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Between lives and economy: Optimal COVID-19 containment policy in open economies

Wen-Tai HSU
Singapore Management University, WENTAIHSU@smu.edu.sg

Hsuan-Chih Luke LIN

YANG Han

Between Lives and Economy: Optimal COVID-19 Containment Policy in Open Economies*

Wen-Tai Hsu† Hsuan-Chih (Luke) Lin‡ Han Yang§

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Abstract

This paper studies optimal containment policy for combating a pandemic in an open-economy context. It does so via quantitative analyses using a model that incorporates a standard epidemiological compartmental model in a multi-country, multi-sector Ricardian model of international trade with full-fledged input-output linkages. We devise a novel approach in computing optimal national policies in the long run, and contrast these policies with a baseline in which countries maintain their current policies until vaccine availability. The welfare gains under optimal policies are asymmetric as the gains for the set of countries which should tighten up the containment measures are much larger than those which should relax. We also find that the welfare implications of optimal policies in open economies differ significantly from those in closed ones.

Keywords: COVID-19, pandemic, welfare analysis, containment policy, optimal policy, open economy, trade, input-output linkages

JEL Classification: I18; F11; F40; E27

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†School of Economics, Singapore Management University. Email: wentaihsu@smu.edu.sg.

‡Institute of Economics, Academia Sinica, Taiwan. Email: linhc@econ.sinica.edu.tw.

§Institute of Economics, Academia Sinica, Taiwan. Email: hanyang@econ.sinica.edu.tw.

1 Introduction

One of the most important questions in a pandemic such as the one we are facing, COVID-19, is how stringent the containment policies should be. There are heated debates on this in many countries, and the large cross-country variation in the stringency of containment policies is apparent. The key tradeoff is obvious: lives vs economy. But striking the right balance is not a simple task due to the complexity of the economy and its delicate interaction with the epidemiological evolution of the disease. There has been a surge of research on optimal containment policy in macroeconomics literature, but these studies are mostly, if not all, in closed-economy contexts. As the global economy is inter-linked across countries, a country's containment policy may have repercussions on other countries' economies through various trade linkages, which may in turn affect the considerations of other countries' containment policies and the ensuing health outcomes.

This paper attempts to answer questions regarding optimal containment policy in an open-economy context. We do so by conducting quantitative analyses using a model that incorporates a standard epidemiological compartmental model (**S**usceptible-**I**nfected-**R**ecovered; SIR) in a multi-country, multi-sector Ricardian model of international trade with full-fledged input-output linkages (Eaton and Kortum (2002) and Caliendo and Parro (2015)). In particular, our model builds on that of Caliendo and Parro (2015); key additions are the modeling of how the pandemic shocks different sectors and countries differently due to the heterogeneity in containment policy and work-from-home (WFH) capacity. To compute optimal policies in such a multi-country, multi-sector, multi-period framework in which containment policies may interact across countries, the key challenge is to devise a reasonable and tractable approach to reduce the huge space of candidate policies so as to compute optimal policies efficiently.

Our welfare measure is equivalent to the sum of individual expected utilities, which are concerned with risks in a pandemic, as, ex ante, no one knows how he/she would fare during the pandemic. In the special case where people are risk-neutral, our welfare measure is reduced to real income, and the cost of death is simply the long-run loss in real income due to the loss of labor endowment. Under general risk aversion, an increase in the probabilities of death or infection worsens welfare, ceteris paribus.

We calibrate the model to the pre-COVID-19 economy mainly using the World Input-Output Database (WIOD). We use official data on the number of confirmed cases to estimate each country i's *basic reproduction number* $R_{0,i}$, taking into account the effects of containment policies on disease spread. We then use these estimated $R_{0,i}$ to back out key country-specific parameters of disease transmission at the workplace and through general activities.

Based on the calibrated model, we first simulate the losses in welfare and real income due to the COVID-19 shocks by comparing the economy under these shocks (which are inclusive of the epidemiological evolution, the history of containment policies, and work-from-home capacity) with an economy which runs as if there were no such shocks from January 1 to July 22.[1] The average loss of welfare and real income, weighted by population, are 37.0% and 19.5%, respectively. Interestingly, the ranking of the welfare losses is not the same as that of the income losses, because countries differ substantially in their time volatility in real income, which matters for welfare due to risk aversion.

Our first question on containment policy is how countries would fare differently from the onset of the disease until now,[2] if alternative polices had been adopted. To this end, we experiment with South Korea's policy, as it has often been heralded as one of the successful stories in combating COVID-19. As the speed of disease spread can be essentially summarized by the *effective reproduction number* R_e, which is the central concern of the epidemiologists and doctors who lead governments' responses, we choose South Korea's average effective reproduction number as the policy target for other countries in the counter-factual. We find that most countries suffer in both welfare and real income up to now even more if they adopt South Korea's policy. In other words, South Korea's policy is too stringent for them. For the 42 countries in our sample as a whole, adopting Korean policy adds 3.6% and 4.9% to the welfare and real-income losses under the actual policies, respectively.

To consider the long-run effects of containment policies and compare with optimal policies, we assume a baseline in which countries maintain their current policies until vaccine availability. Similar to our Korean-policy experiment, our investigation of optimal policies uses effective reproduction number R_e as the policy target, instead of optimizing over the entire time path of policies which is infeasible in this quantitative model, with its rich cross-section interactions across countries, sectors, and input-output linkages. As mentioned, it is also a reasonable target/representation since R_e reflects the speed of disease spread and is the central concern for epidemiologists and doctors who lead government responses. Moreover, targeting R_e implies that the containment measures should be stringent initially and generally become more lenient over time, which is a pattern found in several recent studies in the macroeconomic literature which focus on the dynamics of optimal policies in closed-economy contexts; see, e.g., Alvarez

[1] The measure of containment policy is taken from the Government Response Index from Oxford COVID-19 Government Response Tracker (OxCGRT; Hale et al. (2020)). The country-sector-specific WFH capacities are constructed from the data from Dingel and Neiman (2020). July 22 was the last date of the Government Response Index available for our sample of countries when this paper was written.

[2] Actually until July 19, 2020, the last date on which the containment-measure data is available for all of our sample countries when this paper was written.

et al. (2020) and Jones et al. (2020).

We compute optimal policies in two steps. In the first step, we consider a global social planner who seeks to maximize global welfare by deciding on an effective reproduction number that applies to all countries. In this step, we find that most countries' welfare and real income improves under an optimal uniform R_e, and in terms of global welfare and real income, there is an interesting divergence when the policy is laissez-faire. In this case, there is actually a gain in real income compared with the baseline, even though this is still sub-optimal, as the optimal one requires a relatively stringent policy. But the welfare loss compared with the baseline under the laissez-faire policy is substantial, which indicates that the effect of the time volatility of real income in a short period (a two-year-plus period) caused by the pandemic on the long-run welfare is significant under risk aversion.

In the second step, we solve each country's optimal effective reproduction number $R_{e,i}$ given other countries' optimal choices $R_{e,-i}$; this is, indeed, a Nash equilibrium of national optimal policies. Information from the first step helps ease the computational burden in this step as it suggests how the grid search can be efficiently conducted. The first main result is that all countries' welfare and real income improve by adopting the optimal policies, and some countries should relax their containment measures whereas others should tighten up. This is in stark contrast to the short-run results of matching Korean policy. For the set of countries which should tighten up to match optimal policies, they suffer from short-run losses when also tightening up to match Korean policy. This contrast highlights the cost of mortality in the long run as it is a sudden and permanent loss of labor and consumption. Moreover, as the psychological cost of mortality is intentionally left out of the model, our results suggest that when it is incorporated, those countries which should tighten up should definitely tighten up even more, whereas the conclusions for those which should relax might become ambiguous.

The second main result is that the welfare gains are much larger for those which need to tighten up than those which need to relax. Long-run cost of mortality factors in both the real income and welfare, but it weighs more in welfare because a larger probability of death worsens the expected utility (probabilities of different states do not matter in real income). For the countries which need to relax, there would be more deaths, and, in welfare terms, this negative side is amplified to offset some of the positive gains in increased production and consumption to entail relatively small welfare gains. For the countries which need to tighten up, more lives are saved, and this increases the countries' (long-run) real income despite the loss in production and consumption from those who are alive due to more stringent policies. The positive gains in real income due to saved lives are amplified to entail large welfare gains.

To examine the role of international trade in optimal policies, we also compute optimal policies when countries are shut down to autarkies. In this scenario, as there are no links between countries' containment policies, the so-computed optimal policies are actually those in closed economies. For more countries than not, open economies imply a more stringent policy. Optimal policies in open economies differ substantially from those in closed economies in welfare terms, as the difference in welfare improvement between the two scenarios relative to the welfare improvement in open economies is 112%. Excluding Luxembourg, which is an outlier due to its high trade dependence, the relative difference remains high at 65%.

As we choose to work with a trade model with full-fledged input-output linkages, it is also natural to ask whether incorporating these linkages is quantitatively relevant. For more countries than not, incorporating input-output linkages also implies a more stringent policy. The quantitative importance of this incorporation is of similar order of magnitude to the previous exercise on international trade.

Related Macro Literature. There has been a surge of research from macroeconomic perspectives studying optimal containment policies: these studies embed variants of the classic SIR model proposed by Kermack et al. (1927) into macroeconomic models to study various aspects of the tradeoff between lives and economy. See, for examples, Acemoglu et al. (2020), Alvarez et al. (2020), Atkeson (2020), Eichenbaum et al. (2020), Farboodi et al. (2020), Jones et al. (2020), Krueger et al. (2020), and Piguillem and Shi (2020). In particular, Eichenbaum et al. (2020) investigate how individuals cut down on consumption and work to reduce the severity of the epidemic, and find that the best containment policy increases the severity of the recession, but can save roughly half a million lives in the U.S. Jones et al. (2020) assume that the government cares about two externalities: an infection externality and a health-care externality, and find that it is optimal to adopt a front-loaded containment policy. Acemoglu et al. (2020) focus on the heterogeneity in health risk across different sub-populations, and show that targeted policies and increasing testing and isolation better minimize economic losses and deaths. Krueger et al. (2020) highlight the role of sectoral heterogeneity in WFH and consumption substitutability across sectors in mitigating both economic losses and the spread of disease.

Our work differs from all of the above in our focus on analyzing optimal containment policies in an open-economy context; we are not aware of any other work that does the same, as of the date when this paper was written.

Related Trade Literature. Closely related are Bonadio et al. (2020) and Sforza and Steininger (2020), who have both studied the role of international input-output linkages in transmitting foreign pandemic shocks on domestic economies. However, these studies do not incorporate disease dynamics or analyze optimal containment policies, which are our main focuses. More broadly related are the studies by Antrás et al. (2020), Fajgelbaum et al. (2020), and Argente et al. (2020) who have all considered disease dynamics in a general equilibrium model of trade. Antrás et al. (2020) analyze the complex interactions between trade and disease dynamics as international business travel helps transmit the disease. Fajgelbaum et al. (2020) study the optimal lockdown problem when different districts of a city can adopt different degrees of lockdown. Also in a city context, Argente et al. (2020) study the role of information disclosure in mitigating the disease spread within the city, and find that the associated economic cost is substantially lower than a city-wide lockdown. Our work differs from Antrás et al. (2020) mainly due to our focus on optimal containment policies, and it differs from Fajgelbaum et al. (2020) and Argente et al. (2020) by our focus on country-level containment policies and the role of trade on optimal policies.

The rest of the paper is organized as follows. Section 2 describes the model, Section 3 introduces the data and how the model is calibrated, Section 4 presents the quantitative analyses on containment policies, and Section 5 concludes.

2 Model

This section introduces our model, which essentially incorporates the evolution of the pandemic and the labor productivity shocks arising from the pandemic into a Caliendo and Parro (2015) trade model, a general equilibrium Eaton and Kortum (2002) model with multiple sectors and full-fledged input-output linkages.

2.1 Preference

There are K countries, each of which has a population of $N_i, i \in \{1, 2, ..., K\}$. There are J sectors, each of which consists of a unit continuum of varieties. The final-good consumption of an individual in country i in period t, $q_{i,t}$, consists of a Cobb-Douglas bundle of sectoral goods $q_{i,t}^{F,j}$:

$$q_{i,t} = \prod_{j=1}^{J} (q_{i,t}^{F,j})^{\alpha_i^j},$$

where α_i^j is the consumption expenditure share of country i's consumers on sector-j good, and each sectoral good is made of a CES composite:

$$q_{i,t}^{F,j} = \left[\int_0^1 q_{i,t}^{F,j}(\omega)^{\frac{\kappa-1}{\kappa}} d\omega \right]^{\frac{\kappa}{1-\kappa}}, \tag{1}$$

where $q_{i,t}^{F,j}(\omega)$ is the amount of variety ω used for final-consumption purposes, and $\kappa > 1$ is the elasticity of substitution. The life-time utility of an individual (in a dynastic sense) is given by

$$u_i = \sum_{t=0}^{T} \rho^t u\left(q_{i,t}\right),$$

where T is either a positive integer or infinity, ρ is the discount factor, and u is a concave and strictly increasing function.

