Long-Run Belief-Scarring Effects of COVID-19 in a Global Economy*

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Abstract

While COVID-19 lockdown measures disrupt production worldwide, they also shock workers' perceptions and beliefs about the economy and may hence have long-lasting effects after the pandemic. We study a belief-scarring mechanism in the context of labor markets and embed this mechanism into a multi-country, multi-sector Ricardian trade model with input-output linkages. Our quantitative analysis indicates that pandemic shocks leave persistent and substantial belief-driven negative impacts on the post-COVID economy. We find that international trade (without sectoral input-output linkages) worsens the post-COVID economic losses due to a labor-misallocation effect when workers misconceive comparative advantages, whereas input-output linkages dampen such losses. When allowing both trade and input-output linkages, a third and negative effect emerges because the presence of the global supply chain amplifies the stake of efficient allocation according to true comparative advantages and hence makes information friction even more costly. Thus, trade, with input-output linkages, exacerbates the post-COVID losses for most countries.

Keywords: pandemic, COVID-19, Bayesian learning, belief-scarring effect, international trade, sectoral input-output linkages, labor misallocation

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1 Introduction

The COVID-19 pandemic is one of the largest disruptions to the global economy in modern times. During 2020–2021, countries around the globe went through waves of rapid infections and various degrees of containment/lock-down measures in order to "flatten the curve". As a result, global production and supply chains were severely shocked by these containment measures. One important approach to coping with such containment measures is to encourage workers to work from home (henceforth WFH) as much as possible. With the mass vaccination, cumulative infections, and recently available cures in 2022, most countries have adopted a "living with COVID-19" policy, but COVID's economic aftermath may endure long after all containment measures have been lifted.

Based on the idea that the economic shocks of COVID vary across sectors and countries and that such shocks may persist through workers' imperfect adjustment in their beliefs about the economy, in this paper we study a *belief-scarring* mechanism of sectoral labor markets and investigate its properties and quantitative relevance. In particular, when workers are shocked during the pandemic, their beliefs about sectoral real wages change, therefore affecting their sectoral choices. In a Bayesian learning process, the larger the shock, the longer it takes to recover the original belief even when the economy is similar to the pre-COVID situation.

Sectors differ in their WFH capacities; sectors with larger WFH capacities are shocked less. Countries differ in their stringency in containing COVID; countries with more stringent containment measures are more adversely impacted. These factors interact, and shocks transmit across countries and sectors through the system of international trade. Thus, it is essential to study the belief-scarring mechanism in a general-equilibrium model of international trade with sectoral input-output linkages. To do so, we embed the belief-scarring mechanism into the model of Caliendo and Parro (2015), which extends the Ricardian model of Eaton and Kortum (2002) to incorporate input-output linkages.

We briefly explain the Bayesian learning process and how sectoral labor supply is determined. Workers have idiosyncratic preferences towards working in different sectors. With Type-I extreme value distribution, sectoral labor shares are determined by a standard logistic formula in which the key determinants are workers' forecasts of sectoral real wages. At period 0 and for each country and sector, there is a distribution of beliefs about the sector's real wages centered around the forecasted sectoral real wages. At the end of each period, workers learn about the realized real wages, and interpret these as unbiased pieces of data that inform them about the underlying changes in the economy. The Bayesian updating implies that the mean of the posterior distribution (the forecasted sectoral real wages for the next period) is a convex combination of the mean of the prior distribution (the forecasted sectoral real wages for the current period) and the realized real wages in the current period. This captures the scarring effect, because past information always carries weight. Even when the pandemic is over and there are no new shocks, workers do not fully adjust to the new situation.

Next, we describe how pandemic shocks are modeled. We first use information from Dingel and Neiman (2020) to derive a country's sectoral WFH capacity μ_i^j for each sector j and country i. Let the containment measure be denoted $\eta_{i,t}$. Then, $\eta_{i,t}\left(1-\mu_i^j\right)$ fraction of workers in sector j is locked away, and the effective labor supplied per worker is reduced to $B_{i,t}^j \equiv 1-\eta_{i,t}\left(1-\mu_i^j\right) < 1$. In our trade model that features constant returns to scale and Hicks-neutral productivity, the pandemic shocks $B_{i,t}^j$ can also be interpreted as productivity shocks. As such, the pandemic shocks reshape the comparative advantages across sectors and countries. Sectoral labor shares and real wages change accordingly.

Using the World Input-Output Database (WIOD), the model is calibrated to the pre-COVID economy. The stringency of the containment measures is derived from the Stringency Index by the Oxford COVID-19 Government Response Tracker (OxCGRT) constructed by Hale et al. (2021). We scale this index so that the model-generated reduction of world GDP matches the data counterpart during 2020. As most countries had adopted a "living with COVID-19" policy at the time of writing this paper in 2022, in our simulation we assume that by the first quarter of 2022 all countries in our sample have abolished all of the containment measures. We simulate the model for 50 years starting from 2022 and evaluate the economic loss by contrasting the path with that from a perfect-information equilibrium in which agents correctly anticipate the realized real wages.

In our baseline scenario, post-pandemic real income does not bounce back to the pre-pandemic level upon termination of the containment measures. Across countries, the cumulative post-COVID losses due to the belief-scarring mechanism range from 0.68% to 2.42% of the pre-COVID annual real income. These post-COVID losses are substantial because they are 14.0–61.7% of the economic losses during the pandemic. When these post-COVID losses are combined globally, they are 21.9% of the global economic losses during the pandemic.

We investigate the roles of international trade and input-output linkages by comparing the baseline economy with those in alternative settings. First, to highlight the role of trade, we abstract away input-output linkages and compare the economic after-effects under trade and those under autarky. Contrary to Bonadio et al. (2021) and Hsu, Lin and Yang (2020) who show that trade can mitigate the impact of containment measures, we find that trade worsens the post-pandemic long-run losses for most countries. The key difference is the role of information. In Eaton and Kortum's (2002) Ricardian framework, the sectoral allocation of labor is efficient in the perfect-information equilibrium, but this is not the case under our belief-scarring mechanism. As workers make their sectoral choices based on misperceived comparative advantages, there is labor misallocation in each country. Also, as the stakes of efficient allocation are larger in an open economy than in an autarkic world, trade openness exacerbates the effects of such labor misallocation.

To highlight the role of input-output linkages, we compare two autarkic worlds in which every country is an autarky, one with such linkages and one without. We find that the existence of domestic supply chains mitigates the post-pandemic long-run losses for most countries. This is because the opportunities for sourcing allow firms to indirectly tap the resources of the most efficient producers while reducing the role of labor.

Finally, we compare post-pandemic economic losses under open economy and under autarky when input-output linkages are present. Compared with an autarkic world, most countries suffer greater long-run losses under open economy, while only four countries suffer less. As explained, trade worsens long-run economic losses by a *labor misallocation effect* in the case without input-output linkages. Such an effect is still present here, albeit to a lesser degree because the use of intermediate inputs lowers the importance of labor in the production process. However, trade can amplify the above-mentioned sourcing benefits 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*. Furthermore, there emerges a new and negative effect due to the combination of international trade and input-output linkages because the existence of global supply chains amplifies the stake of efficient allocation according to comparative advantages. It turns out the two negative effects dominate the positive international sourcing effect for all but four countries. Thus, when input-output linkages are present, trade amplifies global post-COVID losses in the pre-COVID global real income by a larger magnitude than when input-output linkages are absent.

