Globalization, Labor Market Adjustment, and the Long-Run Belief-Scarring Effects of COVID-19*

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Abstract

COVID-19 lockdown measures disrupt not only the global production network, but also the belief on the future prospects of the economy. Since workers make labor supply decisions in accordance with beliefs on the future states, temporary containment measures may have long-term economic consequences. We quantify very long-run impacts of COVID in an open economy through interactions among belief formation, labor market friction and global value chains. We find that, even when the pandemic is eradicated, COVID will leave considerable and persistent negative impacts on economies around the world. Finally, we show that long-term negative impacts are amplified by international trade, since trade strengthens misperceived comparative advantages resulted from belief. On the other hand, input-output linkages mitigate the long-term negative impacts, because the importance of labor as the primary input in production is being diluted.

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1 Introduction

One of the most important question we are facing today, is evaluating the economic costs of COVID-19. The pandemic will be eradicated as effective vaccines being developed and deployed, and social distancing and lockdown measures will be lifted eventually. However, the COVID's economic side effects could linger for years and decades to come. We aim to formalize and quantify the very-long-term economic impacts of COVID under an open economy, and investigate how the persistent economic side effects are propagated through global value chains and international trade.

The global spread of COVID creates an enormous disruption in the production around the world, as well as peoples' belief on the future prospect of the economy. While the disruption on the production vanishes with the eradication of the disease, the disruption on the belief could continue as people gather new information. We incorporate this novel mechanism of the scarring effect into a standard epidemiological compartmental model (Susceptible-Infected-Recovered; SIR) and a multi-country, multi-sector Ricardian trade model of with full-fledged input-output linkages, as in Eaton and Kortum (2002) and 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.

We calibrate the model to the pre-COVID 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.

In our baseline scenario, post-pandemic real income does not bounce back to the pre-pandemic level upon the termination of the disease and containment measures. Take the U.S. as an example, the post-COVID real income starts about 5% below the pre-COVID level, then the real income gap shrinks gradually, but never fully recovers. We also calculate the belief-driven post-COVID loss in terms of annual income, and we find that temporary COVID containment measures leave considerable long-term impacts for economies around the world. The post-COVID loss ranges from 9.1% up to 23.76% of annual real income. Countries experience the most pronounced post-pandemic loss are Canada, the United States and Ireland, which implement relative stricter containment measure during the pandemic. While countries such as Slovakia, Taiwan and Indonesia, have the smallest post-Covid loss, since the containment measures are relatively more leniently implemented in these countries.

Finally, we examine the role of international trade and input-output linkages, and examine whether they would amplify or mitigate the post-pandemic loss due to belief updating. By comparing the scenario of under open economy and under autarky without global value chains, our simulation shows that international trade would amplify the long-term loss by 51.08%. Trade strengthens the comparative advantage of each country, however, the comparative advantages are misguided by the scarring effects stemming from belief updating. On the other hand, by comparing the baseline environment against a scenario without input-output linkages, we find that global value chains mitigate the post-pandemic long-term loss by 51.85%, since the usage of intermediate goods and input-output structure buffer the mis-allocation caused by labor market friction and belief updating.

Related 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.

Closely related literature on international trade 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 vast majority of the literature study the short-term effects of the pandemic, in this paper, we emphasize the very-long-term impacts even when COVID is completely eliminated. Kozlowski et al. (2020) also focus on the persistent effects via learning, and find that the post-pandemic loss is many times greater than the temporary short-run loss. Elenev et al. (2020) use beleif and financial frictions to analyze the balance sheet effect under the COVID shocks. Our work differ from the literature in our focus on evaluating the long-term persistent effect of temporary containment policies in an open-economy framework. We emphasize how the persistent negative impact of COVID propagates through international trade and global value chains, and quantify accompanying side effects in distorting comparative advantages of economies around the world in the very long run.

2 Model

This section introduces our model, which builds on the Caliendo and Parro (2015) trade model to incorporate the evolution of the pandemic, the labor productivity shocks arising from the pandemic, belief formation and updating, and their consequent effects on workers' sectoral choices that come back to influence the economy and disease spread.

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 $q_{i,t}^{F,j}$:

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

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, and $\kappa > 1$ is the elasticity of substitution.

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 $M^j_{i,t}(\omega)$ denote the use of the composite intermediate goods by the firms producing variety ω in sector j and country i; it is made of a Cobb-Douglas composite:

$$M^j_{i,t} = \prod_{l=1}^{j} (q^{M,l}_{i,t})^{\gamma^{j,l}_i}, \tag{2}$$

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

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

$$y^j_{i,t}(\omega) = \frac{z^j_i(\omega) \left[B^j_{i,t} L^j_{i,t}(\omega)\right]^{\beta^j_i} M^j_{i,t}(\omega)^{1-\beta^j_i}}{(\beta^j_i)^{\beta^j_i} (1-\beta^j_i)^{1-\beta^j_i}}, \tag{3}$$

where $L^j_{i,t}(\omega)$ is the labor hired for this variety, β^j_i is the labor share, and the Hicks-neutral productivity $z^j_i(\omega)$ is drawn *i.i.d.* from a Fréchet distribution: $\Pr(x < z) = \exp(-T^j_i z^{-\theta})$, where $T^j_i > 0$ 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.

The trade cost is of the standard iceberg-cost form: to deliver one unit of sector-j variety from country i to country n, $\tau^j_{i,n} \geq 1$ 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 $c^j_{i,t}\tau^j_{i,n}/z^j_{i,t}(\omega)$, where

$$c^j_{i,t} = \left(\frac{w^j_{i,t}}{B^j_{i,t}}\right)^{\beta^j_i} \left(P^{M,j}_{i,t}\right)^{1-\beta^j_i}, \tag{4}$$

where $w^j_{i,t}$ and $P^{M,j}_{i,t}$ are country i in sector j's wages and its sector j's price for obtaining the intermediate input bundle, respectively. Here, $c^j_{i,t}$ 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: $p^j_{n,t}(\omega) =$

$\min_i \left\{ c^j_{i,t} \tau^j_{i,n} / z^j_{i,t}(\omega) \right\}$. Standard derivation yields the price indices:

$$P^j_{i,t} = \left(\int_0^1 p^j_{i,t}(\omega)^{1-\kappa} \right)^{\frac{1}{1-\kappa}}, \quad P^{M,j}_{i,t} = \prod_{l=1}^{J} \left[P^l_{i,t} \right]^{\gamma^{j,l}_i}, \quad P_{i,t} = \prod_{j=1}^{J} \left[P^j_{i,t} \right]^{\alpha^j_i}. \tag{5}$$

2.3 Belief Formation and Sectoral Labor Supply

At period $t-1$, a worker chooses which sector to go to for period t. Assume that in addition to caring about the sectoral real wages $\omega^j_{i,t} \equiv w^j_{i,t}/P_{i,t}$, workers have idiosyncratic preferences toward working in different sectors. That is, given workers' forecast of sectoral real wages $\{\bar{\omega}^j_{i,t}\}_{j=1}^J$ and realized values of the idiosyncratic preferences $\{\epsilon^{j,o}_{i,t}\}_{j=1}^J$ for worker o, the optimal sectoral choice for this worker is determined by

$$\max_j \left\{ \bar{\omega}^j_{i,t} + \phi \epsilon^{j,o}_{i,t} \right\}, \tag{6}$$

where ϕ is the parameter controlling for the effect of these idiosyncratic preferences. Assume that $\epsilon^j_{i,t}$ is *i.i.d.* across individuals and is drawn from a Type-I extreme value distribution $F(\epsilon) = \exp[-\exp(-\epsilon - \bar{\gamma})]$, where $\bar{\gamma}$ is the Euler constant. Then, the average of expected utility of workers in sector j is given by

$$\mathbf{E}_\epsilon \left[\bar{\omega}^j_{i,t} + \phi \epsilon^j_{i,t} \right] = \phi \log \left(\sum_{j=1}^{J} \exp \left(\bar{\omega}^j_{i,t} \right)^{\frac{1}{\phi}} \right).$$

Consequently, the sectoral labor share is given by

$$\ell^j_{i,t} = \frac{\exp \left(\bar{\omega}^k_{i,t} \right)^{1/\phi}}{\sum_{k=1}^{J} \exp \left(\bar{\omega}^k_{i,t} \right)^{1/\phi}}. \tag{7}$$

We now specify how forecasts on real wages form and evolve over time. At period 0, workers in country i have initial prior belief about the real wage for each sector j given by

$$\ln(\widetilde{\omega}^j_{i,0}) \sim N \left(\ln(\bar{\omega}^j_{i,0}), (\widetilde{\sigma}^j_{i,0})^2 \right), \ \forall i, j. \tag{8}$$

Assume that the workers do not fully understand the workings of the economy and could not project correct realization of real wages $\{\omega^j_{i,t}\}_{j,t}$. At the end of period $t-1$, workers receive a signal which is the observed real wages $\{\omega^j_{i,t-1}\}_{j=1}^J$. Workers interpret the signal as an unbiased piece of data about $\ln(\widetilde{\omega}^j_{i,t-1})$ with precision $1/\sigma_i^2$. Namely,

$$\ln(\omega^j_{i,t-1}) = \ln(\widetilde{\omega}^j_{i,t-1}) + \varepsilon^j_{i,t-1},$$

where $\varepsilon^j_{i,t-1} \sim N \left(0, \sigma_i^2 \right)$.