2.2 Production

Labor is the fundamental input for production, and the production in each sector potentially uses intermediate inputs from all sectors. Countries differ in their productivities across sectors and varieties. Production technology exhibits constant returns to scale. Both the goods and factor markets are perfectly competitive. Let $M_{i,t}^j(\omega)$ denote the use of the composite intermediate goods by the firms producing variety ω in sector j and in country i; it is made of a Cobb-Douglas composite:

$$M_{i,t}^j = \prod_{l=1}^{j} (q_{i,t}^{M,l})^{\gamma_i^{j,l}}, \tag{2}$$

where the sectoral good $q_{i,t}^{M,l}$ is made by the same CES aggregator across varieties as in (1) with the inputs being $q_{i,t}^{M,j}(.)$. Note that each sector j's intermediate composite's expenditure share on sector l's good, $\gamma_i^{j,l}$, is country-specific.

Denote a country-sector-time-specific pandemic shock parameter on the production function by $B_{i,t}^j$, which will be specified later; for the pre-COVID-19 economy, this term drops out as $B_{i,t}^j = 1$. The production function of a variety ω in sector j and country i is given by

$$y_{i,t}^j(\omega) = \frac{z_i^j(\omega)\left[B_{i,t}^j L_{i,t}^j(\omega)\right]^{\beta_i^j} M_{i,t}^j(\omega)^{1-\beta_i^j}}{(\beta_i^j)^{\beta_i^j}(1-\beta_i^j)^{1-\beta_i^j}}, \tag{3}$$

where $L_{i,t}^j(\omega)$ is the labor hired for this variety, β_i^j is the labor share, and the Hicks-neutral productivity $z_i^j(\omega)$ is drawn *i.i.d.* from a Fréchet distribution: $\Pr(x < z) = \exp(-T_i^j z^{-\theta})$, where $T_i^j > 0$ is the country-sector-specific scaling parameter and $\theta > 1$ is the shape parameter. The draws are also independent across countries and sectors. The denominator of the production function (3) is simply a normalizing constant for a clean expression of the unit cost; it is a normalization as it is isomorphic to the scaling parameter T_i^j, which will be calibrated for our quantitative analysis.

The trade cost is of the standard iceberg-cost form: to deliver one unit of sector-j variety from country i to country n, $\tau_{i,n}^j \geq 1$ units are required to ship. We assume that trade is balanced. The unit cost of delivering a good from country i to country n is $c_{i,t}^j \tau_{i,n}^j / z_{i,t}^j(\omega)$, where

$$c_{i,t}^j = \left(\frac{w_{i,t}}{B_{i,t}^j} \right)^{\beta_i^j} (P_{i,t}^{M,j})^{1-\beta_i^j}, \tag{4}$$

where $w_{i,t}$ and $P_{i,t}^{M,j}$ are country i's wages and its sector j's price for obtaining the intermediate input bundle specified in (2), respectively. Here, $c_{i,t}^j$ is indeed the unit cost to produce a sector j variety under unit productivity.

In this environment with perfect competition and constant returns to scale, prices equal the (delivered) marginal costs, and each country n buys from the cheapest source:

$$p_{n,t}^j(\omega) = \min_i \left\{ \frac{c_{i,t}^j \tau_{i,n}^j}{z_{i,t}^j(\omega)} \right\}. \tag{5}$$

Standard derivation yields the CES price indices for sectoral goods:

$$P_{i,t}^j = \left(\int_0^1 p_{i,t}^j(\omega)^{1-\kappa} \right)^{\frac{1}{1-\kappa}}. \tag{6}$$

Consequently, the price index of an intermediate good bundle in country i and for sector j is

$$P_{i,t}^{M,j} = \prod_{l=1}^{J} \left[P_{i,t}^l \right]^{\gamma_i^{j,l}}, \tag{7}$$

and the price index for the final good is

$$P_{i,t} = \prod_{j=1}^{J} \left[P_{i,t}^j \right]^{\alpha_i^j}. \tag{8}$$

The input-output linkage structure implies a circular feature such that the price indices of intermediate goods depend on the price indices of sectoral goods via (7), which in turn depend on the price indices of intermediate goods via (4–6).

2.3 Pandemic and Economy

This subsection introduces how epidemiology is incorporated into our model.

2.3.1 An SIR Model

We incorporate a standard epidemiological model, i.e., an SIR model, as follows. At any period t, the population of country i, N_i consists of people who are **S**usceptible ($S_{i,t}$, people who have not been exposed to the disease), **I**nfectious ($I_{i,t}$, people who have contracted the disease), **R**ecovered ($R_{i,t}$, people who have recovered and are immune), and **D**eceased ($D_{i,t}$, died from the disease). That is, $N_i = S_{i,t} + I_{i,t} + R_{i,t} + D_{i,t}$.

The epidemiology is characterized by

$$
\begin{aligned}
S_{i,t+1} &= S_{i,t} - T_{i,t} \\
I_{i,t+1} &= I_{i,t} + T_{i,t} - (\pi^r + \pi^d_{i,t}) I_{i,t} \\
R_{i,t+1} &= R_{i,t} + \pi^r I_{i,t} \\
D_{i,t+1} &= D_{i,t} + \pi^d_{i,t} I_{i,t},
\end{aligned}
$$

where π^r and $\pi^d_{i,t}$ are the probabilities of recovering from the infectious status in a period t and of death, respectively, and $T_{i,t}$ is the number of newly infected people. To capture the fact that the strain of the number of infectious people on the medical system generally increases the mortality rate $\pi^d_{i,t}$, we assume

$$\pi^d_{i,t} = \pi^d + \delta \times \frac{I_{i,t}}{N_i}, \tag{9}$$

where $\delta > 0$ and π^d is the base mortality rate. This linear form is also assumed by Alvarez et al. (2020). It is simple, but as the plots of actual morality rates against the fraction of infectious people in various countries can be either concave, convex, or approximately linear, a simple linear form is a reasonable compromise.

2.3.2 Containment Policy and Work from Home

Next we link the SIR model back to our macro-trade environment. As deaths reduce the labor force, and infections negatively affect individuals' labor supply, the effective labor force at time t is

$$L_{i,t} = S_{i,t} + R_{i,t} + \alpha^I I_{i,t}, \tag{10}$$

as $1 - \alpha^I$ fraction of labor time is lost from contracting the disease. Before any considerations on the containment policy and the ability to work from home, the number of newly infected is given by

$$T_{i,t} = \frac{\pi^I_i (S_{i,t} I_{i,t}) + \pi^L_i \sum_{j=1}^{J} \ell^j_{i,t} (S_{i,t} I_{i,t})}{N_i}, \tag{11}$$

where $\ell^j_{i,t}$ is sector j's employment share in country i at time t, and π^L_i and π^I_i are the infection rates from interactions at workplaces and from general activities other than working, respectively. Similar forms have been used in Eichenbaum et al. (2020) and Jones et al. (2020).

Even when a country is in a total lockdown, the economy does not simply freeze because firms encourage people to work from home as much as possible. Let $\mu^j_i \in [0, 1]$ be the capacity to work from home for sector j in country i, and let $\eta_{i,t} \in [0, 1]$ be the degree of the containment

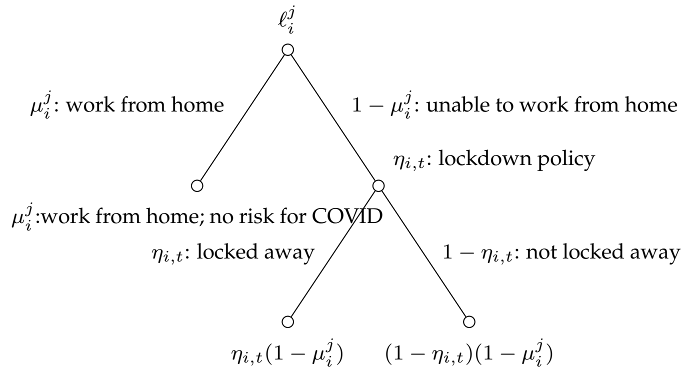


Figure 1: Containment Policy and Work from Home

measure in country i at time t; $\eta_{i,t} = 1$ means a total lockdown whereas $\eta_{i,t} = 0$ means totally laissez-faire, but a containment policy can be anywhere in between. As illustrated by Figure 1, during a pandemic and for sector j in country i, workers who can work from home (the fraction of such workers is μ_i^j) work from home regardless of the containment policy, but for those workers who are unable to work from home, they must still meet in workplaces if allowed. If a country's containment measure is $\eta_{i,t}$, then $\eta_{i,t}(1-\mu_i^j)$ fraction of workers are locked away. Only those who are not locked away still meet, and the fraction of such workers is $(1-\eta_{i,t})(1-\mu_i^j)$. Assuming that the containment measure also applies to interactions in general activities, (11) should therefore be rewritten as

$$T_{i,t} = \frac{(1-\eta_{i,t})\pi_i^I S_{i,t} I_{i,t} + \pi_i^L \times \sum_{j=1}^J \left[(1-\eta_{i,t})(1-\mu_i^j)\ell_{i,t}^j\right] S_{i,t} I_{i,t}}{N_i}. \tag{12}$$

What is the effect of containment policy and work from home on production? As the effective labor time supplied per worker in sector j and country i is reduced to $\mu_i^j + (1-\eta_{i,t})(1-\mu_i^j) = 1-\eta_{i,t}(1-\mu_i^j)$, the employers can choose to lay off workers or hire part-time; or, the employers can pay the full wage even when worker's effective time supplied is reduced. In the former case, the workers absorb the shocks directly, whereas it is the employers who absorb the shocks in the latter case. Both scenarios are present in reality, but to keep the model tractable, we choose the latter case. Thus, the pandemic-shock parameter in the production function (3) is $B_{i,t}^j \equiv 1-\eta_{i,t}(1-\mu_i^j) \in [0,1]$. In the case where $\eta_{i,t} = 0$ (as would be the case when there is no pandemic or when a laissez-faire policy is adopted), $B_{i,t}^j = 1$.

Observing (3) and (12), a more stringent containment measure (higher $\eta_{i,t}$) reduces infections but hurts production; these effects are mitigated if the sector of concern has a larger work-from-home capacity. Both dimensions differ by country, and the international division of labor reflected by $\{\ell_{i,t}^j\}$ provides another source of heterogeneity in the rate of transmission. That is, a country specializing more on work-from-home sectors (those sectors with larger μ_{i}^{j}) enjoys a smaller rate of transmission, ceteris paribus. It is important to note that we allow for π_i^I and π_i^L to differ in i, as these may reflect country-specific environments such as geography, climate, or culture that potentially affect the rate of disease transmission given the same intensity of interactions in workplaces and in general.

Following standard procedures in Eaton and Kortum (2002) and Caliendo and Parro (2015) and assuming $\kappa < \theta + 1$, the price index of a sectoral good is given by

$$P_{n,t}^j = \zeta \left(\sum_{k=1}^{K} T_k^j \left[\left(w_{k,t}/B_{k,t}^j \right)^{\beta_k^j} \left(P_{k,t}^{M,j} \right)^{1-\beta_k^j} \tau_{k,n}^j \right]^{-\theta} \right)^{-\frac{1}{\theta}}, \tag{13}$$

where $\zeta \equiv \left[\Gamma \left(\frac{\theta+1-\kappa}{\theta} \right) \right]^{1/(1-\kappa)}$, and the expenditure share of sector-j goods that country n purchases from country i is given by

$$\pi_{i,n,t}^j = \frac{T_i^j \left[\left(w_{i,t}/B_{i,t}^j \right)^{\beta_i^j} \left(P_{i,t}^{M,j} \right)^{1-\beta_i^j} \tau_{i,n}^j \right]^{-\theta}}{\sum_{k=1}^{K} T_k^j \left[\left(w_{k,t}/B_{k,t}^j \right)^{\beta_k^j} \left(P_{k,t}^{M,j} \right)^{1-\beta_k^j} \tau_{k,n}^j \right]^{-\theta}}. \tag{14}$$

Containment policies combined with work-from-home capacity reshape comparative advantages. If all countries adopt the same containment policy, a country i gains comparative advantage in those high μ_i^j sectors if it has larger presences in these sectors due to higher T_i^j or lower $\tau_{i,n}^j$ on average. Such comparative advantages are strengthened/dampened when country i's containment measure becomes less/more stringent.

