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

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

August 26, 2023

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 the globe as a whole.

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

*For helpful comments, we thank Julian Kozlowski, Matt Shapiro, two anonymous referees, and the seminar participants at Academia Sinica and Singapore Management University.

†Institute of Economics, Academia Sinica, wthsu@econ.sinica.edu.tw.

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

§Institute of Economics, Academia Sinica, han.yang271@gmail.com.

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. Even though COVID has effectively ended as of now (the year 2023), 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 real wages change, 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 are transmitted 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 for working in different sectors. With Type-I extreme value distribution, sectoral employment 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 some 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 employment shares and real wages change accordingly.

The parameterization consists of three parts. First, the baseline model without pandemic shocks is calibrated to the pre-COVID economy using the World Input-Output Database (WIOD). Second, to calibrate the pandemic shocks $B_{i,t}^j$, the stringency of the containment measures ($\eta_{i,t}$) 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 of $\eta_{i,t}$ so that the model-generated reduction of the world's real GDP matches the data counterpart during 2020–2021. Third, we calibrate the information parameters using the historical data on wages and model-consistent price indices so that the dispersion of real wages within and across sectors can be calculated.

For our quantitative exercises, we 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, all containment measures are lifted ($\eta_{i,t}=0$) in the first quarter of 2022,[1] and the economy evolves for 30 years from 2022. We 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. These post-COVID losses are substantial because, when combined globally, they are 12.4% relative to 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 (2023), who show that trade can mitigate the impact of containment measures, we find that trade worsens the global

[1] See the detailed justification for this assumption in Section 3.2.

post-pandemic long-run losses. 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. In this case, the global post-pandemic loss is 48.5% larger under trade than that of under autarky, similar to the number when input-output linkages are absent (50.6%).

To understand why the presence of input-output linkages does not substantially mitigate the adverse effect of trade on the global post-pandemic loss, it is useful to dissect various countervailing forces here. 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 positive 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 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. The two effects due to input-output linkages counteract each other, rendering a similar effect of trade to the case without such linkages.

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.[2] Therefore, the vast majority of these recent studies concern the short-run effects. This paper emphasizes 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*a*), 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 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 studied 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) and LaBelle, Leibovici and Santacreu (2021) study the role of the global supply chain in transmitting foreign pandemic shocks to domestic economies. Our work differs from these studies in our focus on the role of the global supply chain in terms of the long-run after-effects of the pandemic. Also related is the work by Hsu, Lin and Yang (2023), who study optimal containment policies on the tradeoff between lives and the economy in a multi-country multi-sector model with disease dynamics, and that by Leibovici and Santacreu (2023), who study optimal trade policies for essential medical goods during a pandemic for a small open economy. 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 in the context of international trade or cities.

Our approach of using Bayesian learning with the log-normal distribution of the variable on which agents have imperfect information is standard and widely applied in macroeconomics and finance, e.g., Bonatti, Cisternas and Toikka (2017), Cisternas (2018), Cogley and Sargent (2008), and Fogli and Veldkamp (2011). However, to the best of our knowledge, our study is the first in the literature on the quantitative analysis of trade to apply such a Bayesian learning mechanism. The closest to our work may be Porcher (2022), which simplifies trade and production and studies how migration and information friction interact. In contrast, we focus on how trade, sectoral pandemic shocks, and information frictions interact. As in the literature on the role of learning and information in macroeconomics, we choose this Bayesian learning approach mainly due to its tractability. Another notable approach is developed by Kozlowski, Veldkamp and Venkateswaran (2020*b*), who assume agents estimate the distribution of the shocks nonpara-

[2]See, for examples, Acemoglu et al. (2021), He et al. (2017), 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).

metrically in each period based on all available historical data. With the flexibility in functional form and tail events carrying heavy weights, transitory shocks may have permanent effects. We do not adopt this approach as there is no historical data on the pandemic shocks prior to COVID.

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 of post-COVID economic losses and investigates the roles of international trade and sectoral input-output linkages. This section also conducts a variety of robustness checks and extends the model to add the information friction on the pandemic shocks. 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 Preferences and Endowments

There are I countries, each of which has a population of $L_i, i \in \{1, 2, ..., I\}$, and a fixed endowment of capital K_i. Assume that the capital endowment in each country is jointly and evenly owned by the population there. 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:

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

where $q_{i,t}^{F,j}(v)$ is the amount of variety v 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 lifetime 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.[3]

[3]Here, the lifetime utility simply refers to the discounted sum of period utilities over time in a dynastic preference of the representative consumer. The model here does not feature saving and intertemporal substitution, and hence the curvature of the period utility function is less important. Thus, we assume linear period utility for simplicity.