With the new signal/data $\{\omega_{i,t-1}^j\}_{j=1}^J$, workers then update their belief using Bayes' rule. Standard procedure entails the result that workers form posterior mean as a linear combination of the mean of the prior and the signal, where the weight of each component is the relative precision given by the inverse of the corresponding variance:

$$\ln(\bar{\omega}_{i,t}^j) = \frac{\frac{1}{(\widetilde{\sigma}_{i,t-1}^j)^2} \times \ln(\bar{\omega}_{i,t-1}^j) + \frac{1}{\sigma_i^2} \times \ln\left(\omega_{i,t-1}^j\right)}{\frac{1}{(\widetilde{\sigma}_{i,t-1}^j)^2} + \frac{1}{\sigma_i^2}}. \tag{9}$$

The posterior variance is the inverse of the sum of the prior precision and the signal precision.

$$(\widetilde{\sigma}_{i,t}^j)^2 = \left[(\widetilde{\sigma}_{i,t-1}^j)^{-2} + \sigma_i^{-2}\right]^{-1}.$$

The so-formed posterior at the end of period $t-1$ then becomes the prior at the beginning of period t.

2.4 Pandemic and Economy

We incorporate a standard epidemiological model, i.e., an SIRD model, as follows. At any period t, the population of country i, N_i consists of people who are **S**usceptible ($S_{i,t}$, have not been exposed to the disease), **I**nfectious ($I_{i,t}$, have contracted the disease), **R**ecovered ($R_{i,t}$, 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

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

where π^r and $\pi_{i,t}^d$ 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 $\pi_{i,t}^d$, we assume $\pi_{i,t}^d = \pi^d + \delta I_{i,t}/N_i$, where $\delta > 0$ and π^d is the base mortality rate. This linear form is also assumed by Alvarez et al. (2020).

Next we link the SIRD 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.

Let $\mu_i^j \in [0,1]$ 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 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. Assume that during a pandemic, 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, the number of newly infected individuals is given by

$$T_{i,t} = \frac{(1-\eta_{i,t})\pi_i^I S_{i,t} I_{i,t} + \pi_i^L \times \sum_{j=1}^{J} \left[(1-\eta_{i,t})(1-\mu_i^j)\ell_{i,t}^j\right] S_{i,t} I_{i,t}}{N_i}, \tag{11}$$

where $\ell_{i,t}^j$ is sector j's employment share in country i at time t, and π_i^L 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). The key difference from these macroeconomic models is that instead of focusing on how households react to the pandemic by cutting their consumption and labor supply, we expand in the country and sector dimensions to study how sectoral employment shares $\ell_{i,t}^j$ react to changing circumstances and subsequently affect the speed of disease spread, as we will elaborate shortly.

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 focus on 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 (11), 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 WFH capacity. Both dimensions differ by country, and the international division of labor reflected by $\{\ell_{i,t}^j\}$ provides an *endogenous source* of cross-country heterogeneity in the rate of transmission. A country specializing more on WFH sectors 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.

Assuming $\kappa < \theta + 1$, the price index of a sectoral good is given by

$$P^j_{n,t} = \zeta \left(\sum_{k=1}^{K} T^j_k \left[\left(w^j_{k,t}/B^j_{k,t} \right)^{\beta^j_k} \left(P^{M,j}_{k,t} \right)^{1-\beta^j_k} \tau^j_{k,n} \right]^{-\theta} \right)^{-\frac{1}{\theta}}, \tag{12}$$

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

$$\pi^j_{i,n,t} = \frac{T^j_i \left[\left(w^j_{i,t}/B^j_{i,t} \right)^{\beta^j_i} \left(P^{M,j}_{i,t} \right)^{1-\beta^j_i} \tau^j_{i,n} \right]^{-\theta}}{\sum_{k=1}^{K} T^j_k \left[\left(w^j_{k,t}/B^j_{k,t} \right)^{\beta^j_k} \left(P^{M,j}_{k,t} \right)^{1-\beta^j_k} \tau^j_{k,n} \right]^{-\theta}}. \tag{13}$$

The pandemic shocks $B_{i,t} = 1 - \eta_{i,t}(1 - \mu^j_i)$ reshape comparative advantages. If all countries adopt the same containment policy, a country i gains comparative advantage in those high μ^j_i sectors if it has larger presences in these sectors due to higher T^j_i or lower $\tau^j_{i,n}$ on average. Such comparative advantages are strengthened/dampened when country i's containment measure becomes less/more stringent.

2.5 Equilibrium

Let $R^j_{i,t}$ denote the total revenue of country i's sector j, and let $X^j_{n,t}$ denote the total expenditure of country n on goods in sector j, and $X_{n,t}$ denote the total expenditure of country n. Given sectoral labor supply $L^j_{i,t} = L_{i,t}\ell^j_{i,t}$, the labor market clearing condition for sector j in country i is

$$w^j_{i,t} L^j_{i,t} = \sum_{j=1}^{J} \beta^j_i R^j_{i,t} = \sum_{n=1}^{K} \beta^j_i \pi^j_{i,n,t} X^j_{n,t}. \tag{14}$$

where $\sum_{n=1}^{K} \pi^j_{i,n,t} X^j_{n,t}$ is the total revenue of country i's sector j. By the definition of $X^j_{i,t}$, which satisfies

$$X^j_{i,t} = \alpha^j_i \sum_{k=1}^{J} w^k_{i,t} L^k_{i,t} + \sum_{l=1}^{J} \gamma^{l,j}_i (1 - \beta^l_i) \sum_{n=1}^{K} \pi^l_{i,n,t} X^l_{n,t} \tag{15}$$

where the first term on the right-hand side is the final consumption of sector j goods in country i, and the second term on the right-hand side is the total consumption of sector j goods as intermediates. These two terms together are the total demand toward sector j goods in country i. This is indeed a system of linear equations with consumption as intercepts.

We briefly describe the equilibrium algorithm as follows, and the full details are relegated to the online appendix. First, given the SIRD objects, realized real wages and sectoral labor shares at period $t-1$, $\{S_{i,t-1}, I_{i,t-1}, R_{i,t-1}, D_{i,t-1}, \omega^j_{i,t-1}, \ell^j_{i,t-1}\}$, the forecast for real wages at period t, $\widetilde{\omega}^j_{i,t} = \exp(\tilde{\lambda}^j_{i,t})$, is determined by (9), sectoral labor shares $\ell^j_{i,t}$ by (7), the number of newly infected $T_{i,t-1}$ by (11), the effective labor force by (10), and sectoral labor force by $L^j_{i,t} = \ell^j_{i,t} L_{i,t}$. Then, given $L^j_{i,t}$, $\{w^j_{i,t}, P^{M,j}_{i,t}, P_{i,t}, P^j_{i,t}, \pi^j_{i,n,t}, X^j_{k,t}\}$ are obtained from (5) and (12–15).

The key model mechanism can be briefly summarized as follows. The adverse effects of pandemic shocks differ across countries and sectors, and in general shock the non-WFH sectors more than than the WFH sectors. This changes the the sectoral real incomes drastically during the pandemic period, subsequently changing the sectoral employment shares $\ell^j_{i,t}$. Such effects linger even after the pandemic is over because of slow adjustment on beliefs on sectoral real wages that affect workers sectoral choice. Such information friction can cause significance economic loss in the long run.

3 Quantification

Our model consists of three sets of parameters: economic, epidemiological and information parameters. We briefly describe how they are calibrated and estimated in order. Full details on the data and calibration is given in the online Appendix.

3.1 Economic Parameters

We calibrate the economic environment to the world economy prior to the COVID pandemic using the World Input-Output Database (WIOD) and Centre d'Études Prospectives et d'Informations Internationales (CEPII) data. The country Malta is dropped as it is not included in the data on containment measures; this leaves us with 42 countries from the WIOD. 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, we set $K = 42$ and $J = 15$.

From the World-Input-Output Database (WIOD), we obtain data of 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 $\gamma^{j,l}_i$ as the shares of total intermediate use by sector j on goods from sector l. The final consumption shares α^j_i are computed by total sector-j final consumption over the total final consumption. The shares of intermediate in gross output, $1-\beta^j_i$, are calculated by the total intermediate use over the gross production.

Given the data of trade shares and geography from the WIOD and CEPII, the model's gravity equations and hence trade costs $\{\tau^j_{i,n}\}$ can be estimated. Following Simonovska and Waugh (2014), we set the value of trade elasticity $\theta = 4$. Following Caliendo et al. (2019), we set the labor supply elasticity $\phi = 5.34$. Given trade and labor-supply elasticities, estimated trade costs, various share parameters $\{\alpha_i^j, \beta_i^j, \gamma_i^{j,l}\}$, and data on sectoral wages obtained from the Social Economic Account in WIOD, the productivity parameters $\{T_i^j\}$ can then be uncovered using the model structure.

The values of WFH capacity $\{\mu_i^j\}$ are obtained from Dingel and Neiman (2020), who compute such capacity by occupation and then aggregate to NAICS industries. We map their 3-digit NAICS results to WIOD industries and our aggregate sectors. The containment measures $\{\eta_{i,t}\}$ are obtained from the *Stringency 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 closures, stay-at-home requirements, border control, and restrictions on gathering, public events, public transport, and internal movements, as well as public information campaigns.

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

$$\pi^r + \pi^d = \frac{1}{18} \;\; \forall i, \tag{16}$$

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 $\pi^d = 0.037 \times \frac{1}{18}$.[1] Following Alvarez et al. (2020), we set $\delta = 0.05 \times \frac{1}{18}$. As a WHO COVID-19 Situation Report[2] indicates that 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, the key parameters for which are the two infection probabilities $\{\pi_i^I, \pi_i^L\}$ in (11). Also, 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 and must be estimated 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. For each country, parameters $\{\pi_i^I, \pi_i^L, I_{i,0}\}$ are estimated by the non-linear least-squares method that minimizes the sum of squared distances in the total confirmed cases between data and model at daily frequency. The data on total confirmed cases are downloaded from the Humanitarian Data Exchange website.[3] Our estimated

[1] 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.

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

[3] https://t.ly/MVRk

model fits the data reasonably well, as the cross-country average and standard deviation of R^2 are 0.88 and 0.067, respectively.