Related Literature

There has been a surge of research from macroeconomic perspectives studying the effects of the pandemic. Most of these studies focus on the tradeoff between lives and the economy during the pandemic by embedding variants of the classic SIR model proposed by Kermack, McKendrick and Walker (1927) into macroeconomic models.[1] Therefore, the vast majority of these recent studies concern the short-run effects. In this paper, we emphasize the long-run impacts due to the belief-scarring mechanism after the containment measures have been completely lifted. The most related study is by Kozlowski, Veldkamp and Venkateswaran (2020) who first studied the long-run belief-scarring effect of COVID-19 via a neoclassical model with information friction on the default rate in the capital market. Our work differs from theirs in that we focus on the information friction in sectoral labor markets and study the role of international trade and input-output linkages. Also closely related is the work by Elenev, Landvoigt and Van Nieuwerburgh (2022) who also study the long-run aftermath of COVID-19 by using financial frictions to analyze the balance-sheet effect.

In the literature of international trade, Bonadio et al. (2021) study the role of international input-output linkages in transmitting foreign pandemic shocks on domestic economies. Hsu, Lin and Yang (2020) study optimal containment policies on the tradeoff between lives and the economy in a multi-country multi-sector model with disease dynamics. More broadly related are the studies by Antrás, Redding and Rossi-Hansberg (2020), Fajgelbaum et al. (2021), and Argente, Hsieh and Lee (2022) who all consider the interaction between disease dynamics and the economy in general equilibrium models

[1] See, for examples, Acemoglu et al. (2021), Alvarez, Argente and Lippi (2021), Atkeson (2020), Eichenbaum, Rebelo and Trabandt (2021), Farboodi, Jarosch and Shimer (2021), Jones, Philippon and Venkateswaran (2021), Krueger, Uhlig and Xie (2022), and Piguillem and Shi (2022).

in the context of international trade or cities.

The rest of the paper is organized as follows. Section 2 lays out the model, defines equilibrium conditions, and describes the algorithm. Section 3 details how the model is parameterized. Section 4 conducts a quantitative analysis on post-COVID economic losses and investigates the roles of international trade and sectoral input-output linkages. Section 5 concludes.

2 Model

This section introduces the model, which embeds pandemic shocks, worker's sectoral choices, and the Bayesian learning process into a Caliendo and Parro (2015) trade model.

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 instantaneous utility 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. Suppose the time horizon is $\bar{t}$, which can be either finite or infinite. The life time utility of the representative consumer in country i is given by $U_i = \sum_{t=0}^{\bar{t}} \rho^t q_{i,t}$, where ρ is the discount factor.

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 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 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 Frechet 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.

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. 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

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

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

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 the end of period $t-1$, a worker chooses which sector to work at 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 $\{\bar{\omega}^j_{i,t}\}^J_{j=1}$ and realized values of the idiosyncratic preferences $\{\epsilon^j_{i,t}\}^J_{j=1}$, the optimal sectoral choice for this worker is determined by

$$V_{i,t} \equiv \max_j \left\{\bar{\omega}^j_{i,t} + \phi\epsilon^j_{i,t}\right\}, \tag{6}$$

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, sectors, and periods, 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 ex ante expected utility of a worker is given by

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

Consequently, the sectoral labor employment 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 agents' forecasts on real wages evolve over time. At period 0, workers in country i have initial prior belief about the real wage for each sector j given by

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

Assume that the workers do not fully understand the workings of the economy and cannot project the 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 $\{\omega^j_{i,t-1}\}^J_{j=1}$. Workers interpret this signal as an unbiased piece of data about $\ln(\widetilde{\omega}^j_{i,t-1})$ with precision $1/\sigma^2_i$. Namely,

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

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

With the new signal/data $\{\omega_{i,t-1}^{j}\}_{j=1}^{J}$, workers then update their beliefs using Bayes' rule. Standard procedure entails that workers form the 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:

$$\ln(\bar{\omega}_{i,t}^{j}) = \frac{\frac{1}{(\widetilde{\sigma}_{i,t-1}^{j})^2} \times \ln(\bar{\omega}_{i,t-1}^{j}) + \frac{1}{\sigma_i^2} \times \ln\left(\omega_{i,t-1}^{j}\right)}{\frac{1}{(\widetilde{\sigma}_{i,t-1}^{j})^2} + \frac{1}{\sigma_i^2}}. \tag{8}$$

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. That is, $\ln(\widetilde{\omega}_{i,t}^{j}) \sim N\left(\ln(\bar{\omega}_{i,t}^{j}), (\widetilde{\sigma}_{i,t}^{j})^2\right)$.

2.4 Pandemic Shocks

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. Note that $\eta_{i,t} = 1$ means a total lockdown whereas $\eta_{i,t} = 0$ means totally laissez-faire, but a containment policy can be anywhere in between. 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 workers who are unable to work from home 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; the fraction of such workers is $(1-\eta_{i,t})(1-\mu_i^j)$.

As the effective labor 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 freeze pay to workers who are locked away; or, the employers can pay the full wage even when a worker's effective time supplied is reduced. In the former case, workers absorb the shocks directly, whereas it is 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), $B^j_{i,t} = 1$.

Observing (3), a more stringent containment measure (higher $\eta_{i,t}$) can be interpreted as productivity shock; these effects are mitigated if the sector of concern has a larger WFH capacity (higher μ^j_i). Both dimensions differ by country. Assuming $\kappa < \theta + 1$, the price index of a sectoral good is given by

$$P^j_{n,t} = \zeta \left(\sum_{k=1}^{K} T^j_k \left[\left(w^j_{k,t}/B^j_{k,t} \right)^{\beta^j_k} \left(P^{M,j}_{k,t} \right)^{1-\beta^j_k} \tau^j_{k,n} \right]^{-\theta} \right)^{-\frac{1}{\theta}}, \tag{9}$$

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

$$\pi^j_{i,n,t} = \frac{T^j_i \left[\left(w^j_{i,t}/B^j_{i,t} \right)^{\beta^j_i} \left(P^{M,j}_{i,t} \right)^{1-\beta^j_i} \tau^j_{i,n} \right]^{-\theta}}{\sum_{k=1}^{K} T^j_k \left[\left(w^j_{k,t}/B^j_{k,t} \right)^{\beta^j_k} \left(P^{M,j}_{k,t} \right)^{1-\beta^j_k} \tau^j_{k,n} \right]^{-\theta}}. \tag{10}$$

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 a comparative advantage in those high μ^j_i sectors if it has a larger presence 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 measures become 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 the goods in sector j, and $X_{n,t}$ denote the total expenditure of country n. Given sectoral labor supply $L^j_{i,t} = N_i \ell^j_{i,t}$ (where $\ell^j_{i,t}$ is given by [7]), the labor market clearing condition for sector j in country i is

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

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

$$X^j_{i,t} = \alpha^j_i \sum_{k=1}^{J} w^k_{i,t} L^k_{i,t} + \sum_{l=1}^{J} \gamma^{l,j}_i (1 - \beta^l_i) \sum_{n=1}^{K} \pi^l_{i,n,t} X^l_{n,t} \tag{11}$$

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 expenditure toward sector-j goods in country i. This is indeed a system of linear equations of $\{X^j_{i,t}\}_{i,j}$ with the intercepts being the final-good expenditures.