2.2 Production

Production of any good requires labor, capital, and intermediate inputs. 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 $M^j_{i,t}(v)$ denote the use of the composite intermediate goods by the firms producing variety v 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 v in sector j and country i is given by

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

where $L^j_{i,t}(v)$ and $K^j_{i,t}(v)$ are the labor and capital hired for this variety, $\beta^{L,j}_i$ and $\beta^{K,j}_i$ are the labor and capital share, and the Hicks-neutral productivity $z^j_i(v)$ 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. Trade is balanced. The unit cost of delivering a good from country i to country n is $c^j_{i,t}\tau^j_{i,n}/z^j_{i,t}(v)$, where

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

where $w^j_{i,t}$ and $P^{M,j}_{i,t}$ are sector j's wages and its price for obtaining the intermediate input bundle, respectively. Capital is freely mobile across sectors in a country, and $r_{i,t}$ denotes the rental price of capital. Here, $c^j_{i,t}$ 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: $p^j_{n,t}(v) = \min_i \left\{ c^j_{i,t}\tau^j_{i,n}/z^j_{i,t}(v) \right\}$. Standard derivation yields the price indices:

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

2.3 Belief Formation and Sectoral Labor Supply

At the end of period $t-1$, a worker chooses which sector to work in at period t. We will show shortly that the workers' capital income does not affect their sectoral choices, and hence, for now we focus on their labor income. 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

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

Consequently, the sectoral labor employment share is given by

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

We now specify how agents' forecasts of 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 $\varepsilon^j_{i,t-1} \sim N\left(0, \sigma_i^2\right)$.

With the new signal/data $\{\omega^j_{i,t-1}\}_{j=1}^J$, workers then update their beliefs using Bayes' rule. Standard procedures entail 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:

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

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

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

The so-formed posterior at the end of period $t-1$ then becomes the prior at the beginning of period t. That is, $\ln(\widetilde{\omega}^j_{i,t}) \sim N\left(\ln(\bar{\omega}^j_{i,t}), (\widetilde{\sigma}^j_{i,t})^2\right)$.

We now come back to the question of why workers' capital income does not affect their sectoral choices. Note that a worker's real capital income is $r_{i,t}K_i/(L_iP_{i,t})$, which does not vary across sectors. Denote the workers' forecast of the real price of capital by $\bar{\iota}_{i,t}$. When $\bar{\omega}^j_{i,t}$ in (7) is replaced with $\bar{\omega}^j_{i,t} + \bar{\iota}_{i,t}K_i/L_i$, the real capital income drops out, and (7) is unchanged.

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. 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 $B^j_{i,t} \equiv 1-\eta_{i,t}(1-\mu_i^j) \in [0,1]$. 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_i^j). Both dimensions differ by country. Assuming $\kappa < \theta + 1$, the price index of a sectoral good is given by

$$P_{n,t}^j = \zeta \left(\sum_{k=1}^{I} T_k^j \left[\left(w_{k,t}^j / B_{k,t}^j \right)^{\beta_k^{L,j}} \left(r_{k,t} \right)^{\beta_i^{K,j}} \left(P_{k,t}^{M,j} \right)^{1-\beta_k^{L,j}-\beta_k^{K,j}} \tau_{k,n}^j \right]^{-\theta} \right)^{-\frac{1}{\theta}}, \tag{9}$$

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

$$\pi_{i,n,t}^j = \frac{T_i^j \left[\left(w_{i,t}^j / B_{i,t}^j \right)^{\beta_i^{L,j}} \left(r_{i,t} \right)^{\beta_i^{K,j}} \left(P_{i,t}^{M,j} \right)^{1-\beta_i^{L,j}-\beta_i^{K,j}} \tau_{i,n}^j \right]^{-\theta}}{\sum_{k=1}^{I} T_k^j \left[\left(w_{k,t}^j / B_{k,t}^j \right)^{\beta_k^{L,j}} \left(r_{k,t} \right)^{\beta_k^{K,j}} \left(P_{k,t}^{M,j} \right)^{1-\beta_k^{L,j}-\beta_k^{K,j}} \tau_{k,n}^j \right]^{-\theta}}. \tag{10}$$

The pandemic shocks $B_{i,t} = 1 - \eta_{i,t}(1 - \mu_i^j)$ reshape comparative advantages. If all countries adopt the same containment policy, a country i gains a comparative advantage in those high μ_i^j sectors if it has a larger presence in these sectors due to higher T_i^j or lower $\tau_{i,n}^j$ on average. Such comparative advantages are strengthened (dampened) when country i's containment measures become less (more) stringent.