3.3 Information Parameters

We describe how initial beliefs and learning process are calibrated. We first compute equilibrium sectoral real wages w_i^{j*}/P_i^* when both the pandemic and containment measures are absent. We then use these real wages as the mean of initial prior distribution:

$$\ln(\bar{\omega}_{i,0}^j) = \ln\left(\frac{w_i^{j*}}{P_i^*}\right). \tag{17}$$

We use the WIOD data to calibrate the precision of initial prior belief $\left(\widetilde{\sigma}_{i,0}^2\right)$, as well as the precision of signals $(\sigma_i^j)^2$. For each year included in the WIOD (each year from 2000 to 2014), we calibrate and estimate the respective economic parameters as in Section 3.1, and use the nominal wages in the data and the model structure to calculate corresponding sectoral real wages $w_{i,s}^{j,data}/\hat{P}_{i,s} = \bar{\omega}_{i,s}^j$. Then we run the following regression via OLS:

$$\ln\left(\bar{\omega}_{i,s}^j\right) = D_i^j + D_{i,s} + e_{i,s}^j \tag{18}$$

where D_i^j is a sector-country dummy, and $D_{i,s}$ is a country-year dummy. We retrieve the prediction error of the regression $\hat{e}_{i,s}^j$ and calculate

$$\left(\widetilde{\sigma}_{i,0}^j\right)^2 = \text{Var}\left[\{\hat{e}_{i,s}^j\}_{s\in\{2000,\ldots,2014\}}\right] \tag{19}$$

$$\sigma_i^2 = \text{Var}\left[\{\hat{e}_{i,s}^j\}_{j\in\{1,\ldots,J\},s\in\{2000,\ldots,2014\}}\right]. \tag{20}$$

Namely, we use the variance of prediction error for each (j, i) across time horizon as the precision of initial prior belief; the variance of prediction error for each country i across sectors j and time horizon s as the precision of signal. The calibrated values of the precision of initial prior and signal, $1/\sigma_{i,0}^2$ and $1/\left(\widetilde{\sigma}_{i,0}^j\right)^2$, are provided in the online appendix.

4 The Long-run Aftermath of COVID-19

In this section, we simulate the long-run aftermath of COVID-19, and investigate the roles of international trade and input-output linkages. Our model focuses on how COVID shocks the global economy during the pandemic, and how the beliefs on real wages are reshaped during this period. Then, the long-run aftermath stems from the imperfect adjustment process that negatively affect the post-COVID global economy, in a “scarring-belief” fashion. It is not explicitly a scarring belief about the likelihood of recurring pandemic, but workers’ slow adjustment in beliefs on real wages can be interpreted as having implicitly taken the recurring likelihood into account, among other factors. After all, the key for this economy is the sectoral labor choices. For convenience, we will label the baseline equilibrium as the scarring-belief one.

4.1 Setting Up the Simulation Environment

How will the pandemic end? Even though several vaccines have been successfully developed, how soon the pandemic will end depends on their rollout, as well as other factors. Estimates range from as optimistic as Fall 2021 for the US to as conservative as a few years for the world.[4] For our exercises, we assume that the pandemic ends 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 disease 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).

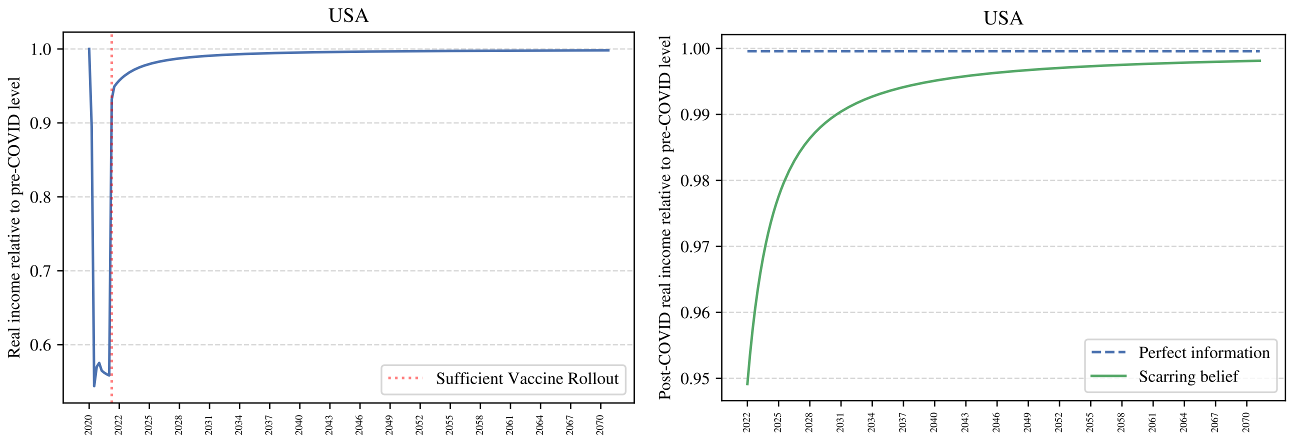
When this paper was written, the latest date for which the Stringency Index was available for all countries in our data set was November 16, 2020. Between November 17, 2020 to December 31, 2021, we fill in the containment measures for each country by the average of the Stringency Index from the last 100 days prior to November 17, 2020.

Because the disease dynamics evolves fast and the containment measure data is available at daily frequency, the evolution of the disease in the quantitative model is simulated at daily frequency. However, because it takes time for workers to switch jobs/sectors and our elasticity of labor supply is taken from Caliendo et al. (2019), who estimate this elasticity using quarterly data, we assume that workers update their beliefs and reconsider their job choices at a quarterly frequency. As a result, sectoral employment shares also change also at a quarterly frequency. Note that the economy can evolve with the disease dynamics at a daily frequency as both total effective labor supply $L_{i,t}$ and containment measures $\eta_{i,t}$ change at a daily frequency. As we aim to examine a very long run by looking at the results over 52 years since 2020, we take the averages of daily $L_{i,t}$ and $\eta_{i,t}$ for each quarter to simulate the evolution of economy at a quarterly frequency to reduce computational burden. More precisely, a quarter is defined as 91 days in our simulation, and we simulate 208 quarters (roughly 52 years).

4.2 The Long-Run Economic Loss of Scarring Belief

Let $W_{i,t} = [\sum_{j=1}^{J} w_{i,t}^j L_{i,t}^j]/P_{i,t}$ be country i's real income at quarter t. Figure 1a shows the time path of real income relative to pre-COVID level in the US since the beginning of year 2020 to

[4] See https://t.ly/LNmb and https://t.ly/mbPu



(a) (b)

Figure 1: The Time Path of Real Income Level Relative to Pre-COVID Level

the end of year 2071 (52 years in total). Containment measures during the pandemic (2020 to 2021) disrupt production and labor market, hence creating a drastic reduction in real income. After sufficient vaccine rollout, containment measures are lifted completely. However, upon the eradication of the pandemic, the US still suffers a 8% real income loss relative to pre-COVID level. The real income does not fully bounce back to pre-COVID level because of the fatality caused by the pandemic. Going forward, as workers receive new information about post-COVID economic outcomes and update their beliefs accordingly, the real-income loss shrinks gradually. However, the negative effects are very persistent, even 50 years after the conclusion of COVID, there is still around 0.18% of real income loss in the US resulted from the two years of pandemic. The qualitative patterns for other countries are similar, but the quantitative magnitudes vary.

To highlight the role of scarring beliefs, we compute an equilibrium with perfect information, in which workers' forecast on the sectoral real wages are exactly the same as the realization of sectoral real wages, and the corresponding sectoral employment shares are also consistent with the equilibrium sectoral real wages.[5] Figure 1b presents the post-COVID real income levels in both the perfect-information and scarring-belief equilibria in the US, relative to its pre-COVID real income level. Under the perfect-information equilibrium, the U.S. economy bounces back to near-pre-COVID level almost immediately[6]. The small difference from pre-COVID level is

[5]See the online appendix for the characterization and the computation of the perfect-information equilibrium. Briefly, note the model feature that sectoral labor supply is determined by perceived wages, and the realized wages are consequently determined by sectoral labor supply. Thus, the perfect-information equilibrium involves finding the fixed point of wages so that perceived wages and realized wages are the same.

[6]Under perfect-information equilibrium, the post-COVID aggregate real income is near the pre-COVID level as the COVID-induced fatality does not lower the aggregate real income by much. Furthermore, it still takes some time for infectious people to move to next states even after the pandemic is over; their effect on the aggregate real income

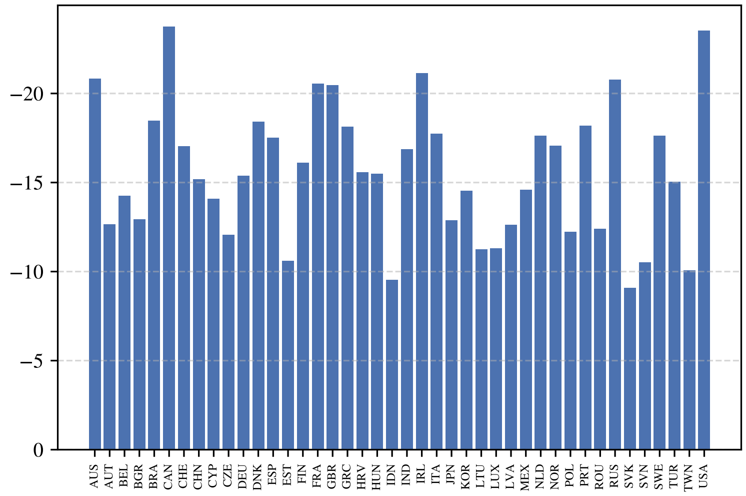


Figure 2: Cumulative Loss in Annual Real Income (%)

resulted from lives lost caused by the pandemic. The patterns in other countries are similar. The quarterly economic loss of a country due to slow belief adjustment is therefore the gap between the two income levels shown in Figure 1b.

