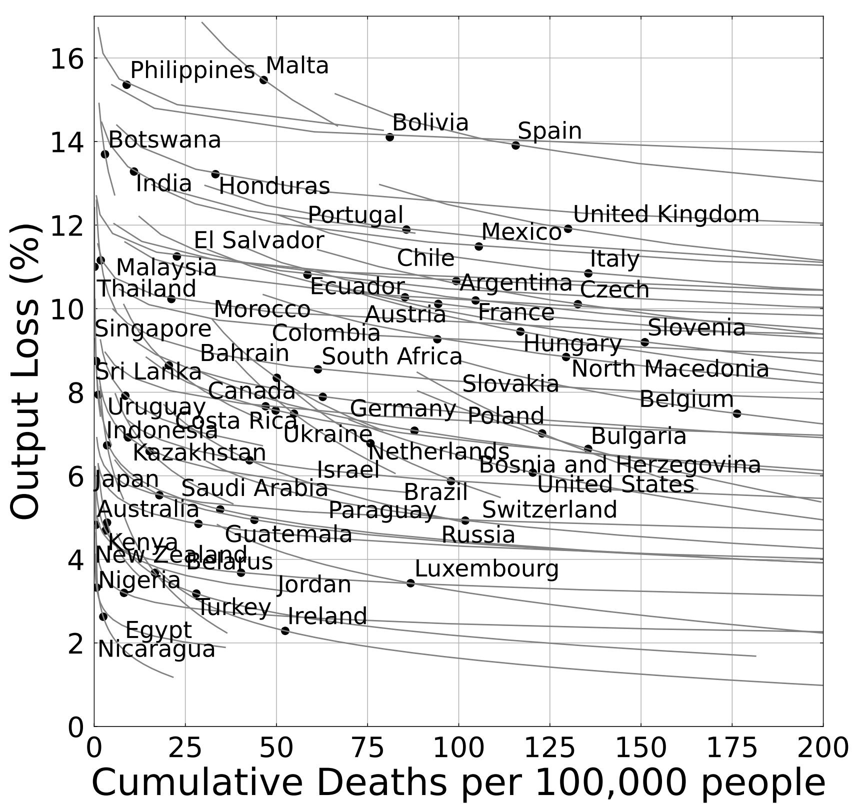
Table 3: Result of the Exercise for the United States and Japan

	Output loss (%)	Cumulative Deaths
United States (original)	6.27	400577
Japan (on the US tradeoff curve)	17.10	17574
United States (on the Japan's tradeoff curve)	0.75	230507
Japan (original)	5.75	4475

lower if Japan's MRS had been as low as that in the U.S. The output loss would have been smaller by five percent, and the number of deaths would have increased by 225,000 people, demonstrating that the difference in the MRS across two countries alone imply a large difference in health and economic outcomes.

3.4 Developing Countries

Figure 11: Conditional tradeoff curve: quarterly GDP



Source: The World Bank - Global Economic Monitor

Thus far, our analysis has been based on a set of countries for which a monthly economic indicator is available from the OECD. This set excludes a number of countries, particularly developing countries. In this section, we apply our framework to a larger number of countries in which quarterly GDP data is available from the World Bank Global Economic Monitor.[17]

Figure 11 shows the estimated conditional tradeoff curves for countries with quarterly GDP data.[18] As we saw in the quarterly data analysis, we see a large variation in the location and shape of the conditional tradeoff curve. .

Table 4: MRS from quarterly GDP data (in million USD of 2015)

Country	MRS	Country	MRS	Country	MRS
Thailand	255.29	Belarus	0.67	Russia	0.14
New Zealand	230.86	United Kingdom	0.64	Bosnia and Herzegovina	0.13
Singapore	165.97	Austria	0.52	India	0.12
Japan	16.05	Nicaragua	0.49	Costa Rica	0.12
Australia	15.26	Belgium	0.45	Paraguay	0.11
Malaysia	6.72	Spain	0.42	Chile	0.08
Botswana	3.35	France	0.39	Ecuador	0.06
Sri Lanka	3.06	Saudi Arabia	0.35	Mexico	0.06
Germany	2.64	Turkey	0.33	Argentina	0.06
Canada	2.49	Bulgaria	0.29	El Salvador	0.06
Netherlands	2.18	Slovenia	0.26	North Macedonia	0.06
Malta	1.80	Kenya	0.25	Guatemala	0.05
Luxembourg	1.60	Indonesia	0.25	South Africa	0.05
Ireland	1.58	Czech	0.25	Morocco	0.05
Bahrain	1.46	Hungary	0.24	Honduras	0.05
Uruguay	1.44	Italy	0.24	Brazil	0.05
Israel	1.42	Portugal	0.23	Ukraine	0.04
Nigeria	1.35	Slovakia	0.22	Jordan	0.03
United States	1.05	Poland	0.21	Colombia	0.03
Kazakhstan	0.96	Philippines	0.21	Bolivia	0.02
Switzerland	0.83	Egypt	0.15	Peru	0.01