2.5 Equilibrium

Let $R_{i,t}^j$ denote the total revenue of country i's sector j, $X_{n,t}^j$ denote the total expenditure of country n on the goods in sector j, and $X_{n,t}$ denote the total expenditure of country n. Given sectoral labor supply $L_{i,t}^j = L_i \ell_{i,t}^j$ (where $\ell_{i,t}^j$ is given by [7]) and capital stock K_i, the factor market clearing condition for sector j in country i is

$$w_{i,t}^j L_{i,t}^j = \beta_i^{L,j} R_{i,t}^j = \beta_i^{L,j} \sum_{n=1}^{I} \pi_{i,n,t}^j X_{n,t}^j \tag{11}$$

$$r_{i,t} K_{i,t}^j = \sum_{j=1}^{J} \beta_i^{K,j} R_{i,t}^j = \sum_{j=1}^{J} \sum_{n=1}^{I} \beta_i^{K,j} \pi_{i,n,t}^j X_{n,t}^j. \tag{12}$$

By the definition of $X_{i,t}^j$,

$$X_{i,t}^j = \alpha_i^j \left(r_{i,t} K_i + \sum_{k=1}^{J} w_{i,t}^k L_{i,t}^k \right) + \sum_{l=1}^{J} \gamma_i^{l,j} (1 - \beta_i^{L,l} - \beta_i^{K,l}) \sum_{n=1}^{I} \pi_{i,n,t}^l X_{n,t}^l \tag{13}$$

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 $\{X_{i,t}^j\}_{i,j}$ with the intercepts being the final-good expenditures.

We briefly describe the equilibrium algorithm and leave the full details in Appendix A. First, given both the forecasted and realized real wages at period $t-1$, $\bar{\omega}_{i,t-1}^j$ and $\omega_{i,t-1}^j$, the forecast for real wages at period t, $\bar{\omega}_{i,t}^j$, is determined by (8), sectoral employment shares $\ell_{i,t}^j$ by (7), and sectoral labor force by $L_{i,t}^j = \ell_{i,t}^j L_i$. Then, given $L_{i,t}^j$ and K_i, $\{w_{i,t}^j, r_{i,t}, P_{i,t}^{M,j}, P_{i,t}, P_{i,t}^j, \pi_{i,n,t}^j, X_{k,t}^j\}$ are obtained from (5) and (9)–(13).

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 the WFH sectors. These reshape the comparative advantages. Sectoral real incomes change drastically during the pandemic, subsequently changing the sectoral employment shares $\ell_{i,t}^j$. Such effects linger even after the pandemic is over because of the imperfect adjustments in 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 the 54 industries in the WIOD to a degree that is roughly comparable to the aggregation by Caliendo, Dvorkin and Parro (2019). This results in 15 sectors;[4] Appendix Table C.2 shows the concordance of our industry aggregation. The last available data year (2014) is used for the calibration.

[4]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.

The WIOD's Social Economic Account provides data on gross output, total labor compensation, total capital compensation, employment (in terms of the total number of persons engaged for each industry), and nominal capital stock for each country and each sector. We utilize the nominal capital stock and the total employment in the data as the capital and labor endowment (K_i and L_i) for individual countries in the model. The labor share $\{\beta_i^{L,j}\}$ and capital share $\{\beta_i^{K,j}\}$ are calculated by total compensation on labor and capital divided by gross output. The shares of intermediates in gross output is therefore $\{1-\beta_i^{L,j}-\beta_i^{K,j}\}$. For each country and each sector, the WIOD's input-output table provides this sector's use of intermediates from various countries and sectors. It also provides data on sectoral final consumption in each country. 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.

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 $\{\alpha_i^j, \beta_i^{L,j}, \beta_i^{K,j}, \gamma_i^{j,l}\}$, and data on sectoral wages and the rental price of capital obtained from the Social Economic Account in the WIOD. See Appendix B.2 for the full details of this procedure.