We briefly describe the equilibrium algorithm as follows, and leave the full details to Appendix A. First, given realized real wages at period $t-1$, $\omega^j_{i,t-1}$, the forecast for real wages at period t, $\bar{\omega}^j_{i,t}$, is determined by (8), sectoral labor shares $\ell^j_{i,t}$ by (7), and sectoral labor force by $L^j_{i,t} = \ell^j_{i,t} N_i$. 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 (9)–(11).

The model mechanism can be briefly summarized as follows. The adverse effects of pandemic shocks differ across countries and sectors and generally shock the non-WFH sectors more than than the WFH sectors. These reshape the comparative advantages. Sectoral real incomes change drastically during the pandemic, subsequently changing the sectoral employment shares $\ell^j_{i,t}$. Such effects linger even after the pandemic is over because of the imperfect adjustments on beliefs of real wages across sectors that affect workers' sectoral choices.

3 Parameterization

Our model consists of three sets of parameters: economic, pandemic, and information parameters. We briefly describe how they are calibrated and estimated. Details on the data and calibration are given in Appendix B.

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'Etudes Prospectives et d'Informations Internationales (CEPII) data. The country of 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 to a degree that is roughly comparable to the aggregation by Caliendo, Dvorkin and Parro (2019). This results in fifteen sectors;[2] Appendix Table C.2 shows the concordance of our industry aggregation.

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

Following Simonovska and Waugh (2014), we set the value of trade elasticity $\theta = 4$, and following Caliendo, Dvorkin and Parro (2019), we set the labor supply elasticity $\phi = 5.34$. By (10), the gravity equation holds in our model at the sectoral level. Thus, trade costs $\{\tau_{i,n}^j\}$ can be estimated using standard gravity-equation estimation, given the value of trade elasticity θ, data on bilateral trade shares from the WIOD, and information about geography from CEPII. For the full details, see Appendix B.2.

Following Fieler (2011) and Ravikumar, Santacreu and Sposi (2019), the productivity parameters $\{T_i^j\}$ can be uncovered by utilizing estimates from the gravity regression and the model structure, 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 the WIOD. See Appendix B.2 for the full details of this procedure.

3.2 Pandemic Parameters

The WFH capacity $\{\mu_i^j\}$ values are obtained from Dingel and Neiman (2020), who compute this 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 $\{\eta_{i,t}^{data}\}$ are obtained from the *Stringency Index* of the Oxford COVID-19 Government Response Tracker (OxCGRT; (Hale et al., 2021)) at a daily frequency. This index

[2] We have fewer sectors than the 22 sectors in Caliendo, Dvorkin and Parro (2019) because we further aggregate service sectors to avoid numerous zero international trade flows. Note that the focus of Caliendo, Dvorkin and Parro (2019) is on labor movements between sectors in the US and is less concerned with international trade flows.

summarizes government responses in terms of various closures and containment, including school or workplace closures, stay-at-home requirements, border controls, and restrictions on gathering, public events, public transport, and internal movements, as well as public information campaigns. The time unit of our analysis is set to quarters; thus we calculate the average of the daily stringency index for each quarter from 2020Q1 to 2021Q4.

Recall that the pandemic shock is $B_{i,t} = 1 - \eta_{i,t}(1 - \mu_i^j)$. If the above-mentioned stringency index $\{\eta_{i,t}^{data}\}$ were directly used as the containment measure $\{\eta_{i,t}\}$, the resulting real GDP reductions would be much larger than the actual reductions during this period. Therefore, we assume that the true and effective containment measure is given by $\eta_{i,t} = (\eta_{i,t}^{data})^\delta$ for some $\delta > 0$. We set $\delta = 7.93$ so that the percentage reduction in world real GDP generated by the model matches the data counterpart in our sample countries.[3]

3.3 Information Parameters

We now describe how the information parameters are calibrated. First, the means of the initial prior distributions of sectoral real wages $\left\{\bar{\omega}_{i,0}^j\right\}_{i,j}$ are assumed to be the sectoral real wages in the steady-state equilibrium, in which the realized real wages are the same as the forecasted real wages. Then, (8) implies that these steady-state real wages can be computed without knowing the precision parameters. Absent pandemic shocks and using the calibrated model (although the precision parameters are unknown at this point), steady-state equilibrium sectoral real wages $\left\{w_i^{j*}/P_i^*\right\}_{i,j}$ are computed, and we set $\bar{\omega}_{i,0}^j = w_i^{j*}/P_i^*$.

Next, we retrieve the sectoral nominal wages $\{w_{i,t}^{j,data}\}$ from the WIOD, for the years spanning 2000 to 2014. Then, for each year during 2000–2014, we compute the corresponding sectoral real wages $\omega_{i,t}^j = w_{i,t}^{j,data}/P_{i,t}$, where $P_{i,t}$ is calculated by plugging $w_{i,t}^{j,data}$ into (5) and (9). Using these sectoral real wages, we run the regression

$$\ln\left(\omega_{i,t}^j\right) = D_i^j + D_{i,t} + e_{i,t}^j,$$

where D_i^j is a sector-country dummy, and $D_{i,t}$ is a country-year dummy. We collect the

[3] As the 2021 GDP data was not available at the time of writing, only the four quarters of GDP data in 2020 were used. Also, only the pandemic shocks in 2020 were used in the model simulation.

prediction error of the regression $\hat{e}^j_{i,t}$. The precision of initial prior belief $\left(\widetilde{\sigma}^2_{i,0}\right)$ and the precision of signals $(\sigma^j_i)^2$ are set to

$$\left(\widetilde{\sigma}^j_{i,0}\right)^2 = s^2\left(\{\hat{e}^j_{i,t}\}_{t=2000,\ldots,2014}\right)$$
$$\sigma^2_i = s^2\left(\{\hat{e}^j_{i,t}\}^{j=1,\ldots,J}_{t=2000,\ldots,2014}\right).$$

Namely, we use the sample variance of the prediction error for each (j,i) across the time horizon as the precision of the initial prior belief and the sample variance of the prediction error for each country i across sectors j and time horizon t as the precision of the signal. In other words, we assume that workers base their Bayesian learning process on this over-time and cross-sector volatility and the above-mentioned steady-state real wages.