[17] There are 68 countries that have available quarterly GDP data from Q1 of 2008 to Q1 of 2021 with adequate data on mobility, new cases, new deaths, and vaccinations. There are pros and cons for using quarterly GDP data for our counterfactual analysis. The pro is that we have available countries for twice as many countries as that in the OECD Economic Indicator

[18] Only the tradeoff curves with positive VoL are plotted. The tradeoff curves with negative MRS are removed.

Table 5: Distribution of MRS (in million USD of 2015)

Mean	Variance	50%	5%	95%
11.52	2229.83	0.26	0.03	15.97

Table 4 displays the MRS for countries with quarterly GDP data. Again, there is a large heterogeneity in the MRS, as we saw earlier in the analysis based on monthly data. Singapore or New Zealand exhibit a very large MRS. These countries imposed strict city-wide lockdowns even when there were a few positive cases of COVID-19. On the other hand, many Latin American countries have small MRS. Table 5 shows the distribution of the MRS in Table 4. As in Table 2, we can confirm a large variance indicating a large degree of heterogeneity in MRS.

One concern with this analysis is that there is less information about economic fluctuations in a quarterly data than in a monthly data and that the results would be less precise. Fortunately, as explained in Appendix C, it turns out that the estimates of MRS from monthly GDP and quarterly GDP are strongly correlated among countries with both quarterly and monthly data, indicating that the analysis based on quarterly GDP data is a reliable alternative to the analysis based on monthly economic data.

4 Conclusion

There is a large heterogeneity in health and macroeconomic outcomes across countries during the COVID-19 pandemic. Based on a parsimonious macro-SIR model and the idea of revealed preferences, we have provided a novel framework to understand the source of this heterogeneity. Our framework allows us to decompose the difference in health and macroeconomic outcomes across countries into two components: preferences (MRS) and the constraint.
We find that there is a large heterogeneity in both components. Some countries such as Japan or Australia would accept a large output loss to reduce the number of deaths. The values of MRS might be informative in predicting each country's recovery from the COVID-19 pandemic as well as their infection control policies when the next pandemic occurs. Countries with a large MRS are likely to adopt a careful and gradual process towards normalization of their economy and may be willing to accept a large economic loss again in the next pandemic.

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Appendix

A Sensitivity with respect to the power of matching function k

Figure 12: Sensitivity analysis: power of matching function k

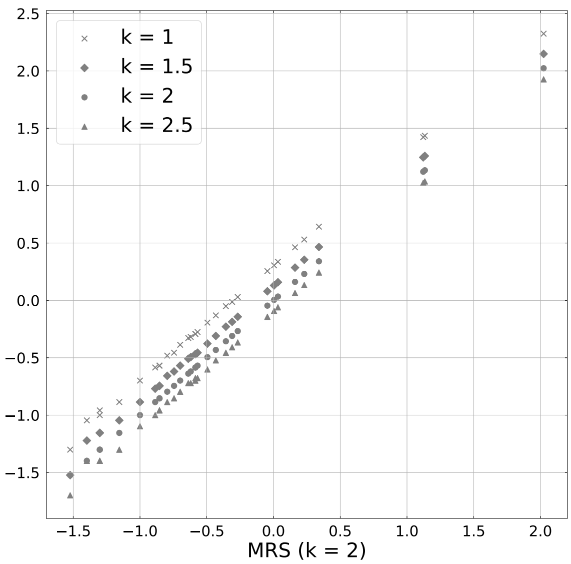


Figure 12 plots the log of MRS from the baseline model ($k = 2$) on the x-axis and the log of MRS from our model with different values of k. We see that the power of matching function k alters the values of MRS uniformly and does not change the ranking of the MRS.