3.2 Pandemic Parameters

To calibrate the pandemic parameters, we must first specify the time frame for our simulation environment. With mass vaccinations, cumulative infections, and the available cures, most countries had already adopted a "living with COVID-19" policy in early 2022 or prior to 2022. Moreover, the fact that the Omicron variant, which started in November 2021 and quickly spread around the world in 2022, was less lethal and much more contagious than previous variants made it more difficult for the few "COVID-zero" countries to insist on strong containment measures. As a result, most of these countries also dropped most containment measures in early 2022, with the last being China in fall 2022. Thus, for our quantitative exercise, 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 30 years from 2022.

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 then 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 summarizes government responses in terms of various closures and containment, including school or workplace closures, stay-at-home requirements, border controls, and restrictions on gatherings, 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. We choose to 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.

Recall that the pandemic shock is $B_{i,t} = 1 - \eta_{i,t}(1 - \mu_i^j)$. If the above-mentioned stringency indices $\{\eta_{i,t}^{data}\}$ were directly used as the containment measures $\{\eta_{i,t}\}$, 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 $\eta_{i,t} = (\eta_{i,t}^{data})^{\delta_1}$ for the four quarters of 2020 and $\eta_{i,t} = (\eta_{i,t}^{data})^{\delta_2}$ for the four quarters of 2021 for some $\delta_1, \delta_2 > 0$. We pick $\delta_1 = 4.30$ and $\delta_2 = 13.45$ so that the percentage reductions in world real GDP in 2020 and 2021 generated by the model match the data counterpart for our sample countries. We allow for different scaling of the containment measures between 2020 and 2021 because the pandemic and economic situations in 2021 were drastically different from 2020 due to the mass vaccination, the substantial fiscal stimulus implemented worldwide, and the fact that people had learned to better cope with the pandemic such as the widespread use of antigen tests and face masks, etc.

3.3 Information Parameters

We now describe how the information parameters are calibrated. First, we assume that the pre-COVID equilibrium is in a steady state, in which the forecasted real wages are the same as the realized real wages, i.e., $\left\{\bar{\omega}_{i,0}^{j}=\omega_{i,0}^{j}\right\}_{i,j}$. Thus, the means of the initial prior distributions of sectoral real wages are also $\left\{\bar{\omega}_{i,0}^{j}=\omega_{i,0}^{j}\right\}_{i,j}$. 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 based on 2014 WIOD data (the precision parameters are unknown at this point), the pre-COVID equilibrium sectoral real wages $\left\{\omega_{i,0}^{j}=w_{i,0}^{j}/P_{i,0}\right\}_{i,j}$ are computed as steady-state equilibrium real wages, and we set $\bar{\omega}_{i,0}^{j}=\omega_{i,0}^{j}$.

Next, we retrieve the sectoral nominal wages and the rental prices of capital $\{w_{i,t}^{j,data}, r_{i,t}^{data}\}$ from the WIOD for each year during 2000–2014. Then, for each year, we compute the price indices $P_{i,t}$ that are consistent with the data values of $\{w_{i,t}^{j,data}, r_{i,t}^{data}\}$ by plugging these data values into (5) and (9) and solving for the fixed point of the sectoral price indices and then the country-level price indices. 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 prediction error of the regression $\hat{e}_{i,t}^{j}$. The precision of initial prior belief $\left(\widetilde{\sigma}_{i,0}^{2}\right)$ and the precision of signals $(\sigma_{i}^{j})^{2}$ are set to

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

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.

3.4 Model Fit

In this subsection, we show the model fit in terms of how the world's real GDP was shocked by the pandemic, as well as some external validity checks.

Recall that we choose scaling parameters δ_1 and δ_2 that scale the containment measures for the years 2020 and 2021 to match the world real GDP in these two years. Figure 1(a) shows the fit of the time series of eight quarters of world real GDP in these two years. The vertical axis in this figure is the percentage changes in the real GDP relative to the pre-COVID level. Generally speaking, the model generates the patterns observed in the data. In particular, despite the differences in magnitude, the model does match all of the directions in the ups and downs