To properly evaluate the COVID aftermath due to scarring belief, the cumulative loss is computed as the discounted sum of quarterly losses, i.e., the quarterly differences between perfect-information and scarring-belief equilibria, $W_{i,t}^{\text{scarred}} - W_{i,t}^{\text{perfect}}$. The annual discount factor is set to 0.96; thus the quarterly discount factor is $\rho = 0.96^{\frac{91}{365}}$. Formally, the cumulative loss relative to the perfect-information equilibrium, dubbed as the *relative cumulative loss*, is

$$(\text{Relative Cumulative Loss})_i = \frac{\sum_{t \geq t^*} \rho^{t-t^*} \left(W_{i,t}^{\text{scarred}} - W_{i,t}^{\text{perfect}} \right)}{\sum_{t \geq t^*} \rho^{t-t^*} W_{i,t}^{\text{perfect}}} \times 100\%,$$

where t^* is the first quarter after the pandemic.

We also compute the cumulative loss relative to post-COVID annual income under perfect-information equilibrium:

$$(\text{Cumulative Loss in Annual})_i = \frac{\sum_{t \geq t^*} \rho^{t-t^*} \left(W_{i,t}^{\text{scarred}} - W_{i,t}^{\text{perfect}} \right)}{W_{i,t^*}^{\text{perfect}}} \times \frac{91}{365} \times 100\%$$

Note here that $W_{i,t}^{\text{perfect}}$ is time-varying simply because it still takes some time for infectious people to move to next states even after the pandemic is over. As their effects are miniscule, $W_{i,t}^{\text{perfect}}$ is almost a constant, and thus for the cumulative loss in annual real income, we choose $W_{i,t^*}^{\text{perfect}}$ to be the denominator. Thus, the two measures of long-run losses are by-construction almost one-to-one; we define these two measures simply for the interest of knowing the magnitudes of these measures.

is miniscule.

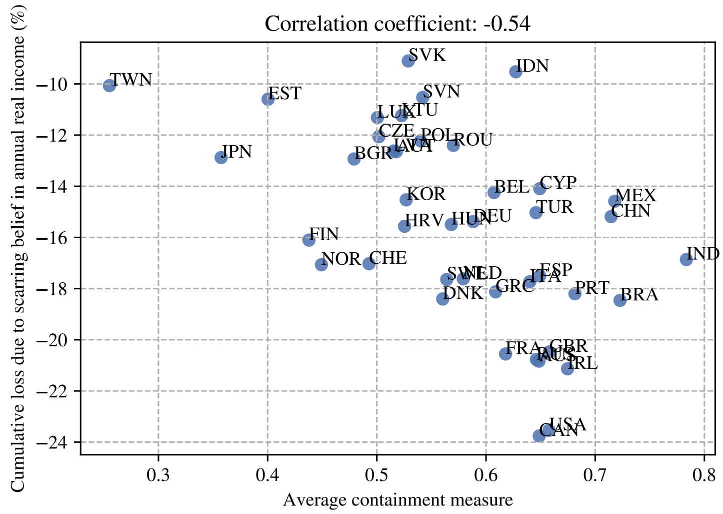
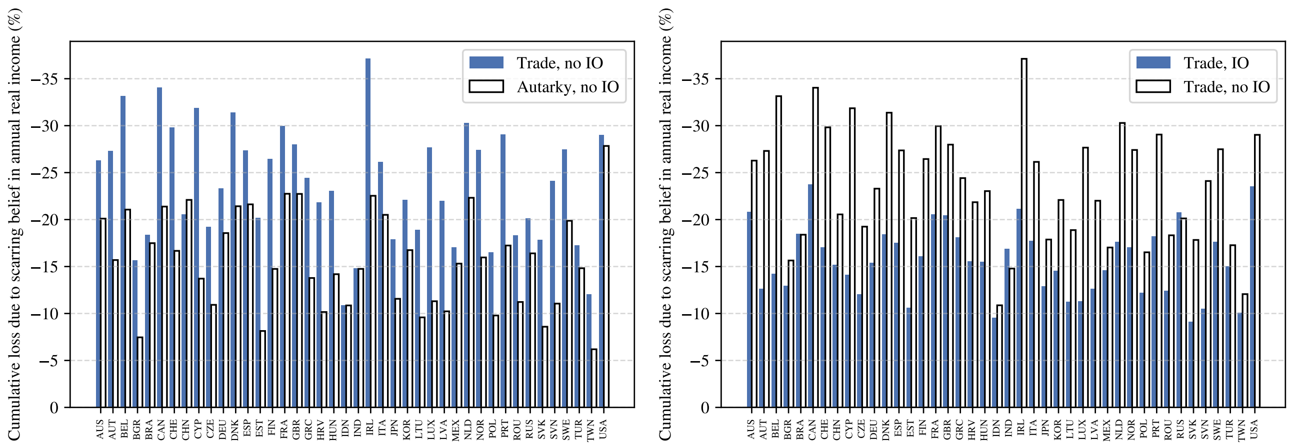


Figure 3: Containment Stringency and the Cumulative Loss Due to Scarring Belief

Figure 2 shows the cumulative loss in annual real income. The cumulative loss in annual real income varies from 9.1% to 23.76%, and the average is 15.62%. The relative cumulative loss varies from 0.42% to 1.1%, and the average is 0.72%. Countries that have more severe containment measures in place, such as Canada, Russia and the U.S. suffer greatly from the slow belief updating process. While countries such as Indonesia, Taiwan, Slovakia and Slovenia, which implement relatively more lenient containment policies, suffer less from belief updating in the post-pandemic world.

As our storylines surround how the interaction between containment policies and WFH capacities creates short-run (2-year) shocks that ripple long after the pandemic is over. Sectoral choices of workers are affected by the fact that the relative wages in WFH sectors are elevated up during the pandemic, and people in the non-WFH sector feel the pain more strongly. Thus, the economy overall leaned toward WFH sectors during the pandemic. The degree of which the beliefs are scarred and the ensuing cumulative losses should be stronger for those countries whose containment measures are more stringent. Figure 3 plots for each country the cumulative loss in annual income against the average containment measures.[7] The pattern shown in the figure confirms with our intuition that the more stringent a country's containment policy is, the more scarred the beliefs would be and the more long-run loss that the country will suffer in the future.

[7]Average containment measure for each country is calculated by the simple average of $\eta_{i,t}$ since the outbreak of COVID till sufficient vaccine rollout.



(a)

(b)

Figure 4: The Roles of International Trade and Input-Output Linkages

4.3 The Roles of International Trade and Input-Output Linkages

This subsection examines the roles of international trade and input-output linkages in the long-run economic loss due scarring belief. To study the role of international trade, we disentangle the effect of international trade from input-output linkages by focusing on a special case in which all input-output linkages are shut down. This is done by setting $\beta_i^j = 1$ for all j and all i so that production requires only labor. We redo all the quantitative exercises for two cases: under trade (that is, using calibrated trade costs) and under autarky (that is, all trade costs are set to infinity).

Figure 4a shows the the cumulative loss in annual real income for each country and for both the trade and autarky cases. International trade exacerbates the long-run economic losses for all countries but China. For many countries, the extra losses under trade are substantial, whereas the magnitude of the improvements for China is rather small. The average cumulative loss in annual real income is 51.08% larger than under autarky.

The main reasoning is that the stake of efficient sectoral labor supply according to comparative advantages is larger in an open-economy environment than a closed one. Thus, as the cumulative loss from scarring belief stems from the misallocation in sectoral labor supply due to imperfect information, such misallocation is exacerbated under trade. Put differently, the misallocation in sectoral labor supply shifts the equilibrium wages and prices of intermediates inputs relative to the perfect-information case (see equation [13]), thus distorting comparative advantages.

Several papers from the literature emphasize the role of international trade in mitigating COVID shocks. **?** and Hsu et al. (2020) show how trade would be able to mitigate the impacts of containment measures in the short-run and long-run, respectively. However, both papers are

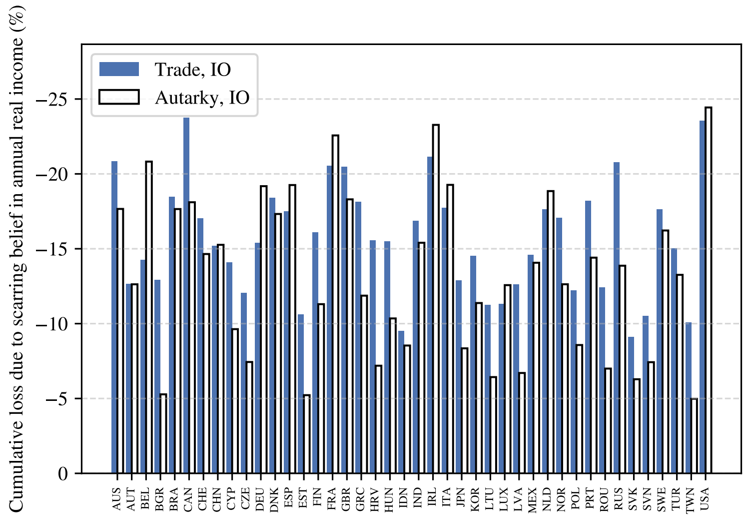


Figure 5: The Role of International Trade When Input-Output Linkages are Present

based on perfect information. This paper demonstrates that trade may amplify the long-run negative effect due to scarring belief and misallocation of sectoral labor supply.

[:later change to I-O linkages after the introduction is written.] We next investigate the role of input-output linkages by comparing the post-pandemic cumulative loss due to scarring belief for the full model and the model with input-output linkages. The result is presented in Figure 4b. Input-output linkages mitigates the long-run economic losses for all but two countries (India and Russia). For many countries, the reduction in losses when the I-O linkages are present is substantial, whereas extra losses for those two exceptions are minor. The average reduction is 51.85% larger than under autarky.

With input-output linkages, more productive producers sell more not only to the final-good markets but also to the other firms as intermediate inputs. Therefore, the highly productive firms are "used" more (and hence hire more workers) in an economy with I-O linkages than the one without. From the viewpoint of the buyers of intermediate inputs, their production relies more on the productive input suppliers than on domestic workers, dampening the negative impacts of sectoral misallocation of labor due to scarring belief.