4 The Long-run Economic After-Effects of COVID-19

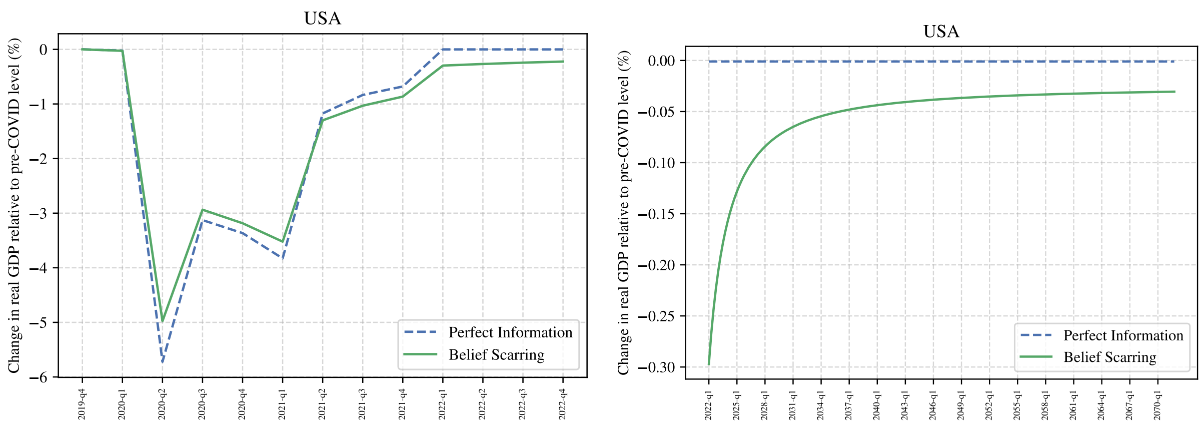
Using the calibrated model, this section quantifies the long-run economic after-effects of COVID-19 containment measures due to the belief-scarring mechanism and analyzes the roles of international trade and input-output linkages.

4.1 Setting Up the Simulation Environment

As the Omicron variant spreads around the world in 2022, the pandemic has not yet finished. However, with mass vaccinations, cumulative infections, and the recently available cures, most countries have adopted a "living with COVID-19" policy. The fact that the Omicron variant is less lethal and much more contagious than previous variants makes it more difficult for the few "COVID-zero" countries to insist on strong containment measures; as a result, these countries have also relaxed their containment measures.[4]

For our purpose, we will simulate the evolution of the global economy starting from a pre-COVID economy which went through the pandemic shocks in the eight quarters of 2020–2021; subsequently, we assume that all containment measures are lifted ($\eta_{i,t} = 0$) in the first quarter of 2022, and the economy evolves for 50 years from 2022. Note that

[4] The only exception is China, as of June 2022 when this paper is written.



(a) Paths of real income during pandemic

(b) Post-COVID paths of real income

Figure 1

the Stringency Index is available at a daily frequency, but we choose to take the quarterly average of the index and conduct the simulation at a quarterly frequency for the following reasons. First, it takes time for workers to switch sectors. Second, our elasticity of labor supply is taken from Caliendo, Dvorkin and Parro (2019), who estimate this elasticity using quarterly data. Third, this reduces the computational burden of simulating 52 years of the global economy. We simulate a total of 209 quarters, as the first quarter is the pre-COVID baseline period.

4.2 The Long-Run Economic After-Effects

Let $W_{i,t} = \left(\sum_{j=1}^{J} w_{i,t}^{j} L_{i,t}^{j}\right) / P_{i,t}$ be country i's real income at quarter t. Figure 1a shows the time path of real income relative to the pre-COVID level in the US from the pre-COVID situation to the last quarter of year 2022. Upon the elimination of containment measures in the first quarter of 2022, the US still suffers a 0.30% real income loss relative to the pre-COVID level. The real income does not fully recover to the pre-COVID level because agents' beliefs still carry information about past economic outcomes during the pandemic. In contrast, in the setting where agents have perfect information, i.e. agents' expected sectoral real wages are exactly the same as realized wages, the real income bounces right back to the pre-COVID level upon the elimination of containment measures.[5]

[5] See Appendix A.2 for the characterization and computation of the perfect-information equilibrium. Briefly, note the model feature that sectoral labor supply is determined by perceived wages, and realized

As we simulate the post-COVID economy for 50 years from 2022, Figure 1b shows the US' paths of the percentage changes in real income during the 50 years from 2022 for both the belief-scarring and perfect-information equilibria. Under the perfect-information equilibrium, the US real income stays at the pre-COVID level throughout. For each quarter, the economic loss of a country due to the belief-scarring mechanism is therefore the gap between the two income levels shown in Figure 1b. The after-effects are persistent — even 50 years after the conclusion of COVID, there is still around 0.03% of real income loss in the US resulting from the two years of pandemic. The qualitative patterns for other countries are similar, but the quantitative magnitudes vary.

To evaluate the cumulative economic losses due to scarred beliefs, we compute the discounted sum of the quarterly losses relative to the pre-COVID annual real income, $W_{i,t}^{\text{scarred}} - W_{i,t}^{\text{perfect}}$ for each quarter t. The annual discount factor is set to 0.96; thus the quarterly discount factor is $\rho = 0.96^{\frac{1}{4}}$. Formally, the *belief-scarring cumulative loss* (henceforth BCL) in terms of the pre-COVID annual real income is calculated by

$$\frac{\sum_{t\geq t^*} \rho^{t-t^*} \left(W_{i,t}^{\text{scarred}} - W_{i,t}^{\text{perfect}}\right)}{W_i^{\text{pre-COVID}}} \times \frac{1}{4} \times 100\%,$$

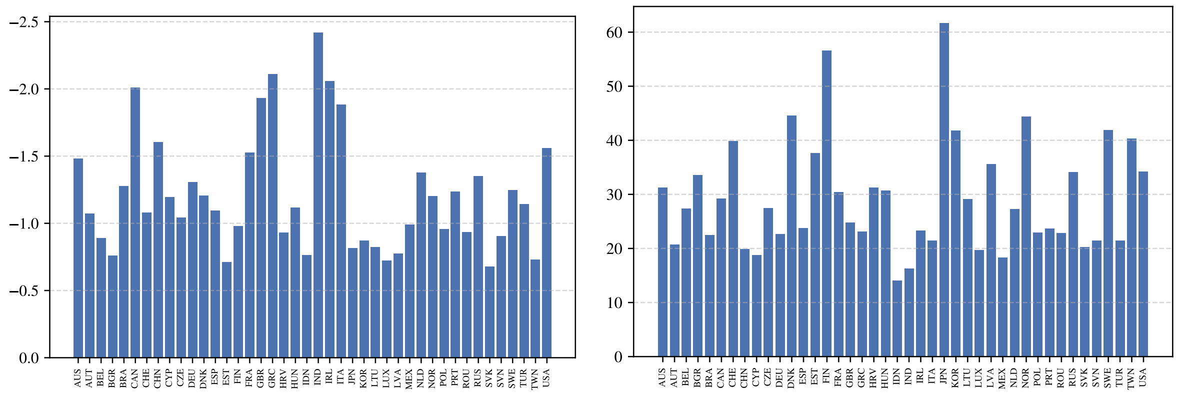
where $t^* = 9$ is the time when the containment measures are lifted. Figure 2a summarizes the BCL in the pre-COVID annual real income. Across countries this varies from 0.68% to 2.42%, and the (unweighted) average is 1.21%.