2.4 Equilibrium

Let $R_{i,t}^j$ denote the total revenue of country i's sector j, $X_{n,t}^j$ denote the total expenditure of country n on goods in sector j, and $X_{n,t}$ denote the total expenditure of country n. By definition,

$$R_{i,t}^j = \sum_{n=1}^{K} \pi_{i,n,t}^j X_{n,t}^j.$$

The market clearing condition for labor is therefore

$$w_{i,t} L_{i,t} = \sum_{j=1}^{J} \beta_i^j R_{i,t}^j = \sum_{j=1}^{J} \sum_{n=1}^{K} \beta_i^j \pi_{i,n,t}^j X_{n,t}^j. \tag{15}$$

By the definition of $X^j_{i,t}$,

$$X^j_{i,t} = \underbrace{\underbrace{\alpha^j_i w_{i,t} L_{i,t}}_{\text{consumption}} + \sum_{l=1}^{J} \underbrace{\gamma^{l,j}_i (1-\beta^l_i) R^l_{i,t}}_{\text{as intermediate for sector } l}}_{\text{total demand}}$$

$$= \underbrace{\underbrace{\alpha^j_i w_{i,t} L_{i,t}}_{\text{consumption}} + \sum_{l=1}^{J} \underbrace{\gamma^{l,j}_i (1-\beta^l_i) \sum_{n=1}^{K} \pi^l_{i,n,t} X^l_{n,t}}_{\text{as intermediate for sector } l}}_{\text{total demand}}.$$

This is indeed a system of linear equations with consumption as intercepts. Let $JK \times 1$ vector $\mathbf{X_t} \equiv \{X^j_{i,t}\}$ be ordered as $(j=1, i=1), (j=1, i=2), \ldots, (j=2, i=1), (j=2, i=2), \ldots, (j=J, i=K)$. The system can be expressed as

$$\underset{JK\times 1}{\mathbf{b_t}} = \underset{JK\times JK}{\mathbf{A_t}} \times \underset{JK\times 1}{\mathbf{X_t}}, \tag{16}$$

where the element of each term is

$$[\mathbf{b_t}]_{(j,i)} = -\alpha^j_i w_{i,t} L_{i,t}$$

$$[\mathbf{A_t}]_{(j,i),(l,n)} = \begin{cases} \gamma^{l,j}_i (1-\beta^l_i) \pi^l_{i,n,t}\text{, if } (l,n) \neq (j,i) \\ \gamma^{l,j}_i (1-\beta^l_i) \pi^l_{i,n,t} - 1\text{, if } (l,n) = (j,i) \end{cases}$$

$$[\mathbf{X_t}]_{(j,i)} = X^j_{i,t}.$$

An equilibrium is a path of SIR objects $\{S_{i,t}, I_{i,t}, R_{i,t}, D_{i,t}, T_{i,t}\}$, effective labor forces $\{L_{i,t}\}$, wages $\{w_{i,t}\}$, price indices $\{P^j_{i,t}, P^{M,j}_{i,t}, P_{i,t}\}$, trade shares $\{\pi^j_{i,n,t}\}$, total expenditures on sectoral goods $\{X^j_{k,t}\}$, and sectoral labor shares $\{\ell^j_{i,t}\}$ for all i, j, and t such that all firms maximize their profits, all consumers maximize their utility, all markets are cleared, and the SIR evolution is satisfied.

A brief description of the equilibrium algorithm is given as follows; the detailed algorithm is relegated to the online appendix.[3] We first solve the equilibrium at time t given the SIR objects $\{S_{i,t}, I_{i,t}, R_{i,t}, D_{i,t}\}$ and $\{L_{i,t}\}$ from (10). Given wages $\{w_{i,t}\}$, $\{P^{M,j}_{i,t}, P_{i,t}, P^j_{i,t}, \pi^j_{i,n,t}, X^j_{k,t}\}$ are obtained from (7), (8), (13), (14), and (16). Equilibrium wages are obtained from (15). In particular, sectoral employment shares are computed by $\ell^j_{i,t} = \beta^j_i R^j_{i,t} / \sum_{l=1}^{J} \beta^l_i R^l_{i,t}$. Then, the next-period SIR objects are obtained from the law of motion specified in Section 2.3.1 with the number of newly infected $\{T_{i,t}\}$ given by (12).

[3]The online appendix is available at https://wthsu.weebly.com.

2.5 Welfare

A pandemic poses uncertainty to individuals as to how one would fare in terms of the compartments $\{S_{i,t}, I_{i,t}, R_{i,t}, D_{i,t}\}$. For a country i, its welfare is measured by the sum of individual expected life-time utility in which everyone's probability of falling into each compartment is given by the fraction of people in that compartment.[4] As each period's final-good consumption is given by real income $w_{i,t}/P_{i,t}$, the welfare of country i is given by

$$U_i = \sum_{t=0}^{T} \rho^t \left[(S_{i,t} + R_{i,t})\, u\left(\frac{w_{i,t}}{P_{i,t}}\right) + I_{i,t} u\left(\frac{\alpha^I w_{i,t}}{P_{i,t}}\right) + D_{i,t} u\,(0) \right]. \tag{17}$$

As mentioned, u is concave and strictly increasing. The concavity reflects the degree of risk aversion. This formulation treats the death of an individual as a complete loss of labor, which implies zero income and hence zero consumption. If $u(0) = 0$, then the loss from death is simply the loss of utility from the other two outcomes prior to one's death. In the case of u being linear, i.e., the risk-neutral case, the welfare loss from death becomes the same as the long-run loss of labor endowment in net present value of income or consumption. When $u(0) \neq 0$, its value actually reflects the psychological cost that one may have toward death. As it is difficult to calibrate psychological costs, we set $u(0) = 0$ for a relatively clear benchmark. In most cases, it is easy to predict how the directions of our results would change when psychological costs are incorporated.

When u is linear, i.e., the risk-neutral case, a country i's welfare actually becomes the present value of aggregate real income:

$$U_i = \sum_{t=0}^{T} \rho^t \frac{w_{i,t} L_{i,t}}{P_{i,t}}. \tag{18}$$

We will examine global welfare in some of our quantitative analyses; the global welfare is defined analogously:

$$U = \sum_{i=1}^{K} U_i = \sum_{i=1}^{K} \sum_{t=0}^{T} \rho^t \left[(S_{i,t} + R_{i,t})\, u\left(\frac{w_{i,t}}{P_{i,t}}\right) + I_{i,t} u\left(\frac{\alpha^I w_{i,t}}{P_{i,t}}\right) + D_{i,t} u\,(0) \right]. \tag{19}$$

As U_i is already the aggregate welfare that takes into account the population in country i, the global welfare is simply the sum of individual countries' welfare. Any individual on earth has an ex ante probability of being a country i's citizen given by this country's fraction of the global population. Thus, the global welfare can also be interpreted as the sum of expected life-time utility of individuals on the globe.

A methodological note is that unlike in Caliendo and Parro (2015) and other similar static models in which the main counter-factual analyses are conducted using "hat algebra" and hence

[4] Note that this probability is unconditional viewed at time 0.

calibration for some parameters are avoided, we cannot do the same because of the disease dynamics and the need to aggregate real income or utilities over periods. Hence, we compute the full equilibrium as described in Section 2.4; all model parameters must be calibrated or estimated. We now turn to our quantification.

3 Quantifying the Model

Our model consists of two sets of parameters: economic and epidemiological. We describe how they are calibrated in order.

3.1 Economic Parameters

For our quantitative analyses, we set the per-period utility as

$$u(q) = \frac{(q+1)^{1-\sigma} - 1}{1-\sigma}.$$

We choose this functional form for three reasons. First, this specification is similar to the CRRA (constant relative risk aversion) utility if the term $q+1$ is replaced with q. Thus, it is approximately CRRA when q is large; the parameter σ measures the degree of relative risk aversion. Second, $u(0) = 0$, which satisfies our requirement to leave psychological costs out of the model; note that the exact CRRA utility entails $\lim_{q\to 0} u(q) \to -\infty$ when $\sigma \geq 1$ and is therefore not implementable. Third, $\sigma = 0$ corresponds to the risk-neutral case. Following Low and Pistaferri (2015), the relative risk aversion σ is set to 1.5. Following Farboodi et al. (2020), we set the annual discount rate as 0.95; as daily data is used, $\rho = 0.95^{\frac{1}{365}} \approx 0.99986$.

We calibrate the economic environment to the world economy prior to the COVID-19 pandemic using the World Input-Output Database (WIOD) and Centre d'Études Prospectives et d'Informations Internationales (CEPII) data. There are 43 countries and 56 industries in this data set. The country of Malta is dropped as it is not included in the data on containment measures, which will be explained shortly. We aggregate these industries into six sectors (one primary sector, three manufacturing sectors, and two service sectors distinguished by high skill and low skill). Hence, $K = 42$ and $J = 6$. More details on the data handling of the WIOD are given in Appendix A.1, which includes the lists of countries and sectors.

Also from WIOD, we obtain data on gross production across countries and sectors, as well as each sector-j's use of intermediates across countries and sectors. The data also include sectoral final consumption across countries. We can therefore compute the shares of intermediate use $\gamma_i^{j,l}$ as the shares of total intermediate use by sector j on goods from sector l. The final consumption shares α_i^j are computed by total sector-j final consumption over the total final consumption. The shares of intermediate in gross output, $1 - \beta_i^j$, are calculated by the total intermediate use over the gross production.

Given the data on trade shares and geography from the WIOD and CEPII, the model's gravity equations and hence trade costs $\{\tau_{i,n}^j\}$ can be estimated. Following Simonovska and Waugh (2014), we set the value of trade elasticity $\theta = 4$. Given trade elasticity, estimated trade costs, various share parameters $\{\alpha_i^j, \beta_i^j, \gamma_i^{j,l}\}$, and data on wages obtained from the Social Economic Account in WIOD, the productivity parameters $\{T_i^j\}$ can then be backed out using the model structure. The details of this procedure are relegated to Appendix A.2.

The values of work-from-home capacity $\{\mu_i^j\}$ are obtained from Dingel and Neiman (2020), who compute such capacity by occupation and then aggregate to NAICS industries and cities, etc. We map their 3-digit NAICS results to WIOD industries. In aggregating WIOD industries into six sectors, μ_i^j for each country-sector pair is computed as the average of these capacities across industries in that sector, weighted by the industrial employment in that country given in the WIOD data. The details are relegated to Appendix A.3.

The containment measures $\{\eta_{i,t}\}$ across countries and time are directly obtained from the Government Response Index by the Oxford COVID-19 Government Response Tracker (OxCGRT; Hale et al. 2020) at a daily frequency. This index summarizes a government's responses in terms of various closures and containment, including school or workplace closing, stay-at-home requirements, border control, and restrictions on gathering, public events, public transport, and internal movements, and in terms of various economic supports and health measures (such as public information campaigns, testing policy, and contact tracing).[5]

3.2 Epidemiological Parameters

The epidemiological parameters to be calibrated are $\{\pi^r, \pi^d, \delta, \pi_i^I, \pi_i^L, \alpha^I, I_{i,0}\}$. As in Atkeson (2020) and several other macro-SIR models, we set

$$\pi^r + \pi^d = \frac{1}{18} \;\; \forall i, \tag{20}$$

which means that it takes on average 18 days to either recover or die from the infection.

From Liang et al. (2020), the base mortality rate is set at $\pi^d = 0.037 \times \frac{1}{18}$.[6] Following Alvarez et al. (2020), we set $\delta = 0.05 \times \frac{1}{18}$. As a WHO COVID-19 Situation Report[7] indicates that

[5]For more details, see Hale et al. (2020) and https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

[6]This number is estimated as a case mortality rate. This choice of mortality rate is consistent with our estimation of some key parameters using official data on the number of cases as described below.

[7]https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200306-sitrep-46-covid-19.pdf?sfvrsn=96b04adf_4.

asymptotic and mild cases account for about 80% of the infections, we set $\alpha^I = 0.8$.

For our purpose, it is important to account for the variations in the rate of disease reproduction across countries. For the epidemiological evolution to commence, an estimate of $I_{i,0}$ is required (as $S_{i,0} = N_i - I_{i,0}$ and $R_{i,0} = D_{i,0} = 0$); $I_{i,0}$ is generally unknown because the society might be unaware of, unprepared for, or on low alert for the disease so that the number of the first few reported cases may be quite off. To calibrate the country-specific infection parameters $\{\pi_i^I, \pi_i^L, I_{i,0}\}$, we adopt a simpler approach by assuming that there is no time variation in sectoral employment shares $\{\ell_{i,t}^j\}$. Then, (12) becomes

$$\begin{aligned} T_{i,t} &= (1-\eta_{i,t}) \left[\pi_i^I + \pi_i^L \times \sum_{j=1}^{J} (1-\mu_i^j) \ell_i^j \right] \times \frac{S_{i,t} I_{i,t}}{N_i} \\ &\equiv (1-\eta_{i,t}) \lambda_i \times \frac{S_{i,t} I_{i,t}}{N_i}. \end{aligned}$$

That is, λ_i is actually country i's daily rate of transition from susceptible to infectious compartments before considering government interventions; henceforth this rate is referred to as the *rate of transmission*. Government intervention $\eta_{i,t}$ plays a similar role in immunization as it suppresses the transition. We first estimate the rates of transmission and initial infections, $\{\lambda_i, I_{i,0}\}$, simultaneously, and then back out infection probabilities $\{\pi_i^I, \pi_i^L\}$.

Let t_i^* denote the first date on which country i's number of total confirmed cases exceeds 50 and T the latest available data date of the Government Response Index for all of the countries in our sample (July 19, 2020). For each country i, we estimate the following equation using the nonlinear least-squares method:

$$(\hat{\lambda}_i, \hat{I}_{i,0}) = \text{argmin} \sum_{t=t_i^*}^{T} \left[C_{i,t,data} - C_{i,t}(\lambda_i, I_{i,0}; \boldsymbol{\eta}_{i,T}) \right]^2,$$

where $\boldsymbol{\eta}_{i,T}$ is the full history of $\eta_{i,t}$ up to date T, $C_{i,t}$ is the number of total confirmed cases at date t from the model, and $C_{i,t,data}$ is the number of total confirmed cases downloaded from the Humanitarian Data Exchange website.[8] This website compiles data from the Johns Hopkins University Center for Systems Science and Engineering (JHU CCSE), which documents for COVID-19 the numbers of total cases, total deaths, and daily confirmed cases for more than 200 countries and regions.