Finally, we compare post-pandemic losses due to scarring belief under open economy and under autarky when I-O linkages are present. The result is summarized in Figure 5. Compared with an autarkic world, some countries suffer greater long-term losses, while other countries suffer less. As we have seen from Figure 4a, trade worsens long-run economic losses by the *labor misallocation effect* in the case without I-O linkages. Such effect is still present, albeit to a lesser degree because the presence of I-O linkages lowers the importance of labor in the production process. However, trade can also be beneficial because the opportunities to source from the best input suppliers worldwide enhances production compared with the case in which only domestic sourcing is allowed under autarky. We shall refer to this effect as the *international sourcing effect*. Which of the two effects dominates differs by countries, but on average, international trade exacerbates the cumulative loss by 18.06% when I-O linkages are present.

4.4 Robustness Checks

Two key parameters in our model is the rate of learning from new data that is captured by the precision of the signal, $1/\sigma_i^2$ and the elasticity of sectoral labor supply ϕ. We thus conduct one robustness for each of these two parameters.

The first robustness check is on the rate of learning, let χ be a scaling factor for the precision of the signal, i.e.

$$\sigma_i^2(\chi) = \frac{\left(\sigma_i^2\right)^{\text{benchmark}}}{\chi}. \tag{21}$$

A larger value of χ implies that workers would assign a smaller weight on prior belief, hence learn faster with new information available to them. Our benchmark case corresponds to $\chi = 1$. We test alternative scenarios where the learning rate χ is set to 10 and 0.1, and compute respective post-COVID economic losses, which are shown in the Online Appendix Tables 5 and 6. The results are similar to those shown in Figures 4 and 5 qualitatively. The quantitative magnitudes of the long-run economic losses are similar for the $\chi = 10$ case, whereas they are somewhat smaller for the $\chi = 0.1$ case.[8] Most importantly, the qualitative predictions of the model remains robust.

Next, we change the labor supply parameter from $\phi = 5.34$ to $\phi = 3$. This implies a smaller sectoral labor supply elasticity. Re-performing the same quantitative exercises, we find that the post-COVID economic losses are similar for a different value of ϕ. The results are summarized in the Online Appendix Table 7. The qualitative predictions remain robust except that with the presence of input-output linkages, trade mitigates the long run losses on average instead of exacerbate them as in Figure 5. The reasoning is as follows. As we have explained in 4.3, with the presence of I-O linkages, trade has two counter-veiling effects – the negative labor misallocation effect and the positive international sourcing effect. When the elasticity of sectoral labor supply becomes smaller, the labor misallocation effect of trade also becomes smaller, resulting in an overall positive effect so that trade actually mitigates the long-run losses on average.

[8] A smaller χ (a slower learning rate) implies slower recovery compared with the perfect-information equilibrium. However, a smaller learning rate also implies that COVID shocks the real income to a lesser degree during the pandemic period. The post-pandemic loss due to scarring belief under $\chi = 0.1$ is smaller because the beliefs and the economy are less scarred to begin with.

5 Conclusion

In this paper, we develop a tractable general equilibrium model of international trade, epidemiology dynamic, and learning. Our model formalizes the very-long-term effects of the interactions among short-run COVID lockdown measures, learning, and labor market. Trade models usually assume that workers have perfect foresight regarding the future states of the economy while making decisions. In this paper, we relax this assumption, assuming that workers do not know the future prospects of the economy. We make a reasonable assumption that workers utilize the most up-to-date data to estimate and forecast future economic prospects. Under this scenario, even when the pandemic is completely obliterated, temporary COVID lockdowns have long-lasting effects for years and decades to come.

Conventional wisdom from the trade literature suggest that, through specialization, international trade would strengthen the comparative advantages of countries participating in the global economy. However, in the post-COVID economy with belief updating, each country's specialization is guided by misperceived comparative advantages resulted from learning. As a result, international trade strengthens misperceived comparative advantages, and amplifies the long-term economic loss.

The negative long-term impacts are amplifies by international trade. This is because workers in each country specialize in accordance with misperceived comparative advantages resulted from their learning process. Since trade strengthens the international specialization, it also strengthens the misperceived comparative advantages, leading to even greater long-term losses.

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Online Appendix for Globalization, Labor Market Adjustment, and the Long-run Economic Aftermath of COVID-19*

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February 25, 2021

Abstract

In this online appendix we present more details of the paper which we left out of the main text for reasons of space. Section 1 describes the data source. Section 2 presents additional calibration procedure. Section 3 shows the numerical algorithm on solving the model. Section 4 provides additional tables for reference.

1 Data

To quantify the model, we reply on four data sources: World Input-Output database (WIOD), Centre d'Études Prospectives et d'Informations Internationales (CEPII) data, work-from-home capacity data from Dingel and Neiman (2020), and the Government Response Index by the Oxford COVID-19 Government Response Tracker (OxCGRT).

1.1 WIOD and CEPII

Our main data sources are the World Input-Output database (WIOD) and Centre d'Études Prospectives et d'Informations Internationales (CEPII) data, which contain 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. Under the Social Economic Account, the database also provides information on total labor compensation and total number

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of persons engaged for each industry; these allow for the calculation of country-specific wages. See Timmer et al. (2015).

1.2 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.

1.3 Oxford COVID-19 Government Response Tracker

The Government Response Index by the Oxford COVID-19 Government Response Tracker (OxCGRT) summarizes government's responses at the daily frequency 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). For more details, see Hale et al. (2020) and https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

2 Quantifying the Model

This section provides more details on how we quantify the model and the algorithm on how to solve the model, which we left out of the main text for the reasons of space.

Work-from-Home Capacity

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.

Reproduction Number

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, the number of newly infected people now 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.[1] This website compiles data from the Johns Hop-

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

kins 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.

Next, borrowing from the results in Eichenbaum et al. (2020), we assume that $2/3$ of the infections come from general activities. With estimated $\{\hat{\lambda}_i\}$, $\{\pi_i^I, \pi_i^L\}$ can then be solved from

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

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

where the sectoral employment shares $\{\ell_i^j\}$ are approximated by the pre-COVID-19 equilibrium sectoral shares.

3 Algorithm for Solving the Model

In this section, more details about the model is presented. Recall that the total sectoral expenditure is

$$X_{i,t}^j = \underbrace{\underbrace{\alpha_i^j \sum_{k=1}^{J} w_{i,t}^k L_{i,t}^k}_{\text{consumption}} + \sum_{l=1}^{J} \underbrace{\gamma_i^{l,j}(1 - \beta_i^l) \sum_{n=1}^{N} \pi_{i,n,t}^l X_{n,t}^l}_{\text{as intermediate for sector } l}}_{\text{total demand}}$$

Which can be represented by a system of linear equations with consumption as intercepts. Let $JK \times 1$ vector $\mathbf{X_t} \equiv \{X_{i,t}^j\}$ 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

$$\underset{JK\times 1}{\mathbf{b_t}} = \underset{JK\times JK}{\mathbf{A_t}} \times \underset{JK\times 1}{\mathbf{X_t}}, \tag{3}$$

where the element of each term is

$$[\mathbf{b_t}]_{(j,i)} = -\alpha_i^j \sum_{k=1}^{J} w_{i,t}^k L_{i,t}^k$$

$$[\mathbf{A_t}]_{(j,i),(l,n)} = \begin{cases} \gamma_i^{l,j}(1 - \beta_i^l)\pi_{i,n,t}^l \text{ , if } (l,n) \neq (j,i) \\ \gamma_i^{l,j}(1 - \beta_i^l)\pi_{i,n,t}^l - 1 \text{ , if } (l,n) = (j,i) \end{cases}$$

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

Use other equilibrium conditions and the linear system above, we specify the our procedure to compute the equilibrium.

3.1 Equilibrium Prices

We first start with the procedure to compute the equilibrium prices, such as nominal wages across countries and sectors, and price indices and aggregate price index.

Given $L_{i,t}$, sectoral labor shares $\ell_{i,t}^j$ and containment policies $\eta_{i,t}$ for each period t, we can solve the equilibrium prices period-by-period. Therefore, we drop the time subscript to keep the notation cleaner. There is an inner loop and an outer loop, of which the rounds of iteration are indexed by $r = 0, 1, 2, ...$. For $r = 0$, start with an initial guess of wages $\{w_i(0)\}$ such that it lies in a simplex (as in Alvarez and Lucas (2007)), i.e.,

$$\sum_{j=1}^{J} \sum_{i=1}^{K} w_i^j(0) L_i^j = 1.$$

The equilibrium is computed by the following algorithm.