Figure 13: End of sample period: March 2021

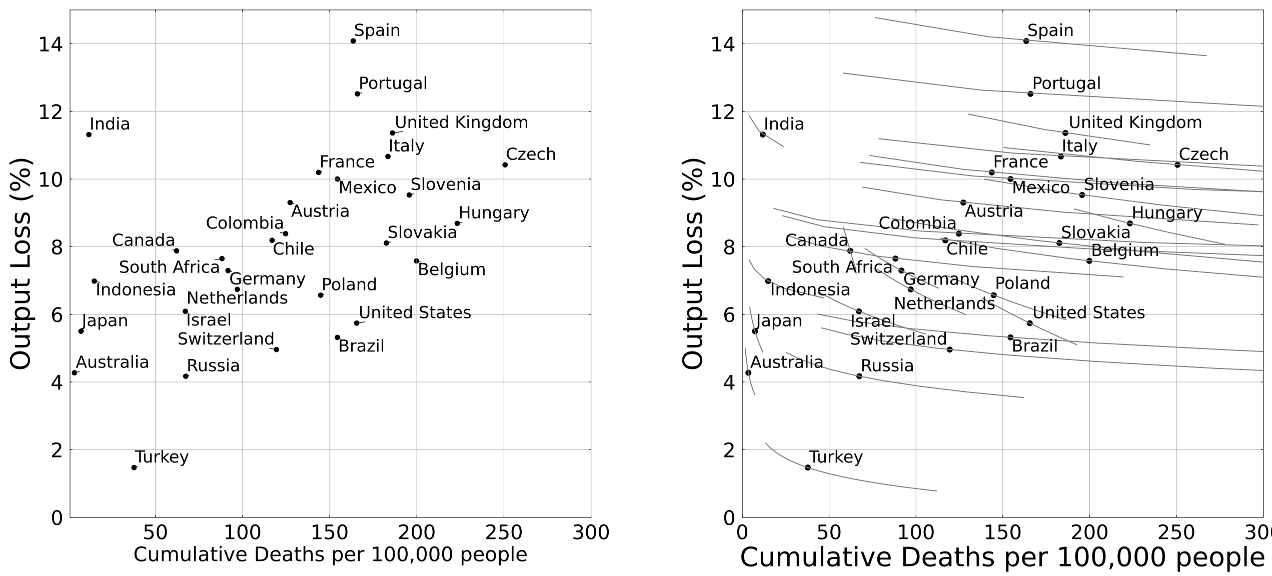


Figure 14: End of sample period: June 2021

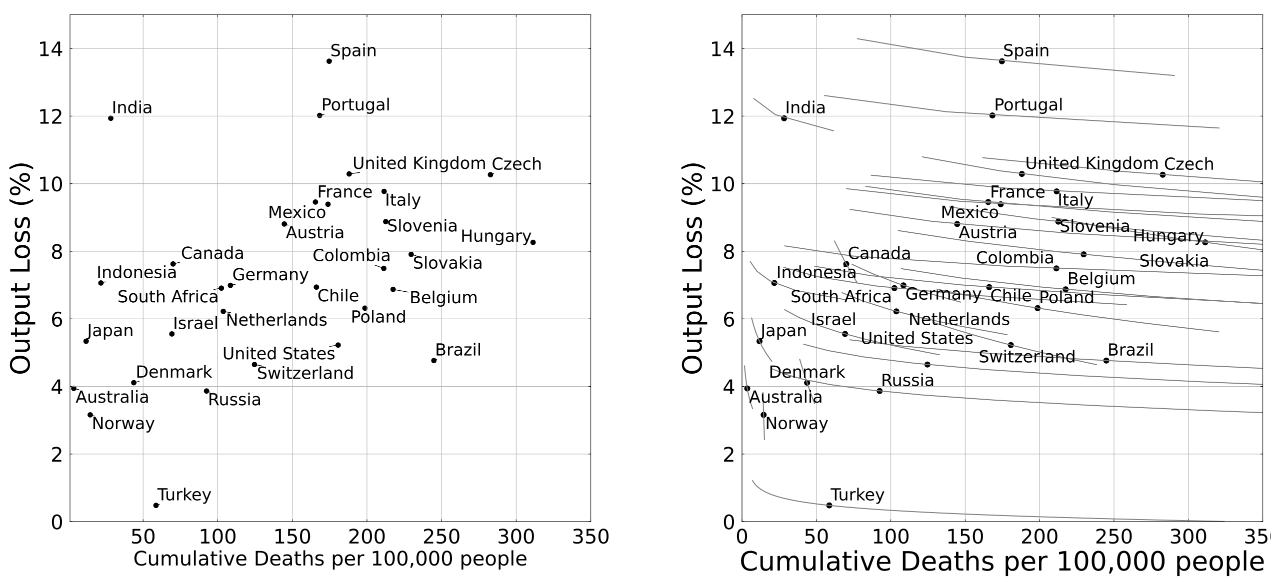