Borrowing from the results in Eichenbaum et al. (2020), we assume that $2/3$ of the infections

[8] Novel Coronavirus (COVID-19) Cases Data https://data.humdata.org/dataset/novel-coronavirus-2019-ncov-cases.

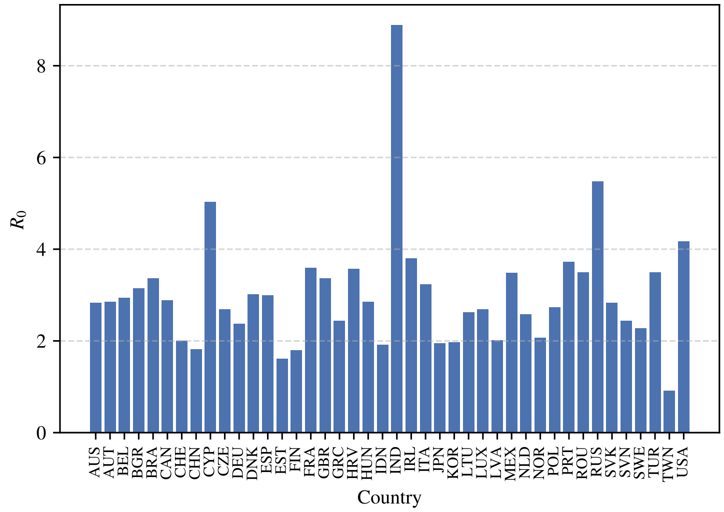


Figure 2: Estimated Basic Reproduction Number $R_{0,i}$

come from general activities. With estimated $\{\hat{\lambda}_i\}$, $\{\pi_i^I, \pi_i^L\}$ can then be solved from

$$\pi_i^I + \pi_i^L \sum_{j=1}^{J} (1 - \mu_i^j)\ell_i^j = \hat{\lambda}_i, \tag{21}$$

$$\frac{\pi_i^I}{\pi_i^I + \pi_i^L \sum_{j=1}^{J} (1 - \mu_i^j)\ell_i^j} = \frac{2}{3}, \tag{22}$$

where the time-invariant sectoral employment shares $\{\ell_i^j\}$ are proxied by the pre-COVID-19 ones.

Note that this estimation method can be applied to our "full" model in which the sectoral employment shares $\{\ell_{i,t}^j\}$ vary with time, in which case the total confirmed cases generated by the model are computed from (12) and tallied over periods. Hence, $\{\pi_i^I, \pi_i^L\}$ will be estimated directly instead of estimating $\{\lambda_i\}$. This approach is, however, computationally cumbersome, as it requires solving the world equilibrium every period for each potential value of $\{\pi_i^I, \pi_i^L, I_{i,0}\}$. It is too cumbersome to be desirable for estimating only two time-invariant parameters. Importantly, our estimated model fits the data reasonably well, as the cross-country average and standard deviation of R^2 are 0.88 and 0.067, respectively.

Moreover, one advantage of our simplified approach is that a λ_i maps to a basic reproduction number $R_{0,i}$, which is easy to interpret. In epidemiology, it is well-known that $R_{0,i}$ is the expected number of cases directly generated by one case before the disease ever starts spreading in the population; this is equal to the ratio of the rate of transmission (λ_i) to the rate of leaving the infectious compartment, the latter which is $1/18$. Thus, $R_{0,i} = 18 \times \lambda_i$.

Such estimated $\{\hat{R}_{0,i} = 18\hat{\lambda}_i\}$ are reported in Figure 2. The average $R_{0,i}$ is 3.0, and for most countries, the $R_{0,i}$ values fall between 1.7 (Estonia) and 4.2 (the US). The exceptions are India

(8.9), Cyprus (5.0), Russia (5.5), and Taiwan (0.9). An important feature here is that when estimating λ_i (and hence $R_{0,i}$) using confirmed cases, the effect of containment measures is incorporated, and hence the estimated $R_{0,i}$ is separate from the containment effect $1-\eta_i$. Thus, our estimated $R_{0,i}$'s may seem higher than those estimates which do not explicitly account for this effect, and should be interpreted as the expected number of cases directly generated by one case when there is no government intervention.

Also note an important point that in our quantitative analyses, the rate of transmission $\lambda_{i,t}$ and the effective reproduction number $R_{e,i,t}$ are still generated from the full model. The effective reproduction number $R_{e,i,t}$ directly generated from one case is given by

$$R_{e,i,t} \equiv \frac{T_{i,t}}{I_{i,t}} \times 18 = (1-\eta_{i,t}) \left[\pi_i^I + \pi_i^L \times \sum_{j=1}^{J} (1-\mu_i^j) \ell_{i,t}^j \right] \times 18 \times \frac{S_{i,t}}{N_i}. \tag{23}$$

4 Quantitative Analyses on Containment Policies

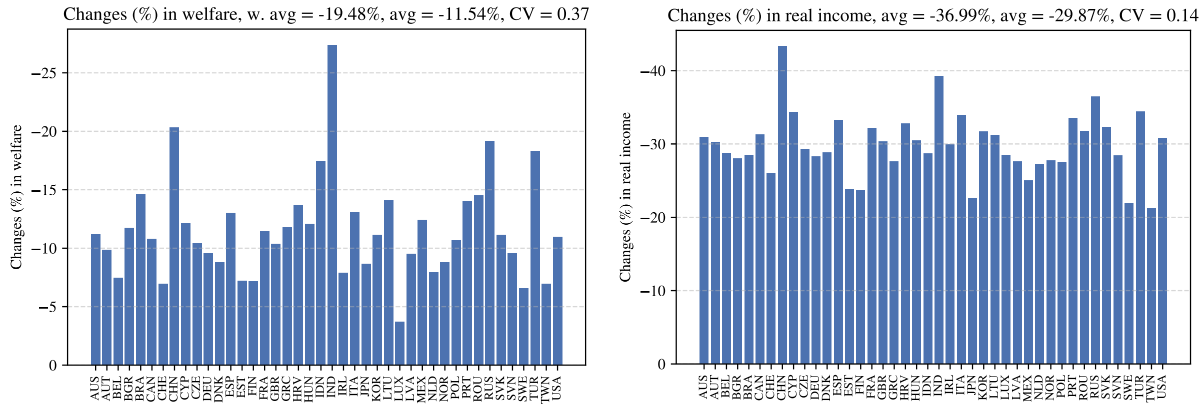
For equilibrium computation and simulations for counterfactuals, the first date ($t=0$) is set as January 1, 2020, which is the first date on which the Government Response Index is available. As mentioned, the SIR evolution for a country i starts at the date on which the total confirmed cases in the data exceed 50; this date is denoted as t_i^*. Then, the estimated $I_{i,0}$ is applied to the previous day (t_i^*-1); for all days between January 1, 2020 and that previous day, $I_{i,t} = R_{i,t} = D_{i,t} = 0$ and $S_{i,t} = N_{i,t}$. Note that it is possible that for those days between January 1, 2020 and the onset of the disease evolution, a country may already adopt some containment measures such as border control.

All of the evaluations in the first two subsections are based on the entire history of the COVID-19 shocks up to now (actually up to T, July 19, 2020, i.e., the last date on which the Government Response Index was available for all of the countries in our sample when this paper was written). We examine long-run welfare and optimal policies from Section 4.3 onward.

4.1 Effects of COVID-19 Shocks

We first examine the losses in welfare and real income due to the COVID-19 shocks by comparing the economy under these shocks (which are inclusive of the disease dynamics, containment policies, and work-from-home capacity) with an economy which runs as if there were no such shock from January 1 to July 22. Figure 3 reports these losses in percentage terms across countries.

The simple and weighted averages of losses in real income are 29.9% and 37.0%, respectively. As the weight is by population, this difference in the two averages indicates that large countries suffer more in general; this is also clear from the figure. The welfare losses are smaller, as the



(a) Welfare loss

(b) Real-income loss

Figure 3: Welfare and Real-Income Losses Due to COVID-19 Shocks

simple and weighted averages of these losses are 11.5% and 19.48%. Again, larger countries tend to suffer more. It is not surprising to find that the welfare losses are smaller than income losses because the utility function u is concave, and $u(c) < c$ for $c > 0$. What is interesting is that the ranking of the welfare losses is not the same as that of the income losses. For example, China and India suffer the first and second largest losses in terms of both income and welfare, but the rankings are different. This is because risk-averse agents prefer smoother consumption over time. The volatility of the real income $L_{i,t}w_{i,t}/P_{i,t}$ over time is much larger in India than in China such that even though India's income loss is smaller, its welfare loss is larger. The difference in volatility over time can be seen from Figure 4, which shows the time series of real income of these two countries and reports the coefficient of variation over time.[9] Note also that the variation in welfare loss across countries is larger than that in real-income loss (the coefficient of variation being 0.37 and 0.14, respectively). This reflects the large cross-country variation in income volatility over time.

4.2 Alternative Policies

Before studying optimal policies, we conduct quantitative analyses on the effects of alternative policies up to now. We ask how countries would fare differently if an alternative containment policy were adopted. For this purpose, we choose South Korea's containment policy as a benchmark, since it has often been heralded as a successful example of containing the disease. As the effective reproduction number reflects the actual speed of disease spread, which varies over time due to changing circumstances and is directly influenced by containment policies (see (23)), we

[9]China's income volatility over this period is smaller because the COVID-19 outbreak there was the earliest, and their stringent containment measures were implemented early and not much loosened even until now.

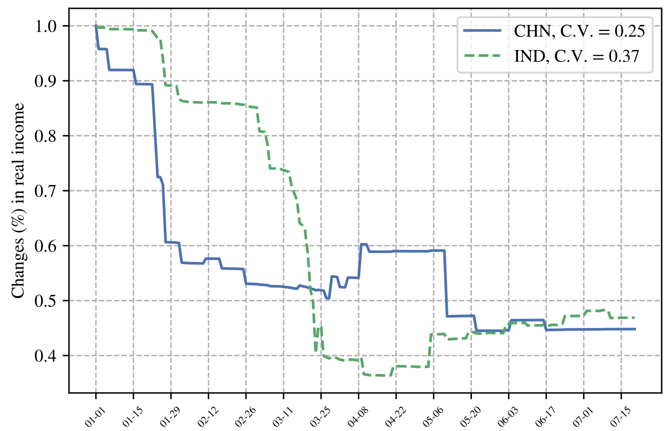


Figure 4: Time Series of Real Income of China and India

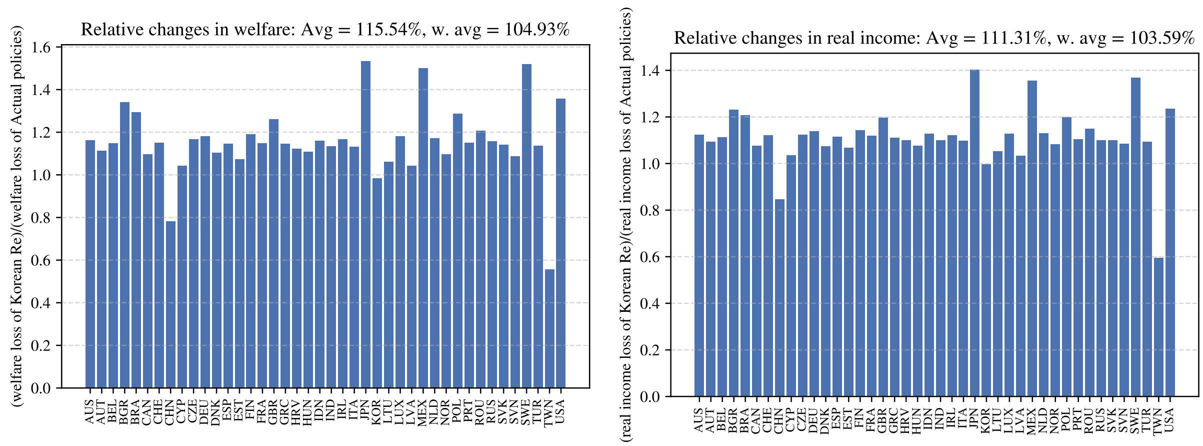
choose this number as a representation of a country's policy target. This is also justified by the fact that the effective reproduction number is also the central concern of epidemiologists and doctors who lead governments' responses for combating pandemics.