Figure 2b shows the BCL relative to the economic losses during the pandemic, which is calculated by

$$\frac{\sum_{t\geq t^*} \rho^{t-t^*} \left(W_{i,t}^{\text{scarred}} - W_{i,t}^{\text{perfect}}\right)}{\sum_{t=1}^{8} \rho^{t-1} \left(W_{i,t}^{\text{scarred}} - W_i^{\text{pre-COVID}}\right)} \times 100\%,$$

where $t = 1, \ldots, 8$ corresponds to the eight quarters during 2020–2021. The BCLs are 14.0–61.7% of the economic losses during the pandemic. When these post-COVID losses are combined globally, they are 21.9% of the global economic losses during the pandemic. Here, the global real income is simply defined by the sum of the real income across countries, $\sum_{i=1}^{K} W_{i,t} = \sum_{i=1}^{K} \left(\sum_{j=1}^{J} w_{i,t}^j L_{i,t}^j\right) / P_{i,t}$; this is indeed proportional to the population-weighted average of real income per capita.

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.



(a) BCL in pre-COVID annual real income (%) (b) BCL relative to loss during pandemic (%)

Figure 2

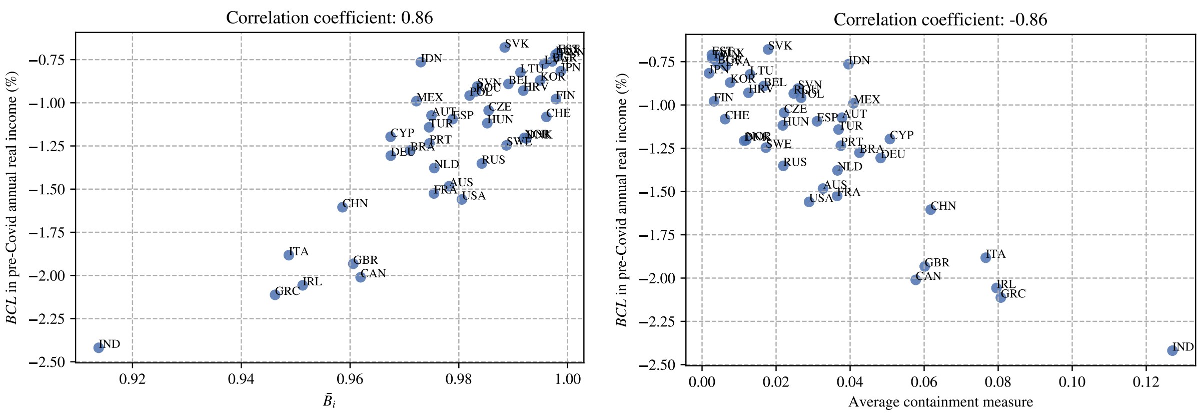
Define $\bar{B}_i$ to be the simple average of the $\bar{B}_{i,t}$ across the eight quarters of 2020–2021, where $\bar{B}_{i,t} = \sum_j \left[1 - \eta_{i,t}(1 - \mu_i^j)\right] \ell_{i,0}^j$ is quarter t's average pandemic shock weighted by the pre-COVID sectoral employment share. As a sanity check, Figure 3a plots the BCLs (in the pre-COVID annual real income) against the average pandemic shocks $\bar{B}_i$. Note that $\bar{B}_i$ is actually an inverse measure of the pandemic shock, as the larger the $\bar{B}_i$, the smaller the shock. Indeed, we see a strong positive correlation (0.86) between BCLs and pandemic shocks. More specifically, Figure 3b plots the BCLs against average containment measures during the pandemic.[6] Indeed, countries that impose more severe containment measures during the pandemic such as India, Greece, and Ireland experience greater BCLs. In contrast, countries such as Luxembourg, Estonia, and Slovakia, which implement relatively more lenient containment policies during the pandemic, incur less BCL.

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 to the belief-scarring mechanism. We will visualize the results in this subsection by figures and report a few key numbers. Detailed results are given in Appendix Table C.3.

To study the role of international trade, we disentangle the effect of international

[6] The average containment measure for each country is calculated by the simple average of $\eta_{i,t}$ across the eight quarters of 2020–2021.



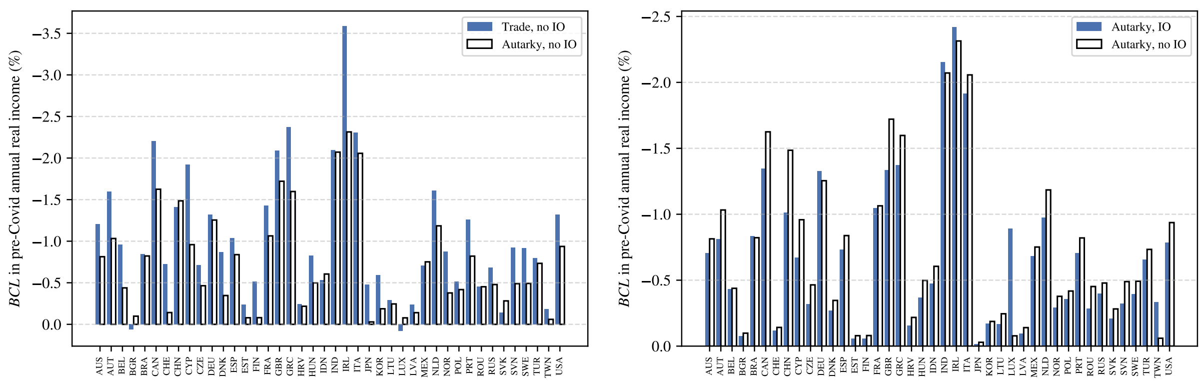
(a) Average pandemic shock $\bar{B}_i$ and BCL (b) Containment stringency and BCL

Figure 3

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 of 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 post-COVID BCL in terms of the pre-COVID annual real income for each country, and for both the trade and autarky cases. International trade exacerbates the long-run economic losses for all but four countries. For many countries, the extra losses under trade are substantial. The global BCL is 4.5% larger under trade than that of under autarky.

The reason is that the stakes of efficient allocation of labor across sectors according to comparative advantages is larger in an open-economy environment than in a closed one. Due to imperfect information, workers choose their sectors based on misperceived comparative advantages, resulting in labor misallocation. This labor-misallocation effect is larger under trade than under autarky. Note that Bonadio et al. (2021) and Hsu, Lin and Yang (2020) show that trade can mitigate the impacts of containment measures. The key difference is that they do not consider the role of information friction. Here we show that the interaction of information friction and trade can be harmful.[7]

[7]Note, however, that there are four countries for which trade reduces the BCLs or even induces long-run gains instead of losses. The terms-of-trade effect may explain the gains enjoyed by two countries, while it is likely the mechanism highlighted in Hsu, Lin and Yang (2020) that mitigates the long-run losses for the other two countries. That is, during the pandemic, trade mitigates the negative impacts of containment measures for some countries, and thus causes workers in these countries to be less scarred to



(a) (b)

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

Next, to highlight the role of input-output linkages, we compare two autarkic worlds in which each country is an autarky, one with such linkages and one without. The BCLs in the pre-COVID annual real income are presented in Figure 4b. The existence of domestic input-output linkages mitigates post-pandemic long-run losses for most countries. For many countries, the reductions in losses when input-output linkages are present are substantial. The global BCL is 20.3% smaller than without input-output linkages.