1. **Inner loop to obtain price indices.** Let $\xi = 1, 2, ...$ index the iteration of the inner loop. Given wages $w_i(r)$, start with an arbitrary initial guess of the price indices of intermediate bundles $\{P_i^{M,j}(0)\}$.

   a. With $\{P_i^{M,j}(\xi)\}$, trade shares and sectoral prices are computed by

$$\begin{aligned}
\pi_{i,n}^j(\xi) =& \frac{T_i^j \left[\left(\frac{w_i^j}{1-\eta_i(1-\mu_i^j)} \right)^{\beta_i^j} P_i^{M,j}(\xi)^{1-\beta_i^j} \tau_{i,n}^j \right]^{-\theta}}{\sum_{k=1}^{K} T_k^j \left[\left(\frac{w_i^j}{1-\eta_k(1-\mu_k^j)} \right)^{\beta_k^j} P_i^{M,j}(\xi)^{1-\beta_k^j} \tau_{k,n}^j \right]^{-\theta}} \\
=& \frac{T_i^j \left[\left(\frac{w_i^j}{1-\eta_i(1-\mu_i^j)} \right)^{\beta_i^j} P_i^{M,j}(\xi)^{1-\beta_i^j} \tau_{i,n}^j \right]^{-\theta}}{\Phi_n^j(\xi)} \\
P_i^j(\xi) =& \Gamma \left(\frac{\theta + 1 - \kappa}{\theta} \right)^{\frac{1}{1-\kappa}} [\Phi_n^j(\xi)]^{-\frac{1}{\theta}}.
\end{aligned}$$

   b. Update the price index of the intermediate-input bundle:

$$P_i^{M,j}(\xi + 1) = \prod_{l=1}^{J} \left[P_i^l(\xi) \right]^{\gamma_i^{j,l}}.$$

   c. Check convergence of $P_i^{M,j}(.)$ by

$$\max_{j,i} ||P_i^{M,j}(\xi + 1) - P_i^{M,j}(\xi)|| < tolerance_{\text{inner loop}}.$$

If the above condition does not hold, go back to Step (a) and start from $P_i^{M,j}(\xi+1)$. If it holds, then assign the following values to the outer loop:

$$
\begin{aligned}
\pi_{i,n}^j(r) &= \pi_{i,n}^j(\xi) \\
P_i^j(r) &= P_i^j(\xi) \\
P_i^{M,j}(r) &= P_i^{M,j}(\xi+1) \\
P_i(r) &= \prod_{j=1}^{J} \left[P_i^j(r)\right]^{\alpha_i^j}.
\end{aligned}
$$

2. By definition of X_i^j,

$$
X_i^j(r) = \alpha_i^j \sum_{k=1}^{J} w_i^k(r)\ell_i^k L_i + \sum_{l=1}^{J} \gamma_i^{l,j}(1-\beta_i^l) \sum_{n=1}^{K} \pi_{i,n}^l(r) X_n^l(r),
$$

which entails a linear system of equations written as

$$
\begin{aligned}
\underset{JK\times 1}{\mathbf{b}(r)} &= \underset{JK\times JK}{\mathbf{A}(r)} \times \underset{JK\times 1}{\mathbf{X}(r)} \\
&= [\widetilde{\mathbf{A}}(r) - \mathbf{I}] \times \mathbf{X}(r),
\end{aligned}
$$

where

$$
\begin{aligned}
[\mathbf{b}(r)]_{(j,i)} &= -\alpha_i^j \sum_{k=1}^{J} w_i^k(r)\ell_i^k L_i \\
[\widetilde{\mathbf{A}}(r)]_{(j,i),(l,n)} &= \gamma_i^{l,j}(1-\beta_i^l)\pi_{i,n}^l(r) \\
[\mathbf{X}(r)]_{(j,i)} &= X_i^j(r).
\end{aligned}
$$

Given $\{w_i(r)\}$ and $\{\pi_{i,n}^l(r)\}$, solve $[\mathbf{X}(r)]_{(j,i)}$.

3. Use the labor-market clearing condition to define excess demand $Z_i(r)$ by

$$
Z_i^j(r) \equiv \frac{1}{w_i^j(r)} \left[\sum_{n=1}^{K} \beta_i^j \pi_{i,n}^j(r) X_n^j(r) - w_i^j(r)\ell_i^j L_i \right].
$$

In a similar fashion to the approach in Alvarez and Lucas (2007), wages are updated by

$$
w_i^j(r+1) = w_i^j(r) \left[1 + \psi \frac{Z_i^j(r)}{\ell_i^j L_i}\right],
$$

where $\psi \in (0,1)$ controls the speed of wage adjustment.

4. Stop iterations if

$$
\max_i \{|Z_i^j(r)|\} < \text{tolerance}.
$$

Otherwise, go back to Step 1.

Given the equilibrium wages $\{w_i^j\}$, the equilibrium price indices can be calculated accordingly.

3.2 Equilibrium Sectoral Labor Supply with Perfect foresight

In this subsection, we discuss the procedure to find sectoral labor share across i and j that are consistent with learning and equilibrium. Agent make decisions regarding the period-t sectoral labor supply at the end of period $t-1$. They have perfect foresight about future containment policies $\eta_{i,t}$.

We use an iterative procedure to solve the equilibrium sectoral labor shares $\ell^j_{i,t}$:

1. Start with an initial guess such that $\ell^j_{i,t}(0)$.

2. Use $\ell^j_{i,t}(r)$ and future of containment measures $\widetilde{\eta}_{i,t}$ to compute real income $\widetilde{\omega}^j_{i,t}(r) = \frac{w^j_{i,t}(r)}{P_{i,t}(r)}$ for each country i and each sector j.

3. Using new sectoral real income to update sectoral labor supply

$$\ell^j_{i,t}(r+1) = \frac{\exp\left(\widetilde{\omega}^j_{i,t}(r)\right)^{1/\phi}}{\sum_{k=1}^J \exp\left(\widetilde{\omega}^k_{i,t}(r)\right)^{1/\phi}}$$

4. Stop iterations procedure if

$$\max_{(j,i)}\{|\ell^j_i(r+1) - \ell^j_i(r)|\} < \text{tolerance}.$$

   Otherwise, go back to Step 2.

For the equilibrium at period t, prices are solved using the actual containment policies $\eta_{i,t}$, and the sectoral labor supply $\ell^j_{i,t}$ determined by agents at the end of period $t-1$.

3.3 Estimation of Productivity Parameters $\{T^j_i\}$ and Trade Costs $\{\tau^j_{i,n}\}$

3.3.1 Gravity Estimation

We use a standard approach in estimating productivity parameters $\{T^j_i\}$ and trade costs $\tau^j_{i,n}$. Start with the model's gravity equation:

$$X^j_{i,n} = \frac{T^j_i(c^j_i\tau^j_i)^{-\theta}}{\Phi^j_n} X^j_n.$$

Taking the logarithm of both sides, we have

$$\ln X^j_{i,n} = \ln[T^j_i(c^j_i)^{-\theta}] + \ln[(\tau^j_{i,n})^{-\theta}] + \ln[X^j_n(\Phi^j_n)^{-1}].$$

Assume that trade costs take the functional form below,

$$-\theta \ln \tau^j_{i,n} = \nu^j_0 \ln(dist_{i,n}) + \nu^j_2 contig_{i,n} + \nu^j_3 comlang_{i,n} + \nu^j_4 colony_{i,n},$$

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

3.3.2 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 $c_i^j = (w_i^j)^{\beta_i^j}(P_i^{M,j})^{1-\beta_i^j}$ is the unit cost of production. As mentioned in Appendix 1.1, wages w_i^j are calculated by dividing total labor compensation of (j,i) by number of people employed in (j,i) from the Social Economic Account in the WIOD. Hence,

$$\hat{T}_i^j = \exp(\hat{D}_i^{j,exp}) \times [w_{i,data}^{\beta_i^j}(\hat{P}_i^{M,j})^{1-\beta_i^j}]^\theta \tag{4}$$

$$\hat{P}_i^{M,j} = \prod_{l=1}^{J}(\hat{P}_i^l)^{\gamma_i^{j,l}} \tag{5}$$

$$\hat{P}_i^j = \Gamma\left(\frac{\theta-1+\kappa}{\theta}\right)\left[\sum_{k=1}^{K}\hat{T}_k^j[w_{i,data}^{\beta_i^j}(\hat{P}_i^{M,j})^{1-\beta_i^j}\hat{\tau}_{i,k}^j]^{-\theta}\right]^{-\frac{1}{\theta}} \tag{6}$$

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 (4) and (6), and that (5) is not used.

4 Tables

[:In this section, we present tables for reference that are omitted in the main text for the reason of space. Table 1 shows the list of countries. Table 2 presents the concordance of WIOD sectors. Table **??** presents the numbers of net present value (NPV) of post-COVID-19 loss due to belief updating of each country under benchmark parameter values. Table **??**, **??**, and **??** the numbers of NPV of post-COVID-19 loss due to belief updating of each country when $\phi = 3$, $\chi = 10$, and $\chi = 0.1$ respectively.....]

Table 1: List of Countries.

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 2: Concordance of WIOD sectors

WIOD description	WIOD code	Industry	j
Crop and animal production.	A01	Agriculture and mining	0
Forestry and logging	A02	Agriculture and mining	0
Fishing and aquaculture	A03	Agriculture and mining	0
Mining and quarrying	B	Agriculture and mining	0
Food products, beverages and tobacco products	C10-C12	Food and texile	10
Textiles, wearing apparel and leather products	C13-C15	Food and texile	10
Wood and cork	C16	Wood, Paper and Printing	6
Paper products	C17	Wood, Paper and Printing	6
Printing and reproduction of recorded media	C18	Wood, Paper and Printing	6
Coke and refined petroleum products	C19	Petroleum, Chemical and Pharmaceutical	1
Chemical products	C20	Petroleum, Chemical and Pharmaceutical	1
Pharmaceutical products	C21	Petroleum, Chemical and Pharmaceutical	1
Rubber and plastic products	C22	Resource Manufacturing	9
Other non-metallic mineral products	C23	Resource Manufacturing	9
Basic metals	C24	Resource Manufacturing	9
Fabricated metal products	C25	Resource Manufacturing	9
Electronic and optical products	C26	Equipment, vehicle and others	14
Electrical equipment	C27	Equipment, vehicle and others	14
Machinery and equipment	C28	Equipment, vehicle and others	14
Motor vehicles	C29	Equipment, vehicle and others	14
Other transport equipment	C30	Equipment, vehicle and others	14
Furniture	C31_C32	Equipment, vehicle and others	14
Repair and installation of machinery	C33	Equipment, vehicle and others	14
Electricity and gas	D35	Utility	13
Water supply	E36	Utility	13
Sewerage and waste	E37-E39	Utility	13
Construction	F	Construction	2
Wholesale and retail vehicles	G45	Trade and repair of motor vehicles	11
Wholesale trade	G46	Trade and repair of motor vehicles	11
Retail trade	G47	Trade and repair of motor vehicles	11
Land transport	H49	Transportation and Storage	12
Water transport	H50	Transportation and Storage	12
Air transport	H51	Transportation and Storage	12
Warehousing	H52	Transportation and Storage	12
Postal activities	H53	Transportation and Storage	12
Accommodation and food	I	Accommodation and food	4
Publishing	J58	Publishing, media and IT	8
Media	J59_J60	Publishing, media and IT	8
Telecommunications	J61	Publishing, media and IT	8
Computer and information	J62_J63	Publishing, media and IT	8
Financial services	K64	Finance and Insurance	3
Insurance	K65	Finance and Insurance	3
Auxiliary to financial services	K66	Finance and Insurance	3
Real estate	L68	Other business sector services	5
Legal and accounting	M69_M70	Other business sector services	5
Architectural	M71	Other business sector services	5
Scientific research	M72	Other business sector services	5
Advertising	M73	Other business sector services	5
Other professional	M74_M75	Other business sector services	5
Administrative	N	Other business sector services	5
Public administration	O84	Public service, and education	7
Education	P85	Public service, and education	7
Human health and social work	Q	Public service, and education	7
Other service	R_S	Public service, and education	7