We simulate a counter-factual in which each country's containment policies are such that the effective reproduction numbers, if possible, equal the average of South Korea's such numbers over time from the COVID-19 outbreak until July 19, 2020; this average is denoted as $\bar{R}_{e,\text{KOR}}$. That is, for each country $i \neq \text{KOR}$, set the policy $\hat{\eta}_{i,t} \in [0,1]$ at date $t \geq t_i^*$ such that

$$R_{e,i,t} = (1 - \hat{\eta}_{i,t}) \left[\pi_i^I + \pi_i^L \sum_{j=1}^{J} (1 - \mu_i^j) \ell_{i,t-1}^j \right] \times 18 \times \frac{S_{i,t}}{N_i} \leq \bar{R}_{e,\text{KOR}},$$

where the equality holds as long as a positive solution $\hat{\eta}_{i,t}$ exists. The inequality is possible when a country's $R_{0,i}$ or the fraction of Susceptible in the population is so low that the equality fails to hold even when $\hat{\eta}_{i,t} = 0$. The actual containment polices before the outbreak of the disease are used in the counter-factual, i.e., $\hat{\eta}_{i,t} = \eta_{i,t}$ for $t < t_i^*$. Note that the sectoral employment shares used in the above calculation are lagged by one day. If the same-day employment shares are used, then the computational burden drastically increases because the same-day employment shares are functions of same-day containment policies, which is a complex fixed-point problem. There is little need for such a complex approach because the variation of equilibrium sectoral employment shares between two consecutive days are rather small. After all, the exercise is to "approximate" South Korea's containment policy.

The results are shown in Figure 5. When adopting the Korean policy, all countries actually suffer from more welfare and real-income losses except for China and Taiwan. The patterns between welfare and real-income losses are similar. South Korea has a relatively low $R_{0,i}$ and its policy has been quite stringent as it was the second earliest country to experience a rapid outbreak (around mid to late February) and has maintained its policies at a relatively stringent



(a) Ratio of welfare loss (%)

(b) Ratio of real Income loss (%)

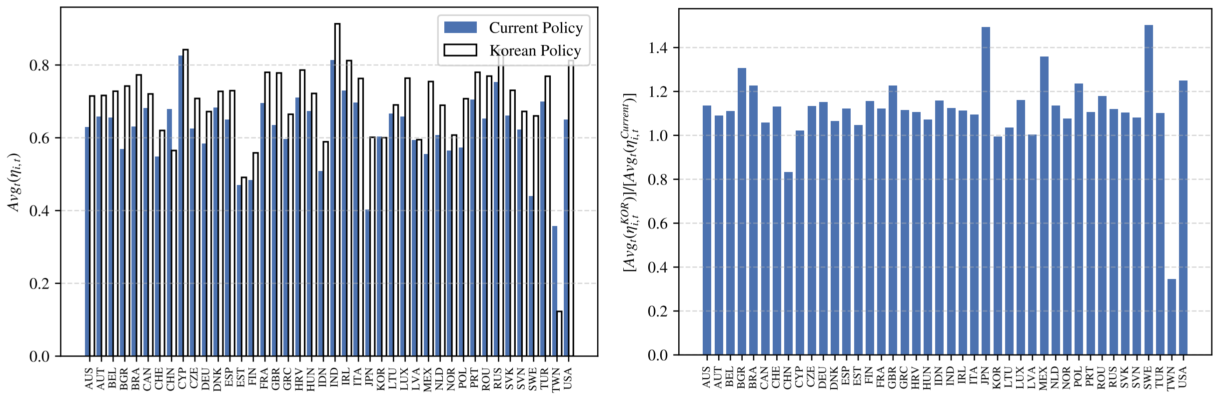
Figure 5: The Impacts of Alternative Policies on Welfare and Real Income

level since. Therefore, the first two components of the effective reproduction number are low. To target $\bar{R}_{e,\text{KOR}}$, most countries must tighten their policies, which consequently strains their economies in terms of both welfare and real income. The direct link between containment policies and the outcomes on welfare and real income is evidenced by Figure 6, which shows the average $\eta_{i,t}$ from the data and in the counter-factual, in levels and in ratios.[10]

Next, we examine the outcomes on disease spread and mortality, which are shown in Figure 7. When adopting Korean policies, more lives are saved in all but seven countries; for several countries which suffer from greater degrees of disease spread, the numbers of lives saved are astonishing.[11] For the 42 countries in our sample as a whole, the additional welfare and real-income loss under the Korean policy is about 4.9% and 3.6%, respectively. However, up to July 19, 2020, 35.6% of lives would be saved under the Korean policy in these countries. Although the difference in these percentage terms is rather large, whether the Korean policy is a worthwhile approach depends on how much psychological cost on mortality one would like to weigh in against the real-income and welfare loss.

[10] To match Korean policy, only China and Taiwan need to relax their policies in terms of average $\eta_{i,t}$. China needs to relax containment polices in our counter-factual, as its actual policy is more draconian than South Korea, while its $R_{0,i}$ is only slightly smaller. Although Taiwan's policies are more relaxed than South Korea's, the fact that its $R_{0,i}$ is about only half of South Korea's implies that its policies need to be even more relaxed in the counter-factual.

[11] The number of deaths increases for seven countries: Cyprus, Estonia, Lithuania, Latvia, and Slovenia, China, and Taiwan. The latter two are expected, whereas the former five exceptions are due to the fact that the average $\eta_{i,t}$'s do not fully reflect the richness of the time paths of policies. However, these exceptions are of relative few cases and deaths. Thus, the matching strategy still provides an intuitive and reasonable guideline.



(a) Avg of η: targeting $\bar{R}_{e,\text{KOR}}$ vs actual policies

(b) Ratio of average η

Figure 6: Containment Policies: Targeting $\bar{R}_{e,\text{KOR}}$ vs Actual Policies

4.3 Setting Up the Long-Run Environment

In the previous subsection, our evaluations are all based on the realized history of containment policies. In this and following subsections, we study optimal policy, for which the evaluations must be for the long run. In particular, economic losses due to the pandemic might be short term, but the deaths caused are permanent.

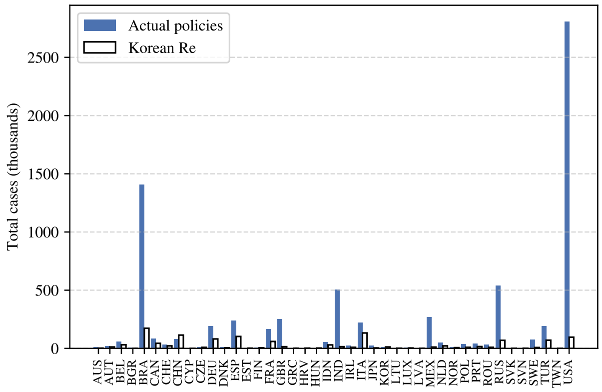
It is infeasible to compute optimal policy by optimizing over the entire time path of containment policies for each of the 42 countries in this full-fledged quantitative model of trade. Thus, we adopt a similar strategy to our study of alternative policy targeting South Korea's effective reproduction number by letting the social planner choose an optimal effective reproduction number. We will also explain in Section 4.4 that using the effective reproduction number as a target actually generates a "front-load" pattern of containment policies over time that is consistent with recent findings in macroeconomics (Alvarez et al. (2020) and Jones et al. (2020)).

To illustrate how optimal policies may improve welfare, real income, and health outcomes in the long run, we compute a baseline in which countries are assumed to keep doing what they have been doing. That is, their policies from July 19, 2020 onward are projected to entail their realized averages of $R_{e,i,t}$ for the period from the onset of the outbreaks to July 19. Their actual policies up to July 19 are used in simulating the baseline.

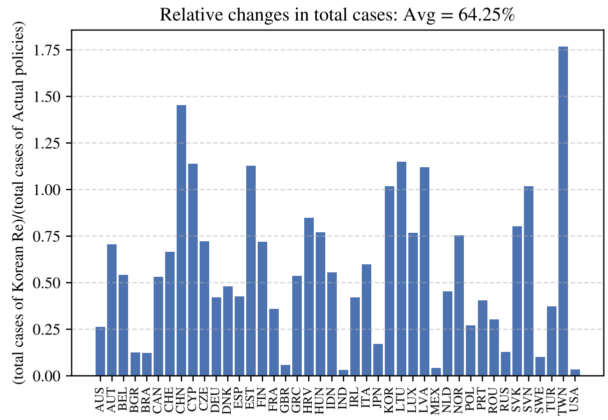
The next question for the long-run evaluation is how would the pandemic end? Given the current containment policies in most countries, it would take a long time to reach herd immunity without a vaccine.[12] Given the multiple fronts on vaccine research, it is reasonable to assume that the pandemic would be ended by the availability of an effective vaccine.[13] We assume that an

[12]Moreover, even though herd immunity may sound attractive, political pressure out of fears over the disease and the pressure to protect the medical system make herd immunity a politically infeasible option for most countries.

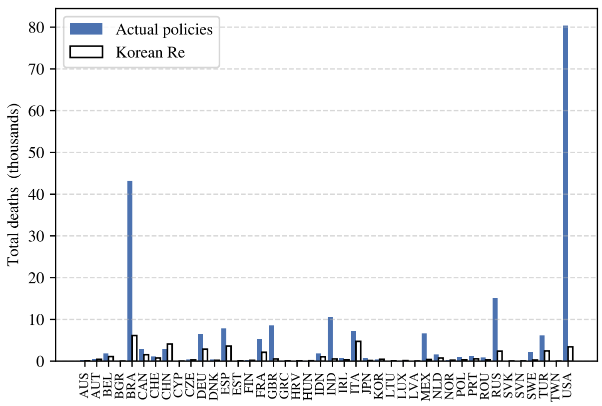
[13]For simplicity, we do not simulate the case of having an effective cure because it is much more complicated as the



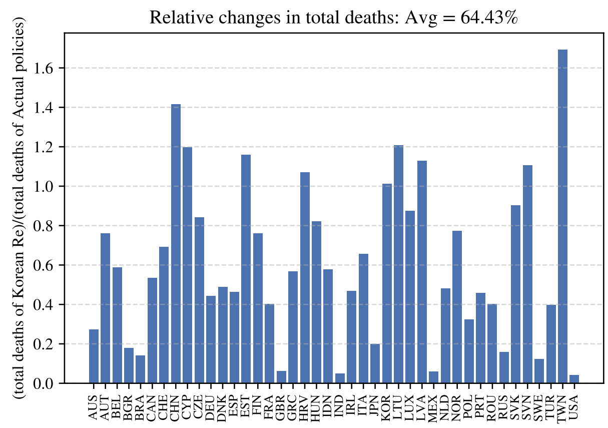
(a) Total cases



(b) Ratio of total cases (%)



(c) Total deaths



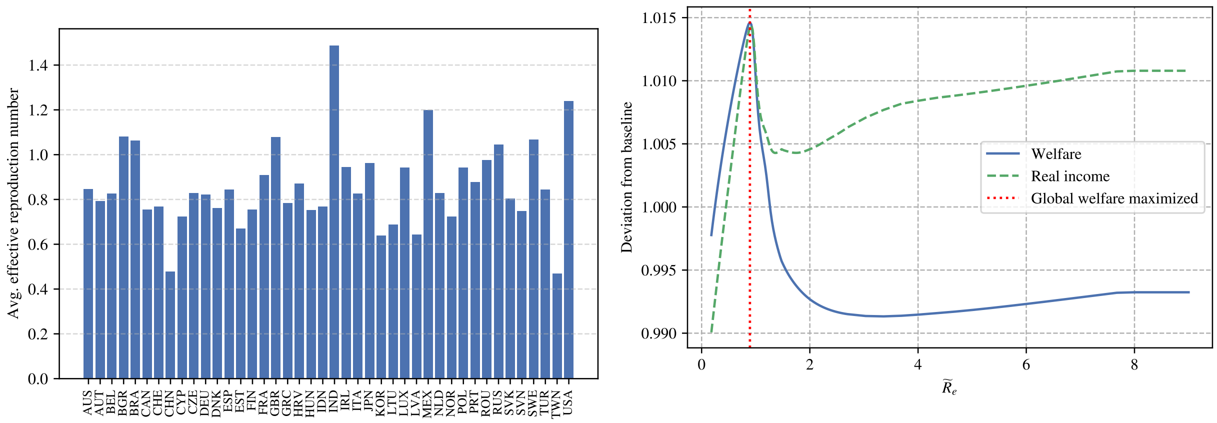
(d) Ratio of total deaths (%)

Figure 7: Total Cases and Deaths: Korean Policy vs Actual Policy

effective vaccine will be developed and become available to most people in two years ($t = 730$) from January 1, 2020. So, π_i^N and π_i^I are set to 0 for $t > 730$, and thus the effective reproduction number also becomes 0. Since Covid-19 is no longer contagious, containment policies are scrapped for $t > 730$. Note that the SIR evolution does not immediately end at $t = 730$, as it takes some time for infectious people to move to the next state (recovery or death).

We examine optimal policies in two steps. In the first step, we consider a simpler problem in which a global social planner decides an effective reproduction number $\widetilde{R}_e$ that applies to all countries such that the global welfare is maximized. In the second step, we explore individual country's optimal policies in a Nash-equilibrium setting. The two steps are useful in two senses: first, the global problem yields a message that would otherwise be obscured in a national context; second, the first step helps the computation for the Nash-equilibrium computation as to which neighborhood to focus on.

disease does not die out soon after having an effective cure. The SIR evolution still goes on for a long period as new infections still occur; the effects are that the recovery from an infection is fast and death rate is reduced.