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

Finally, we compare the post-pandemic BCL under open economy and under autarky when input-output linkages are present. The result is summarized in Figure 5. Compared with the autarkic world, most countries suffer greater long-run losses under the open economy; only four 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 input-output linkages. This effect is still present here, albeit to a lesser degree than

begin with. If this benefit of being less scarred dominates the above-mentioned labor misallocation effect due to information friction, then the BCLs may be dampened.

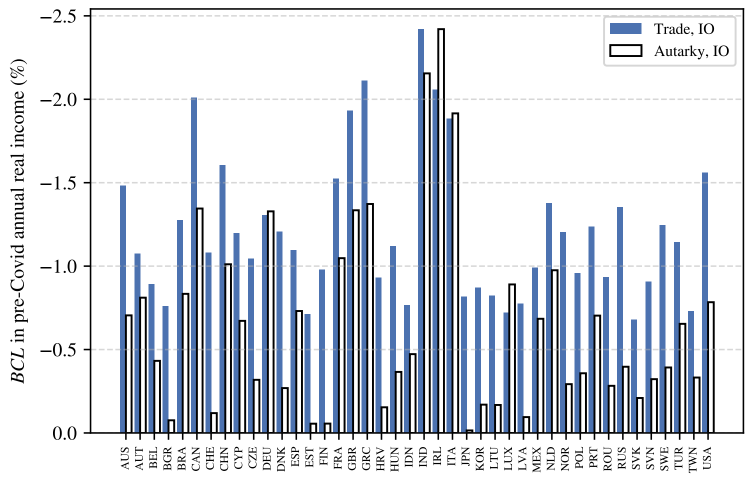


Figure 5: The Role of International Trade When Input-Output Linkages are Present

that in Figure 4a because the use of intermediate inputs lowers the importance of labor in the production process. However, trade can amplify the above-mentioned sourcing benefits 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*. Furthermore, compared with Figure 4a where only the labor misallocation effect is present, there is an interaction from the combination of international trade and input-output linkages because the existence of global supply chains amplifies the stake of efficient allocation according to comparative advantages. This brings another negative effect of the belief-scarring mechanism on the post-COVID long-run losses.

It turns out the two negative effects dominate the positive international sourcing effect for all but four countries. Thus, when input-output linkages are present, trade amplifies the global BCL in the pre-COVID global real income by 44.3%, which is much larger than the effect of trade when input-output linkages are absent (4.5%).

4.4 Robustness Checks

Two key parameters in our model are 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 robustness checks 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.,

$$\sigma_i^2(\chi) = \frac{(\sigma_i^2)^{\text{benchmark}}}{\chi}. \tag{12}$$

A larger value of χ implies that workers assign a smaller weight to prior beliefs and hence learn faster when new information becomes available. 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 the respective post-COVID BCLs. The results are shown in Appendix Table C.4. Again, we find that trade worsens the long-run economic losses due to scarred beliefs. In the benchmark scenario, trade worsens the global BCL by 44.3% ([1.53-1.06]/1.06). In these two robustness checks, trade worsens the global BCL by 39.5% and 57.4% for $\chi = 10$ and $\chi = 0.1$, respectively. Thus, the effect of trade is quantitatively similar in these cases. In terms of comparative statics of the learning rate χ, the global BCLs are 3.9% larger and 30.1% smaller for $\chi = 10$ and $\chi = 0.1$, respectively, in comparison to the benchmark scenario. Thus, the larger the learning rate χ, the larger the global BCLs. A larger χ (a faster learning rate) implies faster recovery compared with the perfect-information equilibrium. However, a faster learning rate also implies that COVID shocks the real income to a larger degree during the pandemic period. The post-pandemic loss due to scarred belief is therefore larger because both the beliefs and the economy are more scarred to begin with.

Next, we change the labor supply parameter from $\phi = 5.34$ to $\phi = 3$ and $\phi = 1.2$. Lowering ϕ reduces the sectoral labor supply elasticity. The results are shown in Appendix Table C.5. We find that trade worsens the global BCL in the case of $\phi = 3$, whereas it mitigates it in the case of $\phi = 1.2$. Recall from the previous subsection that the two negative effects of trade when input-output linkages are present are both associated with labor misallocation. When the sectoral labor supply becomes less elastic, these negative effects are reduced. In the case of $\phi = 3$, the negative effects still dominate the positive international sourcing effect, but we find that they are dominated when the value ϕ falls below 1.2.

5 Conclusion

This paper studies how the interaction between Bayesian learning and pandemic shocks creates post-pandemic long-run after-effects. We study this belief-scarring mechanism in a quantitative trade model with sectoral input-output linkages. We first gauge the quantitative magnitude of this after-effect, and then investigate the roles of trade and input-output linkages. We find that the long-run losses due to the belief-scarring mechanism are substantial, as they are 14.0–61.7% relative to the economic losses during the pandemic. When these post-COVID losses are combined globally, they are 21.9% of the global economic loss during the pandemic. We find that trade generally worsens the long-run losses, while sectoral input-output linkages dampen them. With sectoral input-output linkages, trade also worsens the long-run losses, and this result is robust across different learning rates and a wide range of sectoral labor supply elasticities.

This study on the interaction between the pandemic and trade is rather unique relative to the trade literature for two reasons. First, most trade theories assume perfect information, and here we show that with imperfect information, trade may negatively affect long-run economic outcomes, which is contrary to the findings in recent studies on trade and the pandemic. Input-output linkages alone tend to dampen such losses, but such linkages amplify the negative effect of trade when they work in the open-economy environment. Even though the purpose of this paper is not to evaluate the role of the global supply chain comprehensively from various angles, our findings support the idea that if something goes wrong with trade, it gets worse with extensive global supply chains.

Appendix

A Equilibrium Algorithm

In this section, we present more details about the model. 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

$$\underset{JK\times 1}{\mathbf{b_t}} = \underset{JK\times JK}{\mathbf{A_t}} \times \underset{JK\times 1}{\mathbf{X_t}}, \tag{13}$$

where the element of each term is

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

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

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

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

A.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 simplify the notation. 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

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

   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.