		Precision of Initial Prior Belief: $\frac{1}{(\widetilde{\sigma}_{i,0}^{j})^2}$														
country	$\frac{1}{\sigma_i^2}$	$j=0$	$j=1$	$j=2$	$j=3$	$j=4$	$j=5$	$j=6$	$j=7$	$j=8$	$j=9$	$j=10$	$j=11$	$j=12$	$j=13$	$j=14$
AUS	193.64	132.48	72.28	214.75	97.22	392.74	922.23	234.58	1030.12	776.07	223.96	344.59	472.13	513.94	80.16	448.35
AUT	1719.60	1021.09	1130.53	668.29	3994.81	1221.73	2563.34	4636.65	1083.88	5596.13	8207.44	3726.59	16364.22	5112.28	927.63	4600.41
BEL	482.29	354.90	1293.42	1434.79	1872.96	180.72	402.98	652.26	1984.85	398.53	1011.43	917.77	471.32	1773.50	154.27	962.39
BGR	58.52	90.03	354.81	253.48	32.61	267.28	75.99	44.96	139.94	8.69	201.22	111.20	185.78	90.74	83.72	705.76
BRA	32.67	32.61	37.40	35.41	71.30	103.24	25.14	46.14	229.26	16.91	127.22	354.82	205.37	204.00	5.29	89.15
CAN	60.02	21.15	170.83	73.46	117.44	102.95	77.92	132.48	113.61	122.67	106.00	130.25	99.70	100.75	74.57	86.58
CHE	114.26	138.65	142.16	453.27	47.47	206.37	95.40	402.65	428.79	391.10	984.96	124.51	372.38	2518.13	21.93	212.76
CHN	35.54	31.92	33.00	89.00	24.82	9.05	13.97	23.75	372.97	212.35	83.10	156.75	118.26	97.95	38.68	130.35
CYP	49.27	39.39	10.53	189.29	197.25	73.92	164.44	27.87	211.33	19.11	122.49	160.41	100.05	111.15	74.49	128.93
CZE	1003.13	1917.03	605.20	364.33	1360.10	273.64	4085.40	2660.93	861.94	2611.16	2920.94	3076.86	2512.59	2651.08	1744.05	971.25
DEU	1209.50	416.32	787.66	9833.11	3370.95	485.27	3332.35	881.95	4169.25	788.89	3821.10	4997.23	10152.32	4957.80	1328.54	1023.29
DNK	136.53	102.87	96.13	203.03	175.48	161.71	209.49	185.17	186.65	197.99	224.68	247.54	252.48	175.64	184.95	159.70
ESP	487.88	1035.26	4618.06	267.73	1435.31	214.48	440.98	776.03	1422.46	117.20	909.73	516.80	1740.81	2413.53	2777.10	403.77
EST	57.09	90.19	8.16	94.95	42.85	68.44	239.44	89.56	207.38	85.46	158.54	184.49	211.78	86.14	84.24	160.42
FIN	519.70	1000.17	653.09	634.00	951.62	1174.87	1052.34	807.99	735.71	909.31	784.27	1420.36	592.57	1372.21	691.84	974.84
FRA	863.31	226.84	1104.62	2820.78	1091.16	2256.88	2499.14	2686.19	3329.39	2164.78	1599.47	2001.61	2379.18	2026.10	797.01	661.27
GBR	241.98	178.28	137.62	232.50	90.14	206.14	124.26	663.80	1373.47	257.81	548.65	306.06	1931.17	390.82	217.48	978.85
GRC	92.86	22.58	222.54	226.87	350.62	97.45	106.77	82.38	288.91	32.94	382.27	297.23	305.24	56.59	148.04	376.99
HRV	26.03	23.29	3.34	37.63	34.38	422.65	24.33	58.52	125.14	191.41	241.65	27.93	243.51	184.95	25.68	252.32
HUN	211.07	114.45	132.41	163.39	222.84	152.32	147.67	592.45	259.24	508.13	173.28	233.21	733.94	301.24	414.05	285.51
IDN	14.23	27.27	40.27	25.84	7.07	2.60	7.58	43.57	57.90	37.69	14.28	64.88	53.46	31.15	17.49	83.53
IND	73.41	100.90	67.49	40.71	30.21	61.43	54.16	166.37	442.70	105.90	364.89	203.68	45.80	335.99	308.53	38.44
IRL	131.38	164.98	368.70	203.65	135.99	213.01	401.38	103.08	198.45	276.05	33.35	118.92	237.29	334.06	174.70	88.97
ITA	686.41	1160.41	2083.20	924.86	444.34	361.16	1397.27	1443.39	805.99	1090.71	2226.68	2006.76	1798.87	1233.59	1421.30	2378.61
JPN	267.15	69.39	674.48	422.72	899.62	269.19	404.60	546.67	297.79	124.57	509.18	373.62	1015.91	782.78	157.27	430.09
KOR	73.47	168.86	26.47	324.84	459.22	138.66	37.89	59.86	100.61	171.94	188.34	103.71	449.83	152.45	35.13	29.42
LTU	100.21	46.02	83.36	98.50	43.36	87.54	117.46	387.03	354.27	64.22	108.54	131.20	219.61	179.51	109.36	251.78
LUX	217.13	352.65	124.27	1776.79	1428.45	246.20	275.92	51.54	2191.33	208.95	482.02	754.89	887.49	957.27	238.53	85.40
LVA	88.67	20.31	223.91	29.24	179.88	188.15	322.05	240.21	205.84	157.60	290.10	97.35	321.70	64.91	74.80	326.01
MEX	212.72	407.92	882.88	766.11	116.09	147.11	655.31	393.63	129.24	109.69	108.35	254.57	545.83	440.28	371.78	289.25
NLD	660.49	534.66	139.14	594.09	460.70	280.89	2174.35	3689.53	4889.03	4377.17	3373.34	2146.68	5144.12	2640.56	3144.99	1897.38
NOR	330.46	56.97	996.27	1227.79	186.63	269.68	1176.49	437.07	997.08	737.29	354.04	932.46	627.50	1416.18	669.89	930.39
POL	129.20	48.39	26.72	257.88	190.70	118.19	403.43	271.31	290.97	193.09	507.72	1075.43	563.38	635.79	387.67	120.86
PRT	460.05	1841.24	678.07	484.78	330.53	957.53	874.23	1120.50	307.47	174.11	2948.46	1245.62	5728.74	930.81	246.19	3150.82
ROU	46.54	14.34	43.80	48.69	44.92	15.00	32.98	122.76	151.44	203.83	152.76	65.77	71.64	153.79	166.33	160.62
RUS	71.79	103.84	65.99	122.20	72.26	83.27	20.62	108.19	90.95	588.70	18.37	268.73	108.09	245.47	206.24	470.48
SVK	295.16	2681.24	334.16	1135.07	350.62	57.62	361.91	200.67	399.00	434.58	1965.00	1010.42	283.81	789.54	218.24	365.14
SVN	146.32	49.59	141.46	252.21	187.24	445.43	183.73	353.83	128.81	64.43	371.24	507.17	337.51	464.69	186.97	374.94
SWE	842.57	527.68	647.36	809.52	1440.09	943.13	2117.31	2322.92	1433.51	1726.35	2621.94	2892.81	1739.40	1526.26	1822.77	2431.87
TUR	47.35	23.01	46.56	155.30	29.13	30.01	22.55	130.45	150.09	213.63	292.17	90.65	30.29	89.58	21.69	114.05
TWN	191.30	342.93	765.72	339.30	174.84	41.82	93.51	462.41	494.50	598.48	673.02	1262.64	266.41	1071.37	62.57	623.66
USA	743.94	135.03	2095.47	4283.17	2238.01	1045.96	589.76	836.33	2695.42	330.55	1251.41	3625.50	1038.94	693.04	1803.03	4961.63

Table 3: Precision of initial prior beliefs and signals

Table 4: Real income loss (in annual term) due scarring belief for benchmark parameters.