(a) Average effective reproduction number ($\bar{R}_{e,i}$)

(b) Deviation from the baseline: Global welfare and real income under $\widetilde{R}_e$

Figure 8: Current $\bar{R}_{e,i}$ and Results under a Uniform $\widetilde{R}_e$

4.4 Optimal Uniform Effective Reproduction Number for Global Welfare

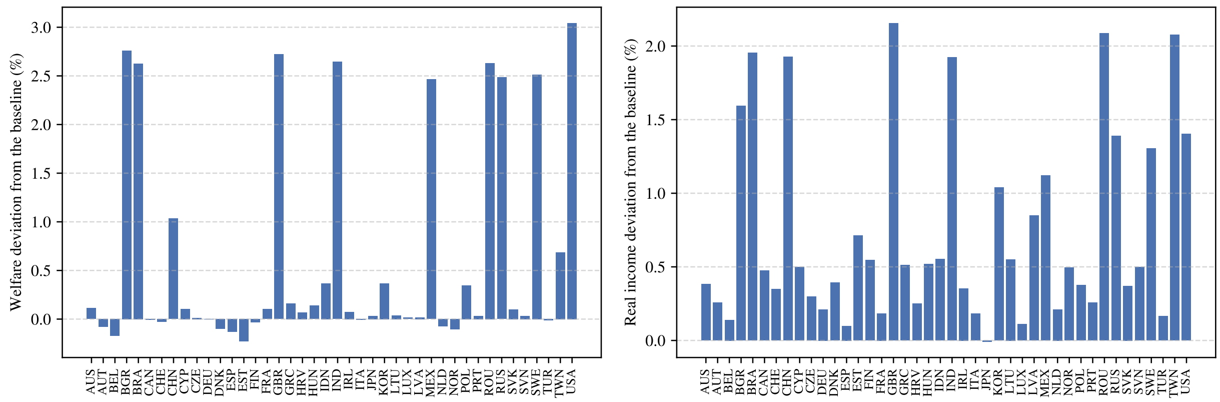
Suppose a global social planner decides on an effective reproduction number $\widetilde{R}_e$ such that all countries set up their containment policies $\widetilde{\eta}_{i,t}$ to match $\widetilde{R}_e$, whenever possible. Namely, for each country i, $\{\widetilde{\eta}_{i,t}\}_{t=t_i^*}^{730}$ satisfy

$$R_{e,i,t} = (1 - \widetilde{\eta}_{i,t}) \left[\pi_i^I + \pi_i^L \sum_{j=1}^{J} (1 - \mu_i^j) \ell_{i,t}^j \right] \times 18 \times \frac{S_{i,t}}{N_i} \leq \widetilde{R}_e, \tag{24}$$

where the equality holds if a positive solution of $\widetilde{\eta}_{i,t}$ exists; otherwise $\widetilde{\eta}_{i,t} = 0$ and the inequality holds. Also, $\widetilde{\eta}_{i,t} = \eta_{i,t}$ for $t < t_i^*$, and $\widetilde{\eta}_{i,t} = 0$ for $t > 730$. The goal of the social planner is to maximize long-run global welfare specified in (19) with $T = \infty$.

Using the effective reproduction number as a policy target actually generates a pattern of containment policy that is stringent initially and gradually relaxed. As mentioned, this pattern is consistent with what has been found in the macroeconomics literature. To see this, observe that the rate of transmission (the bracketed term) in (24) does vary over time because of changes in sectoral employment shares, but the directions of these changes differ across sectors and countries. Hence there is no specific pattern on this rate. In addition, as the workplace term in this rate is essentially a weighted average, the over-time variability of this rate is relatively limited. As the SIR evolves, the fraction of Susceptible in the population $S_{i,t}/N_i$ generally diminishes; with a targeted $\widetilde{R}_e$, this implies that $\widetilde{\eta}_{i,t}$ generally decreases over time. When $\widetilde{\eta}_{i,t}$ decreases to zero and the effective reproduction number is already lower than the target, $\widetilde{\eta}_{i,t}$ remains zero (the containment policy is essentially scrapped).

Before examining the optimal policy, we examine the over-time averages of effective reproduction number under current policies $\bar{R}_{e,i}$, which are shown in Figure 8(a). For many countries,



(a) Welfare improvement. (b) Real-income improvement

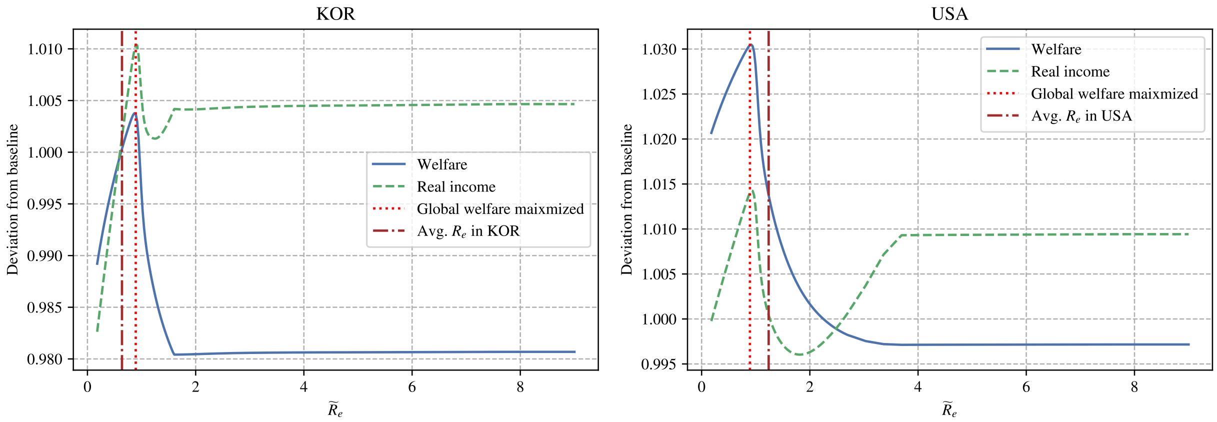
Figure 9: Welfare and Real-Income Improvements under Optimal Uniform Effective Reproduction Number

the $\bar{R}_{e,i}$'s are less than 1, indicating that the disease transmission can be contained by the actual policies. The exceptions are Bulgaria, Brazil, the UK, India, Mexico, Russia, Sweden, and the US.

Using grid search, the uniform effective reproduction number that maximizes global welfare is $\widetilde{R}^*_{e,\text{welfare}} = 0.892$; that which maximizes global real income is $\widetilde{R}^*_{e,\text{income}} = 0.918$. Both are smaller than 1. Figure 8(b) shows the global welfare and real income in $\widetilde{R}_e$. Several observations are in order. First, on both sides of the optimal points, the slopes are rather steep. Second, there is a drastic difference between welfare and real income when $\widetilde{R}_e$ is near a complete laissez-faire policy (when $\widetilde{R}_e$ is greater than 3.2, most countries' $\widetilde{\eta}_{i,t}$ are 0, and the remaining few are near 0). The global income is actually higher than the baseline by 1%, even though it is still lower than what would result under the optimal uniform rate. As to the global welfare, the laissez-faire policy fares worse (1% lower than the baseline). This gap is not trivial considering this is an impact on long-run welfare from the shocks in a two-year plus period.[14] The reason for this gap is due to the volatility of real income during the time of rapid transmission, which adversely affects welfare due to risk aversion. In addition, the probability of getting infected or that of death is larger during that period, amplifying the negative effects on welfare.

Obviously, an optimal uniform effective reproduction number for global welfare is different from the number that would maximize an individual country's welfare: one naturally wonders whether individual countries' welfare actually improves under $\widetilde{R}^*_{e,\text{welfare}}$. Figure 9 shows the welfare and real-income improvements by country under $\widetilde{R}^*_{e,\text{welfare}}$. Compared with the baseline, all countries' real income improves except Japan, and the welfare of all but eight countries improves. Those exceptions are all of minor deterioration, whereas the improvements for some

[14] We let the simulation run about 200 more days after an effective vaccine is available so that epidemiological evolution gradually subsides such that $I_{i,t} \to 0$ for all countries.



(a) KOR (b) USA

Figure 10: Welfare and Real Income of Individual Countries in $\widetilde{R}_e$

countries are substantial.

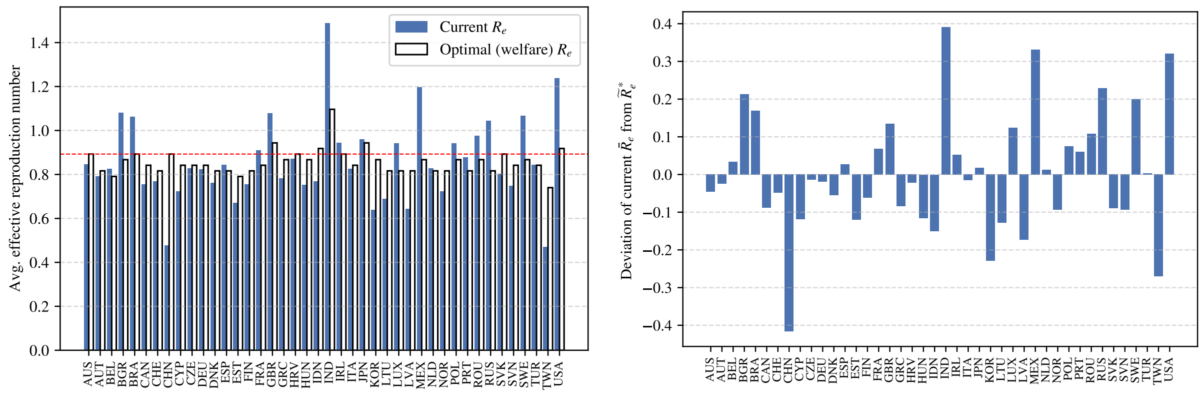
As the global welfare is the sum of individual countries' welfare, the plots in Figure 8(b) are the vertical sums of such plots of each country. How do individual countries' plots differ from Figure 8(b)? The answer is "not much" for most countries. We show such plots for South Korea and the US in Figure 10. Note that the effective reproduction numbers under which the highest welfare and income of these countries are attained are rather close to $\widetilde{R}^*_{e,\text{welfare}}$. This lends support to the next exercise to find optimal points for each country around this neighborhood. We also indicate $\bar{R}_{e,\text{KOR}}$ and $\bar{R}_{e,\text{USA}}$ in the figure; according to $\widetilde{R}^*_{e,\text{welfare}}$, which improves the welfare of both countries, Korea needs to relax and the US needs to tighten up.

4.5 National Social Planners and Optimal Effective Reproduction Numbers

We now consider optimal policies such that each national planner maximizes the country's welfare by choosing the country's effective reproduction number $\widetilde{R}_{e,i}$ (containment policy is solved accordingly in a similar fashion to [24]) given other national planners' choices. The solution is, indeed, a Nash equilibrium of optimal national policies. In this subsection, we focus on the welfare-maximizing case ($\sigma = 1.5$), as the results for the real-income-maximizing case ($\sigma = 0$) are mostly similar.[15]

Given that $\widetilde{R}^*_e$ set by the global social planner already improves most countries' welfare and real income, the information from that exercise is useful for our algorithm of finding a Nash equilibrium of optimal national policies. In particular, we choose as the initial guess for the iterations those points at which the highest welfare for each individual country is attained under uniform $\widetilde{R}_e$ as in Figure 10. Note that the point such that the highest national welfare is attained

[15]The results are available upon request and are easily replicable given the replication files that we provide.



(a) Current $\bar{R}_{e,i}$ and optimal $\widetilde{R}_{e,i}^*$

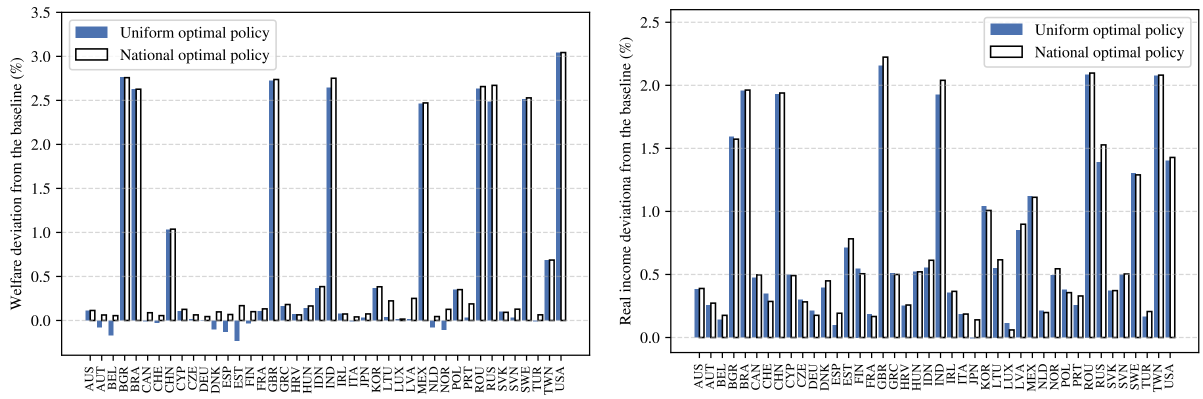
(b) Deviation of $\bar{R}_{e,i}$ from $\widetilde{R}_{e,i}^*$

Figure 11: Optimal Effective Reproduction Numbers vs Actual Ones

is what each national planner would choose if she could set the uniform $\widetilde{R}_e$. Along with other information from the previous subsection, this suggests that the optimal $\widetilde{R}_{e,i}^*$ for each national planner is likely found in the neighborhood of the initial guess. Thus, in our grid search, the grids are much denser in that neighborhood and sparser far away from that neighborhood. This substantially eases the computational burden. Still, the grid search covers the entire range from a total lock-down to a laissez-faire policy. A Nash equilibrium is computed by a standard iterative procedure.