Figure 15: End of sample period: September 2021

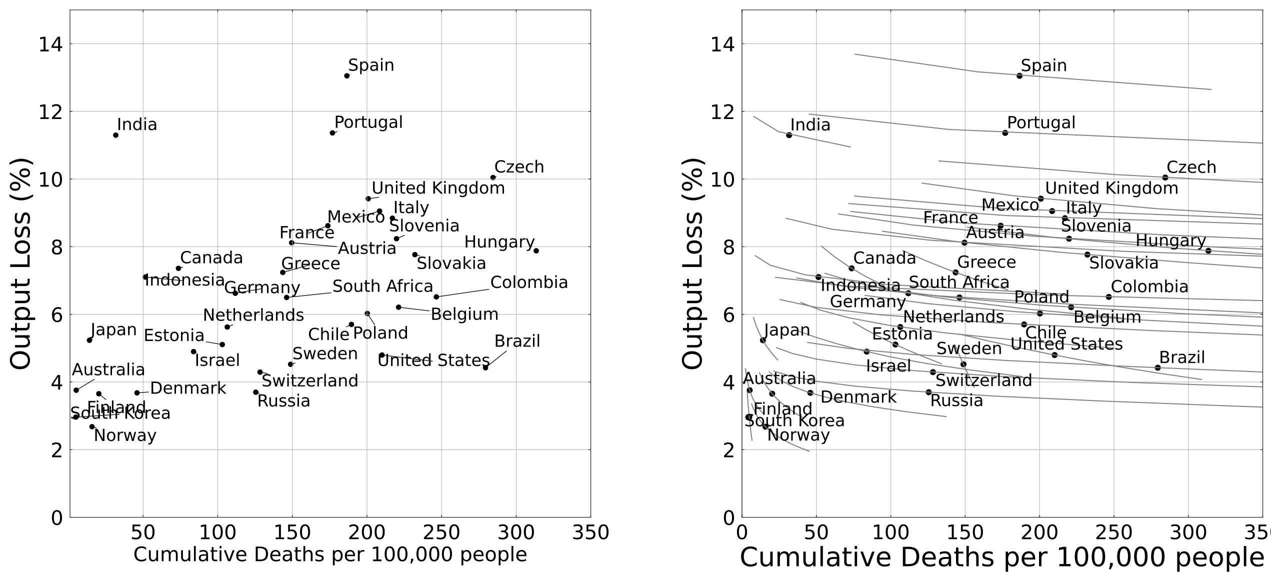
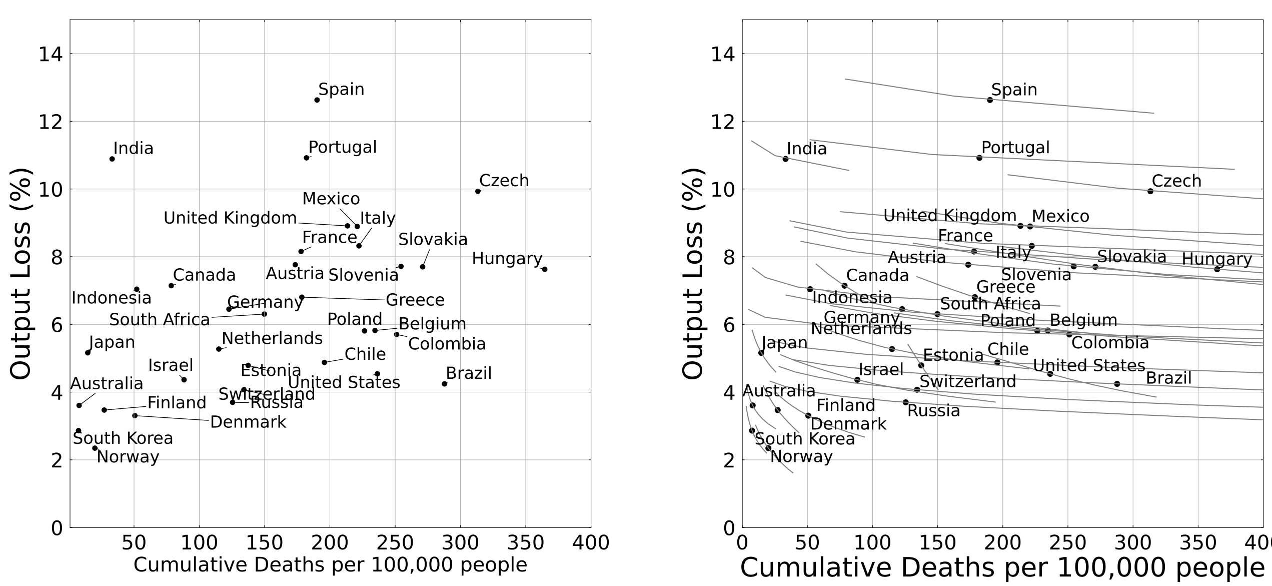