A.2 Equilibrium Sectoral Labor Supply with Perfect Foresight

In this subsection, we discuss the procedure to find the sectoral labor shares across i and j that are consistent with learning and equilibrium. Agents 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 $\ell_{i,t}^{j}$:

1. Start with an initial guess such that $\ell_{i,t}^{j}(0)$.
2. Use $\ell_{i,t}^{j}(r)$ and future of containment measures $\widetilde{\eta}_{i,t}$ to compute real income $\widetilde{\omega}_{i,t}^{j}(r) = \frac{w_{i,t}^{j}(r)}{P_{i,t}(r)}$ for each country i and each sector j.
3. Use the new sectoral real income to update the sectoral labor supply
$$\ell_{i,t}^{j}(r+1) = \frac{\exp\left(\widetilde{\omega}_{i,t}^{j}(r)\right)^{1/\phi}}{\sum_{k=1}^{J}\exp\left(\widetilde{\omega}_{i,t}^{k}(r)\right)^{1/\phi}}.$$
4. Stop the iterative procedure if
$$\max_{(j,i)}\{|\ell_{i}^{j}(r+1) - \ell_{i}^{j}(r)|\} < \text{tolerance}.$$
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 $\ell_{i,t}^{j}$ determined by agents at the end of period $t-1$.

B Parameterization

This section provides more details on how the model is parameterized.

B.1 Data

To quantify the model, we reply on four data sources: the 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).

B.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 C.1 lists the 42 countries in the data. Under the Social Economic Account, the database also provides information on the total labor compensation and the total number of persons engaged for each industry; these allow for the calculation of country-specific wages. See Timmer et al. (2015).

B.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`.

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 to two-digit NAICS, in which case the 2-digit NAICS work-from-home capacities computed by these authors are used. When a WIOD industry maps to 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 fifteen sectors, the work-from-home capacity for each country-sector pair μ_i^j is computed as the average of these capacities across the industries in that sector, weighted by the industrial employment in that country given from the WIOD data.

B.1.3 Oxford COVID-19 Government Response Tracker

The Government Response Index by the Oxford COVID-19 Government Response Tracker (OxCGRT) summarizes government responses at a daily frequency 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, 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. (2021) and https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

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

B.2.1 Gravity Estimation

We use a standard approach in estimating the 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 (2014), we apply OLS to estimate the fixed effects model to obtain estimates of $\{\nu^j, D_i^{j,exp}\}$.

B.2.2 Uncover Technological 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 B.1.1, wages w_i^j are calculated by dividing the total labor compensation of (j,i) by the number of people employed in (j,i) from the Social Economic Account in the WIOD. Hence,

$$\hat{T}_i^j = \exp(\hat{D}_i^{j,exp}) \times [w_{i,data}^{\beta_i^j}(\hat{P}_i^{M,j})^{1-\beta_i^j}]^\theta \tag{14}$$

$$\hat{P}_i^{M,j} = \prod_{l=1}^{J}(\hat{P}_i^l)^{\gamma_i^{j,l}} \tag{15}$$

$$\hat{P}_i^j = \Gamma\left(\frac{\theta - 1 + \kappa}{\theta}\right)\left[\sum_{k=1}^{K} \hat{T}_k^j [w_{i,data}^{\beta_i^j}(\hat{P}_i^{M,j})^{1-\beta_i^j}\hat{\tau}_{i,k}^j]^{-\theta}\right]^{-\frac{1}{\theta}}. \tag{16}$$

The following procedure is used to solve for $\{T_i^j\}$, as in Fieler (2011) and Ravikumar, Santacreu and Sposi (2019). 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: $\hat{P}_i^j(r) = \Gamma\left(\dfrac{\theta-1+\kappa}{\theta}\right)\left[\sum_{k=1}^{K}\hat{T}_k^j(r)(w_{i,data}^{\beta_i^j}\hat{P}_i^{M,j}(r)^{1-\beta_i^j}\hat{\tau}_{i,k}^j)^{-\theta}\right]^{-\frac{1}{\theta}}$.

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 the country-sector-specific productivity parameters.

For the model without input-output linkages, the calibration is the same except that $\beta_i^j = 1$ in (14) and (16), and that (15) is not used.

C Additional Tables

Table C.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 C.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
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
Construction	F	Construction	2
Financial services	K64	Finance and insurance	3
Insurance	K65	Finance and insurance	3
Auxiliary to financial services	K66	Finance and insurance	3
Accommodation and food	I	Accommodation and food	4
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
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
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
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
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
Food products, beverages, and tobacco products	C10–C12	Food and textile	10
Textiles, wearing apparel, and leather products	C13–C15	Food and textile	10
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
Electricity and gas	D35	Utility	13
Water supply	E36	Utility	13
Sewerage and waste	E37–E39	Utility	13
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

Table C.3: BCL in Pre-COVID Annual Real Income

Country	With IO linkages: Open economy	With IO linkages: Autarky	Without IO linkages: Open economy	Without IO linkages: Autarky
Australia	-1.48	-0.70	-1.20	-0.81
Austria	-1.07	-0.81	-1.60	-1.03
Belgium	-0.89	-0.43	-0.96	-0.44
Bulgaria	-0.76	-0.08	0.06	-0.10
Brazil	-1.28	-0.83	-0.85	-0.82
Canada	-2.01	-1.35	-2.20	-1.62
Switzerland	-1.08	-0.12	-0.72	-0.14
China	-1.60	-1.01	-1.41	-1.49
Cyprus	-1.20	-0.67	-1.92	-0.96
Czech Republic	-1.04	-0.32	-0.71	-0.46
Germany	-1.31	-1.33	-1.32	-1.25
Denmark	-1.21	-0.27	-0.87	-0.35
Spain	-1.09	-0.73	-1.04	-0.84
Estonia	-0.71	-0.06	-0.24	-0.08
Finland	-0.98	-0.06	-0.52	-0.08
France	-1.53	-1.05	-1.43	-1.06
United Kingdom	-1.93	-1.33	-2.09	-1.72
Greece	-2.11	-1.37	-2.37	-1.60
Croatia	-0.93	-0.15	-0.24	-0.22
Hungary	-1.12	-0.37	-0.83	-0.50
Indonesia	-0.76	-0.47	-0.53	-0.61
India	-2.42	-2.16	-2.09	-2.07
Ireland	-2.06	-2.42	-3.59	-2.31
Italy	-1.88	-1.92	-2.31	-2.06
Japan	-0.82	-0.02	-0.48	-0.03
South Korea	-0.87	-0.17	-0.59	-0.19
Lithuania	-0.82	-0.17	-0.29	-0.25
Luxembourg	-0.72	-0.89	0.08	-0.08
Latvia	-0.77	-0.10	-0.24	-0.14
Mexico	-0.99	-0.68	-0.71	-0.75
Netherlands	-1.38	-0.98	-1.61	-1.18
Norway	-1.20	-0.29	-0.88	-0.38
Poland	-0.96	-0.36	-0.52	-0.42
Portugal	-1.24	-0.70	-1.26	-0.82
Romania	-0.93	-0.28	-0.45	-0.45
Russia	-1.35	-0.40	-0.68	-0.48
Slovak Republic	-0.68	-0.21	-0.14	-0.28
Slovenia	-0.91	-0.32	-0.92	-0.49
Sweden	-1.25	-0.39	-0.92	-0.49
Turkey	-1.14	-0.65	-0.79	-0.73
Taiwan	-0.73	-0.33	-0.18	-0.06
United States	-1.56	-0.78	-1.32	-0.94
World	-1.53	-1.06	-1.39	-1.33
Average	-1.21	-0.66	-1.02	-0.73

Note: This table reports the post-COVID belief-scarring cumulative losses (BCLs) relative to the pre-COVID annual income for countries in our sample, as well as their simple average. The "World" row reports the global sum of the BCLs in the pre-COVID global annual income. We consider trade/autarky economic environments with/without input-output linkages.