Figure 11 shows the optimal $\widetilde{R}_{e,i}^*$ compared with the current effective reproduction numbers $\bar{R}_{e,i}$; the uniform optimal number $\widetilde{R}_e^*$ is shown by the red dashed line in Panel (a). Panel (b) shows the difference directly. Several observations are in order. First, all of the $\widetilde{R}_{e,i}^*$'s, as well as the optimal uniform number $\widetilde{R}_e^*$, are less than 1, except India's. Second, the optimal number $\widetilde{R}_{e,i}^*$ is relatively close to the optimal uniform number $\widetilde{R}_e^*$, as it can be seen clearly that the variation in actual $\bar{R}_{e,i}$ is much larger than that in optimal $\widetilde{R}_{e,i}^*$. Third, although many countries' optimal numbers are actually similar to the current ones, some countries differ substantially. On one hand, Bulgaria, Brazil, the UK, India, Mexico, Luxembourg, Romania, Russia, Sweden, and the US need to significantly tighten up (by more than 0.1 of $R_{e,i}$). On the other hand, China, Indonesia, South Korea, Latvia, and Taiwan need to significantly relax. Fourth, as we intentionally leave out the psychological cost of mortality, once this cost is incorporated, then those which should tighten up should definitely tighten up even more, whereas the conclusion for those which need to relax might become ambiguous.

Figure 12 shows the welfare and real-income improvements from the baseline under optimal national policies and under a uniform optimal number $\widetilde{R}_e^*$. Unlike the case under the optimal uniform number $\widetilde{R}_e^*$, all countries' welfare and real income improve under the optimal national numbers $\widetilde{R}_{e,i}^*$. Moreover, there is a substantial variation in the magnitudes of improvements.



(a) Welfare improvements from the baseline (b) Real-income improvements from the baseline

Figure 12: Welfare and Real-Income Improvements Under Optimal Policies

Focusing on the welfare improvement, there is an interesting asymmetry between the sets of countries which need to tighten up and those which need to relax. The countries with larger improvements than 2% are exclusively those which need to tighten up significantly (Bulgaria, Brazil, the UK, India, Mexico, Romania, Russia, Sweden, and the US). Except Romania, this set is also exactly the set of countries whose average effective reproduction numbers $\bar{R}_{e,i}$ are greater than 1. Even though Romania's $\bar{R}_{e,i}$ is slightly less than 1, it is actually the highest in the set of $\bar{R}_{e,i} < 1$. It is worth emphasizing that these greater than 2% long-run welfare gains come merely from policy adjustments of a relatively short period (two years plus).

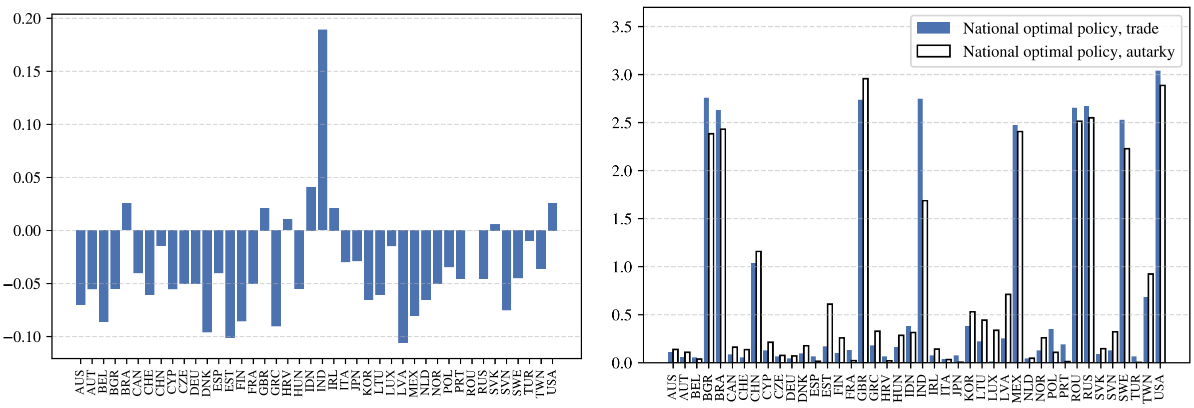
It is also important to compare the results here with the short-run results based on adopting Korean policy. Take India as an example. When adopting Korean policy in the counter-factual, India tightened up in order to match Korean policy, causing losses in both welfare and real income. In terms of both the uniform optimal number $\widetilde{R}_e^*$ and its own optimal policy in the Nash equilibrium, India needs to tighten up also, but the results are that both welfare and real income substantially improve, as seen in Figures 9 and 12. This contrast highlights the role of the costs of mortality and disease spread on both welfare and real income in the long run. Infection can cause a temporary loss in one's income, but the cost of mortality in the long run is substantial because the present value of a death event accounts for the losses of labor force and income for all of the periods afterwards. This explanation for India's case actually applies to all 16 other countries that need to tighten up according to national optimal policies (Figure 11). Note that the above long-run vs short-run comparison does not consider any psychological costs on mortality; with psychological costs, these 17 countries should tighten up even more.

The asymmetry in the welfare gains between those countries which need to tighten up and those which need to relax is intriguing. In this set of countries which need to relax, the gains in real income are also sizeable for China, South Korea, and Taiwan (see Figure 12). To comprehend these patterns, it is critical to understand that the long-run cost of mortality factors in both the real income and welfare, but weighs more in welfare because a larger probability of death worsens the expected utility (probabilities of different states do not matter in real income). On one hand, for China, South Korea, and Taiwan, their containment policies are too tight and their $R_{0,i}$ and $\bar{R}_{e,i}$ are both low; relaxation of containment policy causes a slight increase in the probability of death and hence a slight loss in long-run real income, but the increase in production among those who survive is more than enough to cover the loss. Whereas large increase in real income is observed for these countries, the welfare gains are dampened because of the increase in death probability. On the other hand, $R_{0,i}$ and $\bar{R}_{e,i}$ are both high for the set of countries which need to tighten up. Tightening up implies substantial reduction in the number of deaths; the subsequent increase in (long-run) real income is much larger than the loss of real income from survivors due to more stringent policies. These gains in real income due to saved lives are amplified in terms of welfare.

4.6 Roles of Trade and Input-Output Linkages in Optimal Policies

As discussed in the introduction, there have been numerous studies on optimal containment policies in the macroeconomics literature in closed-economy contexts. Also, as stressed, economies of different countries are inter-linked and pandemic shocks can transmit through these economic links across countries as shown in Bonadio et al. (2020) and Sforza and Steininger (2020). Thus, it is natural to ask whether there is any meaningful difference in optimal policies in an open-economy context. To probe this, we compute the optimal policies under autarky; for this purpose, we focus on computing the Nash-equilibrium optimal policies. Note, however, that once trade costs are prohibitive and countries become autarkies, there are no links between countries' policies; thus the concept of "Nash equilibrium" loses all relevance (we compute this nonetheless). Thus, this exercise actually computes the optimal policies as if each country is its own closed economy.

The results are shown in Figure 13. Panel (a) shows the deviation of optimal $\widetilde{R}^*_{e,i}$ under trade from that under autarky. Due to complex trade linkages, there is no unanimous sign of the deviation, but more countries' (34 out of 42) optimal $\widetilde{R}^*_{e,i}$ under trade are lower than that under autarky, i.e., optimal containment policies are generally tighter under trade than under autarky. This is because gains from trade generally imply more room to buffer pandemic shocks from sourcing intermediate inputs or purchasing final goods from foreign countries, resulting larger real income and welfare under trade. On the tradeoff between lives and economies, national planners can thus afford to adopt more stringent policies for long-run gains by saving lives as short-run losses in production and income are less under trade.



(a) Deviation of optimal $\widetilde{R}^*_{e,i}$ under trade from that under autarky

(b) Welfare improvements from the baseline (%): Trade and autarky

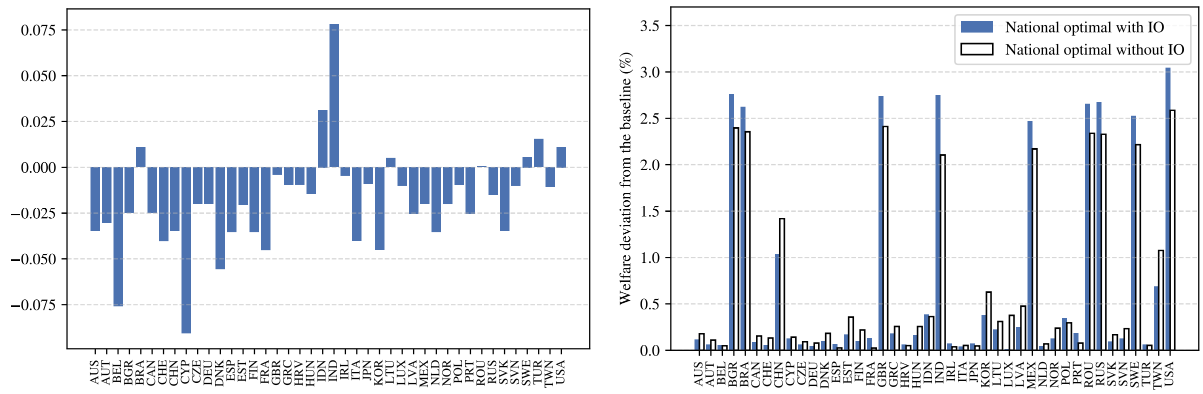
Figure 13: Comparison of Optimal Policies between Trade and Autarky

Panel (b) shows the welfare improvements from the baseline in percentage by adopting optimal policies under autarky and under trade, respectively. The difference in welfare improvement between these two scenarios is marked for those countries whose improvements are relatively large. To further examine the magnitudes of the differences, we calculate the relative difference in absolute value for each country by

$$\frac{|\text{Welfare Improvement under Autarky - Welfare Improvement under Trade}|}{\text{Welfare Improvement under Trade}}.$$

The simple average of the relative difference across countries is 1.13, i.e., the average difference is 113% relative to the welfare improvement under trade. The corresponding standard deviation is 3.10, indicating large variation across countries. The reason for this large relative difference is that for many countries with small welfare improvements under trade, the change in welfare improvement when moving to autarky is relatively substantial. For example, the largest two relative differences are from Luxembourg and Estonia at 20.67 and 2.63, respectively. Luxembourg is an interesting outlier because it is the smallest country in our data set, with a population of around 600 thousands, and its economy is highly dependent on trade. Excluding Luxembourg, the average relative difference drops from 1.13 to 0.65, which is still sizeable. Thus, Figure 13(b) and these relative differences show that incorporating trade is important and quantitatively relevant. We skip showing the results for real income, as they are similar to those for welfare.

We choose a trade model with full-fledged input-output (I-O) linkages; it is also natural to ask whether incorporating these linkages is quantitatively relevant. To examine this, we conduct a similar counter-factual exercise by shutting down all I-O linkages in order to examine the role of such linkages. That is, we set $\beta_i^j = 1$ so that there is no need to use any intermediate inputs in the production process. The results are shown in Figure 14. Panel (a) shows the deviation of



(a) Deviation of optimal $\widetilde{R}^*_{e,i}$ with I-O from that without I-O

(b) Welfare improvements from the baseline (%): I-O and no I-O

Figure 14: Comparison of Optimal Policies between I-O and no I-O

optimal $\widetilde{R}^*_{e,i}$ in the model with I-O linkages from that without these linkages. Similar to Figure 13(a), there is no unanimous sign of the deviation, but more countries' (35 out of 42) optimal $\widetilde{R}^*_{e,i}$ with I-O linkages are lower than those without, i.e., optimal containment policies are generally tighter with I-O linkages. Taking into account trade costs and labor costs, input purchases from the best sources (either domestically or internationally) indirectly utilize the productivities of the best input suppliers, thus amplifying production possibility frontiers. Thus, there is a similar "income effect" by having I-O linkages such that in terms of the tradeoff between lives and economies, national planners can afford to adopt more stringent policies for long-run gains by saving lives as short-run losses in production and income are less with I-O linkages.

Panel (b) shows the welfare improvements from the baseline in percentage by adopting optimal policies in the two scenarios. The difference in welfare improvement is marked for those countries whose improvements are relatively large. Again for each country, we calculate the difference in welfare improvement between the two scenarios in absolute value, relative to the improvement with I-O linkages. The simple average of the relative difference across countries is 1.03, i.e., the average difference is 103% relative to the welfare improvement with I-O linkages. The corresponding standard deviation is 3.47, indicating large variation across countries. The largest two relative differences are from Luxembourg and Switzerland at 23.12 and 1.40, respectively. Not surprisingly, Luxembourg is again an outlier; excluding it, the average relative difference drops from 1.03 to 0.49. In sum, Figure 14(b) and these relative differences show that incorporating I-O linkages is also important and quantitatively relevant.