Figure 16: End of sample period: November 2021



B Sensitivity of MRS with different sample periods

Table 6: MRS (in million USD of 2015) by March 2021

Country	MRS	Country	MRS	Country	MRS
Australia	16.36	Austria	0.31	Italy	0.12
Canada	9.07	Belgium	0.29	Czech	0.1
Japan	7.40	Turkey	0.24	India	0.1
United States	1.75	France	0.24	Portugal	0.09
Netherlands	1.56	Hungary	0.23	Chile	0.06
Germany	1.35	Slovenia	0.21	South Africa	0.04
Israel	0.95	Spain	0.18	Mexico	0.04
Switzerland	0.55	Indonesia	0.14	Brazil	0.04
United Kingdom	0.45	Slovakia	0.12	Colombia	0.02
Poland	0.35	Russia	0.12		

Table 7: MRS (in million USD of 2015) by June 2021

Country	MRS	Country	MRS	Country	MRS
Norway	148.85	Austria	0.29	Czech	0.1
Australia	18.73	Belgium	0.24	Turkey	0.08
Denmark	10.76	France	0.23	Russia	0.07
Canada	5.14	Spain	0.19	Chile	0.07
Japan	4.88	Slovenia	0.18	India	0.05
United States	0.96	Poland	0.15	South Africa	0.04
Germany	0.91	Hungary	0.14	Mexico	0.04
Netherlands	0.84	Slovakia	0.12	Brazil	0.03
Israel	0.69	Italy	0.11	Colombia	0.02
Switzerland	0.53	Indonesia	0.11		
United Kingdom	0.39	Portugal	0.10		

Table 8: MRS (in million USD of 2015) by September 2021

Country	MRS	Country	MRS	Country	MRS
South Korea	24.10	Netherlands	0.54	Czech	0.09
Australia	12.66	Greece	0.53	Hungary	0.09
Sweden	9.03	Switzerland	0.47	Poland	0.08
Norway	5.54	United Kingdom	0.35	Chile	0.05
Japan	4.68	Austria	0.23	Russia	0.05
Finland	4.00	Belgium	0.21	Indonesia	0.04
Canada	2.06	France	0.20	India	0.04
Denmark	1.34	Spain	0.19	Mexico	0.03
United States	0.88	Slovenia	0.12	South Africa	0.03
Estonia	0.72	Slovakia	0.12	Brazil	0.03
Israel	0.69	Italy	0.10	Colombia	0.01
Germany	0.55	Portugal	0.09		

Table 9: MRS (in million USD of 2015) by November 2021

Country	MRS	Country	MRS	Country	MRS
Australia	7.65	Switzerland	0.55	Hungary	0.1
Norway	7.19	Greece	0.44	Poland	0.09
South Korea	5.89	United Kingdom	0.40	Russia	0.05
Japan	4.59	Austria	0.30	Chile	0.05
Finland	4.29	Belgium	0.25	Indonesia	0.04
Estonia	2.31	France	0.22	India	0.04
Denmark	2.20	Spain	0.21	Mexico	0.03
Canada	2.10	Slovenia	0.19	South Africa	0.03
United States	1.20	Slovakia	0.18	Brazil	0.03
Netherlands	0.79	Czech	0.13	Colombia	0.01
Israel	0.72	Italy	0.11		
Germany	0.56	Portugal	0.10		