Table C.4: BCL in Pre-COVID Annual Real Income for Various Learning Rates χ

Country	Learning rate $= 10$ Open economy	Learning rate $= 10$ Autarky	Learning rate $= 0.1$ Open economy	Learning rate $= 0.1$ Autarky
Australia	-1.51	-0.77	-0.97	-0.36
Austria	-1.06	-0.85	-0.89	-0.63
Belgium	-0.85	-0.44	-0.70	-0.28
Bulgaria	-0.67	-0.08	-0.79	-0.06
Brazil	-1.39	-0.94	-0.76	-0.46
Canada	-1.92	-1.38	-1.87	-1.02
Switzerland	-1.01	-0.12	-0.90	-0.07
China	-1.73	-1.13	-1.04	-0.58
Cyprus	-1.12	-0.72	-0.89	-0.38
Czech Republic	-1.02	-0.33	-0.83	-0.23
Germany	-1.38	-1.46	-0.67	-0.68
Denmark	-1.15	-0.27	-1.05	-0.20
Spain	-1.04	-0.74	-0.90	-0.55
Estonia	-0.64	-0.06	-0.59	-0.04
Finland	-0.90	-0.06	-0.91	-0.04
France	-1.52	-1.09	-1.03	-0.60
United Kingdom	-2.05	-1.44	-1.01	-0.80
Greece	-2.15	-1.46	-1.55	-0.89
Croatia	-0.90	-0.17	-0.67	-0.10
Hungary	-1.08	-0.38	-0.95	-0.30
Indonesia	-0.79	-0.51	-0.54	-0.28
India	-2.60	-2.29	-1.61	-1.51
Ireland	-2.06	-2.57	-1.54	-1.52
Italy	-1.85	-1.94	-1.65	-1.56
Japan	-0.79	-0.02	-0.69	-0.00
South Korea	-0.83	-0.17	-0.77	-0.14
Lithuania	-0.79	-0.18	-0.63	-0.12
Luxembourg	-0.75	-1.00	-0.34	-0.49
Latvia	-0.71	-0.10	-0.69	-0.07
Mexico	-0.99	-0.71	-0.85	-0.48
Netherlands	-1.45	-1.10	-0.62	-0.41
Norway	-1.17	-0.31	-0.85	-0.20
Poland	-0.95	-0.38	-0.61	-0.20
Portugal	-1.17	-0.73	-1.23	-0.55
Romania	-0.86	-0.29	-0.99	-0.23
Russia	-1.33	-0.40	-1.17	-0.33
Slovak Republic	-0.60	-0.22	-0.79	-0.15
Slovenia	-0.80	-0.33	-1.02	-0.25
Sweden	-1.21	-0.41	-0.91	-0.26
Turkey	-1.12	-0.68	-1.01	-0.51
Taiwan	-0.67	-0.34	-0.70	-0.26
United States	-1.55	-0.79	-1.18	-0.57
World	-1.59	-1.14	-1.07	-0.68
Average	-1.19	-0.70	-0.94	-0.44

Note: This table reports the post-COVID belief-scarring cumulative losses (BCLs) relative to the pre-COVID annual income for countries in our sample, as well as their simple average. The "World" row reports the global sum of the BCLs in the pre-COVID global annual income. We consider different values of learning rates (χ) and trade/autarky economic environments with the presence of input-output linkages.

Table C.5: BCL in Pre-COVID Annual Real Income for Various Sectoral Labor Supply Elasticities ϕ

	$\phi = 3$		$\phi = 1.2$	
Country	Open economy	Autarky	Open economy	Autarky
Australia	-1.23	-0.84	-0.35	-0.59
Austria	-0.62	-0.95	-0.15	-0.72
Belgium	-0.42	-0.51	-0.14	-0.32
Bulgaria	-0.52	-0.09	0.04	-0.11
Brazil	-1.45	-1.07	-1.11	-1.02
Canada	-1.42	-1.57	-0.18	-1.12
Switzerland	-0.61	-0.16	-0.15	-0.11
China	-1.86	-1.28	-1.44	-1.15
Cyprus	-0.66	-0.87	-0.03	-0.93
Czech Republic	-0.74	-0.40	-0.27	-0.39
Germany	-1.01	-1.40	-0.47	-0.77
Denmark	-0.85	-0.33	-0.27	-0.24
Spain	-0.86	-0.81	-0.16	-0.48
Estonia	-0.42	-0.07	-0.14	-0.07
Finland	-0.67	-0.09	-0.27	-0.08
France	-1.16	-1.16	-0.36	-0.69
United Kingdom	-1.45	-1.31	-0.39	-0.65
Greece	-1.96	-1.91	-0.84	-2.29
Croatia	-0.68	-0.19	-0.18	-0.20
Hungary	-0.91	-0.46	-0.37	-0.47
Indonesia	-1.01	-0.67	-1.21	-0.93
India	-3.37	-3.15	-4.28	-4.34
Ireland	-1.12	-3.10	-0.26	-2.85
Italy	-1.53	-2.05	-0.43	-1.13
Japan	-0.82	-0.04	-0.55	-0.05
South Korea	-0.72	-0.20	-0.18	-0.15
Lithuania	-0.64	-0.22	-0.26	-0.28
Luxembourg	-0.31	-1.20	-0.10	-1.27
Latvia	-0.44	-0.12	0.06	-0.14
Mexico	-1.07	-0.91	-0.75	-0.99
Netherlands	-0.92	-1.10	-0.32	-0.68
Norway	-0.84	-0.36	-0.29	-0.30
Poland	-0.70	-0.42	-0.19	-0.33
Portugal	-0.94	-0.89	-0.15	-0.84
Romania	-0.72	-0.35	-0.06	-0.34
Russia	-1.44	-0.51	-0.96	-0.48
Slovak Republic	-0.25	-0.26	0.27	-0.25
Slovenia	-0.46	-0.40	-0.03	-0.39
Sweden	-0.97	-0.47	-0.42	-0.35
Turkey	-1.24	-0.90	-0.85	-1.00
Taiwan	-0.51	-0.44	0.25	-0.44
United States	-1.48	-0.78	-0.81	-0.32
World	-1.61	-1.33	-1.27	-1.31
Average	-0.98	-0.81	-0.45	-0.72

Note: This table reports the post-COVID belief-scarring cumulative losses (BCLs) relative to the pre-COVID annual income for countries in our sample, as well as their simple average. The "World" row reports the global sum of the BCLs in the pre-COVID global annual income. We consider different values of sectoral labor supply elasticities (ϕ) and trade/autarky economic environments with the presence of input-output linkages.

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