5 Conclusion

This paper attempts to shed light on the debate on the stringency of containment policies with careful quantitative analyses. Its main contribution is to use a novel approach to compute national optimal policies in this highly complex model with rich cross-sectional links across countries and sectors, and with these links interacting with disease dynamics. Despite the need to make assumptions to reduce the space of candidate policies, our quantitative analyses prove to be informative; the main takeaway messages are as follows.

First, most countries would fare worse up to now if they adopted South Korea's containment policy, which is too stringent for them. But in a Nash equilibrium of national optimal policies, some countries should tighten up, and others should relax, whereas all countries' welfare and real income improve compared with the baseline. This long-run result is a stark contrast with the short-run result based on Korean policy, and highlights the pivotal role of the cost of mortality.

Second, an interesting asymmetry is that substantial welfare gains occur only in the countries that need to tighten up significantly. Although psychological costs of mortality are intentionally left out of the model, the policy implications of our study remain clear even when such costs are incorporated: those countries which should tighten up should definitely tighten up, and the welfare implications are even larger.

Third, as highlighted by the global planner's problem, a laissez-faire policy might not be all that bad in terms of long-run real income, but it is a drastically worse policy in welfare terms because of time volatility and risk aversion.

Fourth, the incorporation of trade and input-output linkages are both quantitatively important in welfare terms. For more countries than not, international trade and input-output linkages both imply a more stringent containment policy.

Needless to say, our work does not capture the full potential multiplicity of containment policies by our analyses based on a one-dimensional measure and may have missed other methods to combat a pandemic. As we have demonstrated that open-economy considerations are important for optimal containment policies in welfare terms, we hope that our work has paved the way for future research on containment policies or other policies alike in an open-economy context.

Appendix

A Data and Calibration

A.1 WIOD

Our main data source is the World Input-Output database (WIOD), which contains information on bilateral trade for intermediates and for final goods for 43 countries and 56 industries. The country of Malta is dropped as it is not included in the data on containment policy from the Oxford COVID-19 Government Response Tracker. Table 1 lists the 42 countries in the data. We use the data from year 2014, the latest available year from WIOD, and we aggregate 56 industries into 6 sectors. See Table 2 for the list of industries and sectors. Two industries are left out of our aggregation (activities of households as employers, and activities of extraterritorial organizations and bodies), since there is no corresponding work-from-home capability in Dingel and Neiman (2020).

Under the Social Economic Account, the database also provides information on total labor compensation and total number of persons engaged for each industry; these allow for the calculation of country-specific wages. See Timmer et al. (2015).

A.2 Estimation of Productivity Parameters $\{T_i^j\}$ and Trade Costs $\{\tau_{i,n}^j\}$

A.2.1 Gravity Estimation

We use a standard approach in estimating productivity parameters $\{T_i^j\}$ and trade costs $\tau_{i,n}^j$. Start with the model's gravity equation:

$$X_{i,n}^j = \frac{T_i^j (c_i^j \tau_i^j)^{-\theta}}{\Phi_n^j} X_n^j.$$

Taking the logarithm of both sides, we have

$$\ln X_{i,n}^j = \ln[T_i^j (c_i^j)^{-\theta}] + \ln[(\tau_{i,n}^j)^{-\theta}] + \ln[X_n^j (\Phi_n^j)^{-1}].$$

Assume that trade costs take the functional form below,

$$-\theta \ln \tau_{i,n}^j = \nu_0^j \ln(dist_{i,n}) + \nu_2^j contig_{i,n} + \nu_3^j comlang_{i,n} + \nu_4^j colony_{i,n},$$

where $dist_{i,n}$ is the distance between i and n in thousands of kilometers, and $contig_{i,n}$ equals one if countries i and n share a border. Analogously, $comlang_{i,n}$ and $colony_{i,n}$ indicate whether two countries share the same language and colonial historical links. These variables are obtained from the GeoDist database from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) (see Mayer and Zignago (2011)). Thus, the empirical specification is

$$\ln X_{i,n}^{j} = \nu_0^j \ln(dist_{i,n}) + \nu_2^j contig_{i,n} + \nu_3^j comlang_{i,n} + \nu_4^j colony_{i,n} + D_i^{j,exp} + D_n^{j,imp} + \varepsilon_{i,n}^{j}$$

Following Head and Mayer (2014), we apply OLS to estimate the fixed effects model to obtain estimates of $\{\nu^j, D_i^{j,exp}\}$.

A.2.2 Uncover Parameters

We set $\theta = 4$, following the trade literature, in particular Simonovska and Waugh (2014). Trade costs $\{\tau_{i,n}^j\}$ can be calculated using the estimated coefficients:

$$\hat{\tau}_{i,n}^{j} = \exp\left(\frac{\hat{\nu}_0^j \ln(dist_{i,n}) + \hat{\nu}_2^j contig_{i,n} + \hat{\nu}_3^j comlang_{i,n} + \hat{\nu}_4^j colony_{i,n}}{-\theta}\right).$$

Then, we use the estimated exporter dummies and data on wages to obtain T_i^j by the following procedure. First, observe that

$$\hat{T}_i^j = \exp(\hat{D}_i^{j,exp}) \times (c_i^j)^{\theta},$$

where $c_i^j = w_i^{\beta_i^j}(P_i^{M,j})^{1-\beta_i^j}$ is the unit cost of production. As mentioned in Appendix A.1, wages w_i are observed from the Social Economic Account in the WIOD. Hence,

$$\hat{T}_i^j = \exp(\hat{D}_i^{j,exp}) \times [w_{i,data}^{\beta_i^j}(\hat{P}_i^{M,j})^{1-\beta_i^j}]^{\theta} \tag{25}$$

$$\hat{P}_i^{M,j} = \prod_{l=1}^{J}(\hat{P}_i^l)^{\gamma_i^{j,l}} \tag{26}$$

$$\hat{P}_i^j = \Gamma\left(\frac{\theta - 1 + \kappa}{\theta}\right)\left[\sum_{k=1}^{K}\hat{T}_k^j[w_{i,data}^{\beta_i^j}(\hat{P}_i^{M,j})^{1-\beta_i^j}\hat{\tau}_{i,k}^j]^{-\theta}\right]^{-\frac{1}{\theta}} \tag{27}$$

The following procedure is used to solve for $\{T_i^j\}$. Let r index the rounds of iterations, and start with an initial guess of $\{\hat{P}_i^{M,j}(0)\}$.

1. Update productivity: $\hat{T}_i^j(r) = \exp(\hat{D}_i^{j,exp}) \times [w_{i,data}^{\beta_i^j}\hat{P}_i^{M,j}(r)^{1-\beta_i^j}]^{\theta}$.
2. Update sectoral price indices: $\hat{P}_i^j(r) = \Gamma\left(\frac{\theta-1+\kappa}{\theta}\right)\left[\sum_{k=1}^{K}\hat{T}_k^j(r)(w_{i,data}^{\beta_i^j}\hat{P}_i^{M,j}(r)^{1-\beta_i^j}\hat{\tau}_{i,k}^j)^{-\theta}\right]^{-\frac{1}{\theta}}$.
3. Update the price indices of the intermediate-input bundle: $\hat{P}_i^{M,j}(r+1) = \prod_{l=1}^{J}[\hat{P}_i^l(r)]^{\gamma_i^{j,l}}$.
4. Stop the iterations if

   $$||\hat{P}_i^{M,j}(r+1) - \hat{P}_i^{M,j}(r)|| < tolerance.$$

   Otherwise, go back to Step 1.

5. Take $\hat{T}_i^j = \hat{T}_i^j(r+1)$ as our estimates of country-sector-specific productivity parameters.

For the model without input-output linkages, the calibration is the same except that $\beta_i^j = 1$ in (25) and (27), and that (26) is not used.

A.3 Work-from-Home Capacity

To measure work-from-home capacity by industry, we use the data from Dingel and Neiman (2020), who compute work-from-home capacity by occupation. We use the data aggregated to the 3-digit NAICS and adopt the version in which the capacity of each occupation was manually assigned by these authors by inspecting the definitions of the occupations. Our results remain similar when using the other version, which is algorithm-based. The data was downloaded from https://github.com/jdingel/DingelNeiman-workathome.

To calculate the work-from-home capacity of each WIOD industry, we map each WIOD industry to one or multiple 3-digit NAICS industries according to their definitions. Six WIOD industries map directly into two-digit NAICS, in which cases the 2-digit NAICS work-from-home capacity computed by these authors are used. When a WIOD industry maps into multiple NAICS industries, we proxy the WIOD industry's work-from-home capacity by the average across the corresponding NAICS industries weighted by their industrial employment. The industrial employment data is obtained from the Quarterly Workforce Indicators (QWI) under the LEHD program of the Census Bureau (https://ledextract.ces.census.gov/static/data.html); the fourth quarter of 2014 was used as our WIOD data is for 2014. By-industry and by-state employment data is obtained from QWI, and the industrial employment is the sum across all states. This procedure creates a $\{\mu^j\}$ for WIOD industries.

In our aggregation of WIOD industries into six sectors, the work-from-home capacity for each country-sector pair μ_i^j is computed as the average of these capacities across industries in that sector, weighted by the industrial employment in that country given from the WIOD data.

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ISO-3 code	Country name	ISO-3 code	Country name
AUS	Australia	IND	India
AUT	Austria	IRL	Ireland
BEL	Belgium	ITA	Italy
BGR	Bulgaria	JPN	Japan
BRA	Brazil	KOR	Republic of Korea
CAN	Canada	LTU	Lithuania
CHE	Switzerland	LUX	Luxembourg
CHN	China	LVA	Latvia
CYP	Cyprus	MEX	Mexico
CZE	Czech Republic	NLD	Netherlands
DEU	Germany	NOR	Norway
DNK	Denmark	POL	Poland
ESP	Spain	PRT	Portugal
EST	Estonia	ROU	Romania
FIN	Finland	RUS	Russian Federation
FRA	France	SVK	Slovakia
GBR	United Kingdom	SVN	Slovenia
GRC	Greece	SWE	Sweden
HRV	Croatia	TUR	Turkey
HUN	Hungary	TWN	Taiwan
IDN	Indonesia	USA	United States

Table 1: List of countries

WIOD description	WIOD code	Industry	WIOD description	WIOD code	Industry
Crop and animal production	A01	Agriculture and mining	Wholesale and retail vehicles	G45	Non-high-skilled service
Forestry and logging	A02	Agriculture and mining	Wholesale trade	G46	Non-high-skilled service
Fishing and aquaculture	A03	Agriculture and mining	Retail trade	G47	Non-high-skilled service
Mining and quarrying	B	Agriculture and mining	Land transport	H49	Non-high-skilled service
Food products, beverages and tobacco products	C10-C12	Food and texile	Water transport	H50	Non-high-skilled service
Textiles, wearing apparel and leather products	C13-C15	Food and texile	Air transport	H51	Non-high-skilled service
Wood and cork	C16	Resource Manufacturing	Warehousing	H52	Non-high-skilled service
Paper products	C17	Resource Manufacturing	Postal activities	H53	Non-high-skilled service
Printing and reproduction of recorded media	C18	Resource Manufacturing	Accommodation and food	I	Non-high-skilled service
Coke and refined petroleum products	C19	Resource Manufacturing	Publishing	J58	High-skilled service
Chemical products	C20	Resource Manufacturing	Media	J59_J60	High-skilled service
Pharmaceutical products	C21	Resource Manufacturing	Telecommunications	J61	High-skilled service
Rubber and plastic products	C22	Resource Manufacturing	Computer and information	J62_J63	High-skilled service
Other non-metallic mineral products	C23	Resource Manufacturing	Financial services	K64	High-skilled service
Basic metals	C24	Manufacturing	Insurance	K65	High-skilled service
Fabricated metal products	C25	Manufacturing	Auxiliary to financial services	K66	High-skilled service
Electronic and optical products	C26	Manufacturing	Real estate	L68	High-skilled service
Electrical equipment	C27	Manufacturing	Legal and accounting	M69_M70	High-skilled service
Machinery and equipment	C28	Manufacturing	Architectural	M71	High-skilled service
Motor vehicles	C29	Manufacturing	Scientific research	M72	High-skilled service
Other transport equipment	C30	Manufacturing	Advertising	M73	High-skilled service
Furniture	C31_C32	Manufacturing	Other professional	M74_M75	High-skilled service
Repair and installation of machinery	C33	Non-high-skilled service	Administrative	N	High-skilled service
Electricity and gas	D35	Non-high-skilled service	Public administration	O84	High-skilled service
Water supply	E36	Non-high-skilled service	Education	P85	High-skilled service
Sewerage and waste	E37-E39	Non-high-skilled service	Human health and social work	Q	High-skilled service
Construction	F	Non-high-skilled service	Other service	R_S	High-skilled service

Table 2: Concordance of WIOD sectors