C MRS from monthly GDP and quarterly GDP

Figure 17: Monthly GDP vs. Quarterly GDP

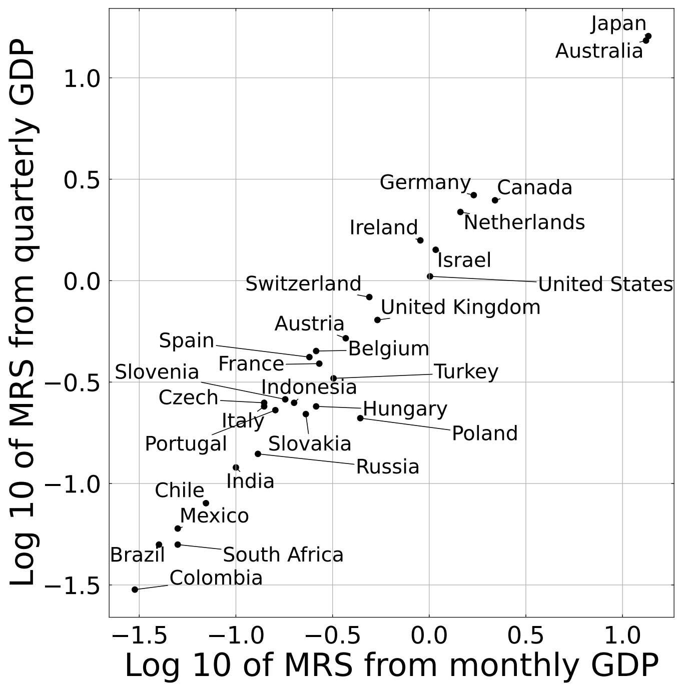


Figure 17 displays the scatterplot of the log of MRS estimated by monthly GDP and by quarterly GDP for the countries where both data are available. We confirm a strong positive correlation between the two measures. Hence, we can obtain a good approximation of MRS for countries where only quarterly GDP data are available.

D MRS in years of annual income

Table 10: MRS from monthly GDP data (years of annual income)

Country	MRS	Country	MRS	Country	MRS
Norway	1380.99	United States	16.45	France	6.7
Japan	371.30	Hungary	16.00	Czech	6.48
Australia	244.71	Russia	12.84	Belgium	5.91
Indonesia	50.91	Slovakia	12.45	Mexico	5.48
India	48.77	United Kingdom	11.23	Switzerland	5.47
Canada	47.80	Ireland	11.19	Brazil	5.05
Germany	38.70	South Africa	8.27	Chile	4.65
Netherlands	28.81	Spain	8.18	Italy	4.2
Poland	28.05	Austria	7.88	Colombia	3.98
Israel	27.30	Portugal	7.26		
Turkey	25.98	Slovenia	7.00		

Numbers shown in Table 10 are the MRS of Table 1 divided by each country's GDP per capita. We can interpret them as the MRS in years of average annual income in each country. Table 11 corresponds to Table 4.

Table 11: MRS from quarterly GDP data (years of annual income)

Country	MRS	Country	MRS	Country	MRS
Thailand	36989.09	Netherlands	43.39	Czech	11.95
New Zealand	5534.42	Egypt	37.69	Slovakia	11.66
Singapore	2470.53	Israel	35.73	Ecuador	11.04
Sri Lanka	684.50	Bulgaria	33.68	Austria	10.89
Nigeria	569.42	Turkey	27.00	Belgium	10.37
Malaysia	569.36	Bosnia and Herzegovina	22.30	North Macedonia	10.26
Botswana	471.32	Ireland	19.29	Slovenia	10.20
Japan	434.12	Paraguay	18.72	Portugal	10.17
Australia	282.26	Ukraine	18.70	France	9.87
Nicaragua	252.22	Honduras	18.47	Switzerland	9.26
Kenya	157.69	Saudi Arabia	17.80	Costa Rica	9.03
Belarus	103.45	United States	17.17	South Africa	8.78
Kazakhstan	84.42	Morocco	16.41	Jordan	7.65
Uruguay	79.64	Hungary	15.20	Italy	7.48
Bahrain	70.75	Luxembourg	14.78	Mexico	6.49
Indonesia	63.06	El Salvador	14.67	Chile	5.80
Malta	60.33	Spain	14.27	Brazil	5.37
Germany	60.08	Russia	13.87	Bolivia	4.92
India	58.59	Guatemala	13.53	Colombia	4.45
Philippines	54.31	United Kingdom	13.36	Argentina	4.41
Canada	54.15	Poland	13.16	Peru	2.03