	With IO linkages		Without IO linkages	
country	Open Economy	Autarky	Open Economy	Autarky
AUS	-20.83	-17.66	-26.28	-20.10
AUT	-12.65	-12.63	-27.31	-15.69
BEL	-14.25	-20.82	-33.14	-21.06
BGR	-12.93	-5.28	-15.65	-7.46
BRA	-18.46	-17.65	-18.39	-17.49
CAN	-23.76	-18.11	-34.04	-21.39
CHE	-17.03	-14.65	-29.82	-16.67
CHN	-15.19	-15.26	-20.55	-22.10
CYP	-14.09	-9.63	-31.85	-13.71
CZE	-12.06	-7.44	-19.25	-10.92
DEU	-15.38	-19.18	-23.29	-18.56
DNK	-18.41	-17.32	-31.38	-21.42
ESP	-17.51	-19.26	-27.37	-21.62
EST	-10.60	-5.22	-20.16	-8.14
FIN	-16.10	-11.30	-26.45	-14.75
FRA	-20.56	-22.57	-29.95	-22.75
GBR	-20.47	-18.30	-27.98	-22.73
GRC	-18.13	-11.87	-24.42	-13.78
HRV	-15.57	-7.19	-21.85	-10.16
HUN	-15.49	-10.35	-23.03	-14.19
IDN	-9.53	-8.54	-10.87	-10.86
IND	-16.86	-15.40	-14.79	-14.75
IRL	-21.14	-23.27	-37.12	-22.53
ITA	-17.73	-19.27	-26.14	-20.51
JPN	-12.88	-8.35	-17.88	-11.56
KOR	-14.53	-11.38	-22.09	-16.75
LTU	-11.24	-6.43	-18.88	-9.59
LUX	-11.32	-12.57	-27.66	-11.31
LVA	-12.62	-6.70	-22.01	-10.23
MEX	-14.59	-14.07	-17.03	-15.31
NLD	-17.62	-18.85	-30.29	-22.32
NOR	-17.07	-12.63	-27.41	-15.97
POL	-12.23	-8.57	-16.52	-9.79
PRT	-18.20	-14.41	-29.05	-17.24
ROU	-12.41	-7.00	-18.33	-11.23
RUS	-20.77	-13.87	-20.12	-16.40
SVK	-9.10	-6.29	-17.83	-8.59
SVN	-10.53	-7.43	-24.11	-11.06
SWE	-17.64	-16.22	-27.49	-19.88
TUR	-15.03	-13.26	-17.27	-14.82
TWN	-10.07	-4.98	-12.06	-6.19
USA	-23.54	-24.44	-29.02	-27.84
Average	-15.62	-13.23	-23.72	-15.70

Table 5: Real income loss (in annual term) due scarring belief for the learning rate $\chi = 10$.

	With IO linkages		Without IO linkages	
country	Open Economy	Autarky	Open Economy	Autarky
AUS	-22.05	-19.35	-28.20	-22.29
AUT	-12.28	-13.10	-26.60	-16.41
BEL	-13.83	-21.81	-34.16	-22.35
BGR	-11.88	-5.50	-14.38	-7.88
BRA	-20.08	-19.53	-21.02	-20.06
CAN	-22.98	-18.58	-33.73	-22.13
CHE	-15.84	-15.15	-29.73	-17.61
CHN	-16.86	-17.16	-23.72	-26.34
CYP	-13.78	-10.54	-31.62	-14.96
CZE	-11.58	-7.74	-18.29	-11.28
DEU	-16.06	-20.28	-24.66	-19.89
DNK	-18.02	-17.77	-31.13	-22.07
ESP	-17.46	-19.94	-27.54	-22.62
EST	-10.02	-5.78	-20.19	-8.93
FIN	-15.38	-11.65	-26.09	-15.24
FRA	-20.93	-23.87	-31.38	-24.40
GBR	-21.51	-19.52	-30.34	-25.07
GRC	-18.05	-12.50	-24.32	-14.63
HRV	-14.34	-7.82	-21.75	-11.02
HUN	-15.24	-10.60	-22.73	-14.61
IDN	-9.92	-9.27	-11.69	-12.03
IND	-18.22	-16.40	-16.34	-16.14
IRL	-21.30	-24.46	-36.72	-23.53
ITA	-17.42	-19.68	-25.92	-21.15
JPN	-12.75	-8.61	-17.87	-11.94
KOR	-14.28	-11.61	-22.24	-17.10
LTU	-10.99	-6.86	-18.76	-10.23
LUX	-10.59	-14.31	-30.16	-13.29
LVA	-12.25	-7.24	-21.43	-10.85
MEX	-14.91	-14.89	-16.89	-16.00
NLD	-18.55	-21.01	-33.92	-25.62
NOR	-17.14	-13.22	-28.04	-16.85
POL	-12.15	-9.05	-16.37	-10.49
PRT	-18.07	-15.43	-28.45	-18.03
ROU	-11.79	-7.23	-17.66	-11.77
RUS	-20.80	-14.13	-20.37	-17.08
SVK	-8.13	-6.73	-15.33	-8.81
SVN	-9.29	-7.53	-22.33	-11.36
SWE	-17.53	-16.79	-27.78	-20.63
TUR	-14.94	-13.66	-17.56	-15.59
TWN	-9.47	-5.08	-11.34	-6.41
USA	-23.70	-25.08	-30.30	-29.28
Average	-15.53	-13.96	-24.02	-16.76

Table 6: Real income loss (in annual term) due scarring belief for the learning rate $\chi = 0.1$.

	With IO linkages		Without IO linkages	
country	Open Economy	Autarky	Open Economy	Autarky
AUS	-11.91	-9.38	-14.53	-10.35
AUT	-11.53	-10.41	-26.37	-12.85
BEL	-11.42	-14.28	-21.26	-13.09
BGR	-12.17	-3.73	-13.54	-5.05
BRA	-11.18	-10.37	-8.91	-8.16
CAN	-20.98	-13.88	-27.04	-15.74
CHE	-14.10	-10.20	-20.80	-10.62
CHN	-9.21	-8.73	-10.15	-9.09
CYP	-9.23	-5.26	-20.62	-7.67
CZE	-9.80	-5.60	-18.58	-8.74
DEU	-8.74	-11.92	-14.06	-11.15
DNK	-15.28	-13.48	-25.76	-16.45
ESP	-12.77	-13.95	-19.81	-14.86
EST	-7.81	-2.79	-13.53	-4.52
FIN	-14.41	-8.53	-21.76	-11.15
FRA	-13.50	-13.76	-18.59	-13.37
GBR	-11.98	-12.11	-15.36	-12.63
GRC	-13.92	-8.15	-17.50	-8.82
HRV	-12.84	-4.62	-14.55	-6.06
HUN	-12.88	-8.38	-19.24	-11.12
IDN	-6.46	-5.09	-6.19	-5.81
IND	-11.11	-10.83	-7.96	-8.80
IRL	-16.16	-15.90	-31.00	-16.25
ITA	-15.04	-15.09	-21.90	-15.87
JPN	-10.51	-6.47	-14.32	-8.98
KOR	-12.30	-9.52	-17.04	-13.42
LTU	-8.16	-4.10	-13.39	-6.07
LUX	-8.10	-6.78	-11.66	-4.99
LVA	-9.66	-4.01	-17.38	-6.71
MEX	-11.41	-9.46	-14.95	-11.40
NLD	-8.88	-9.27	-15.03	-10.21
NOR	-10.93	-8.25	-18.33	-10.19
POL	-8.53	-5.63	-12.71	-6.38
PRT	-17.09	-10.72	-27.62	-13.85
ROU	-11.44	-5.44	-13.89	-7.88
RUS	-17.29	-11.35	-15.73	-12.27
SVK	-10.68	-4.62	-20.29	-6.80
SVN	-13.46	-6.38	-25.23	-9.12
SWE	-12.91	-11.85	-20.60	-14.59
TUR	-12.82	-10.57	-12.38	-10.26
TWN	-8.94	-3.72	-10.14	-4.37
USA	-17.69	-18.12	-18.82	-18.11
Average	-12.03	-9.11	-17.35	-10.33

Table 7: Real income loss (in annual term) due scarring belief for labor supply parameter $\phi = 3$.

country	With IO linkages Open Economy	With IO linkages Autarky	Without IO linkages Open Economy	Without IO linkages Autarky
AUS	-16.83	-20.82	-29.33	-26.43
AUT	-6.69	-14.83	-27.62	-20.55
BEL	-6.69	-24.39	-33.10	-27.24
BGR	-8.97	-7.72	-14.24	-10.18
BRA	-21.07	-23.32	-22.69	-23.41
CAN	-16.16	-21.11	-36.47	-27.66
CHE	-9.50	-16.62	-29.93	-21.88
CHN	-17.35	-19.48	-27.09	-30.94
CYP	-7.81	-12.90	-27.23	-18.97
CZE	-7.70	-9.57	-19.53	-14.33
DEU	-11.23	-20.02	-25.04	-22.81
DNK	-12.02	-20.36	-33.71	-28.08
ESP	-14.55	-22.05	-30.74	-28.53
EST	-5.70	-7.22	-19.75	-11.32
FIN	-9.94	-14.10	-28.94	-19.89
FRA	-15.41	-25.07	-33.81	-29.01
GBR	-14.75	-18.47	-30.73	-29.20
GRC	-15.75	-16.21	-25.80	-19.06
HRV	-10.87	-9.94	-20.88	-13.54
HUN	-12.09	-13.59	-25.46	-18.77
IDN	-12.48	-12.51	-14.75	-15.80
IND	-23.58	-23.19	-20.09	-21.95
IRL	-11.91	-30.18	-35.25	-29.82
ITA	-13.93	-21.03	-29.24	-25.72
JPN	-12.55	-9.59	-21.66	-15.32
KOR	-12.45	-12.80	-25.64	-21.30
LTU	-7.50	-9.45	-18.86	-13.83
LUX	-7.39	-15.92	-18.69	-15.26
LVA	-7.25	-9.37	-21.47	-14.05
MEX	-15.64	-19.57	-21.29	-22.15
NLD	-11.50	-21.17	-34.08	-29.43
NOR	-10.75	-15.10	-29.36	-20.25
POL	-8.35	-10.36	-15.73	-12.31
PRT	-14.39	-18.69	-31.51	-23.03
ROU	-9.44	-9.27	-17.48	-15.26
RUS	-22.28	-18.90	-25.86	-23.29
SVK	-2.95	-8.23	-11.88	-10.82
SVN	-3.75	-9.51	-21.54	-14.42
SWE	-12.14	-18.81	-30.53	-25.77
TUR	-16.07	-18.56	-21.62	-21.58
TWN	-8.06	-6.08	-12.34	-8.05
USA	-21.73	-25.17	-34.72	-35.41
Average	-12.08	-16.22	-25.14	-20.87

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