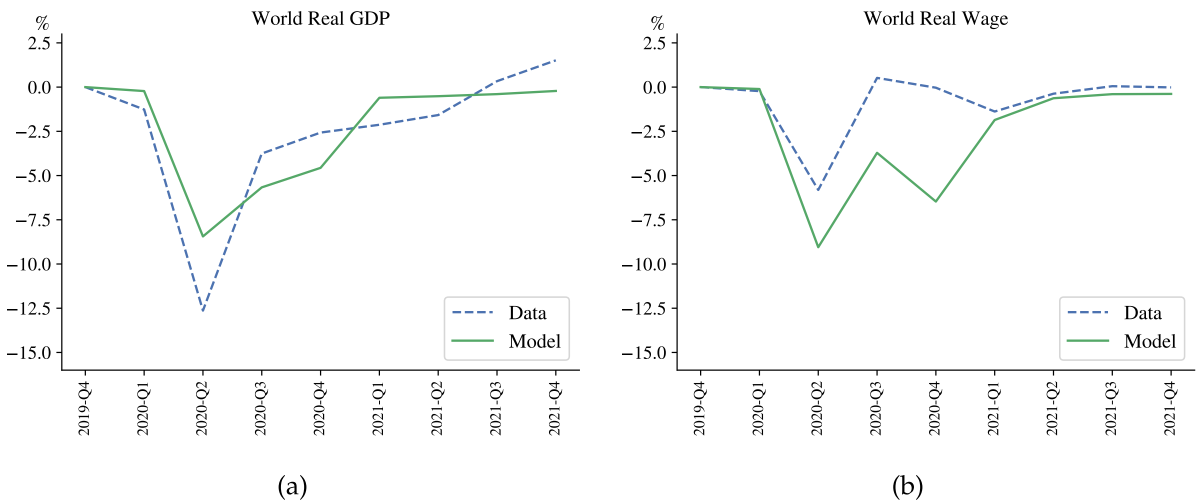


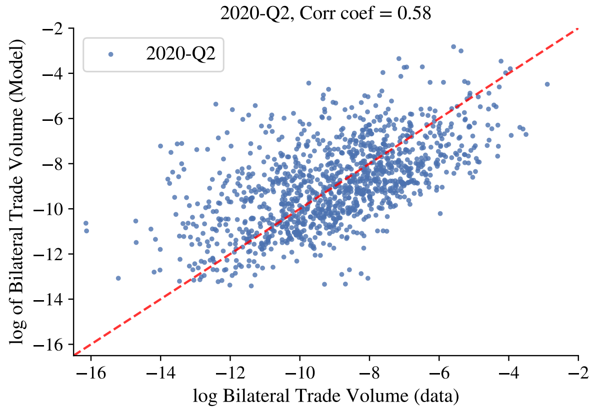
Figure 1: Model Fit in World Real GDP and Real Wages during the Pandemic

observed in the data. Figure 1(b) shows the external validity check in terms of the world's real wages.[5] Not surprisingly, the fit of the real wages is not as good as that of the real GDP, but the model still matches all of the directions in the ups and downs observed in the data except for the first quarter of 2021.

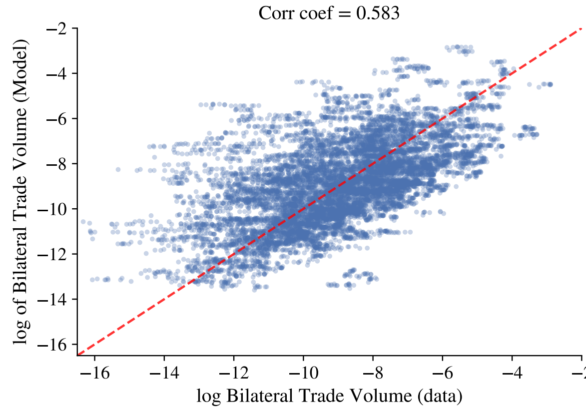
As our model is concerned about the effects of the pandemic on the global economy, we also examine the fit in terms of bilateral trade flows during the pandemic. The quarterly bilateral trade flows during the pandemic are obtained from the OECD's STAN Database. The model fit exercises are limited to the 37 countries that are in both the WIOD and STAN databases. Considering that these 37 countries are not the entire world, we normalize the bilateral trade flows in these countries by their total trade flows. We then compute the model counterparts and plot them against the data values. The red dashed lines in both panels of Figure 2 are the 45-degree lines. Panel (a) shows the fit for the second quarter of 2020, which was when the pandemic hit the economy most severely, as seen clearly by Figure 1, whereas Panel (b) shows the fit for all eight quarters of trade flows in these two years. Even though the plots are a little scattered (the correlation coefficients are 0.580 and 0.583, respectively), they show a reasonably good fit as both plots are centered around the 45-degree lines.

Note that such a good fit in trade flows is also an external validation of the model and the

[5]Quarterly real wages for each country are computed by integrating data on quarterly real GDP, labor shares, and employment levels from the OECD Stan Database. Specifically, labor share is computed using the real GDP – ascertained via the income approach – and the compensation of employees. Then, quarterly real wages are derived by multiplying the quarterly real GDP with the labor share, and then dividing this product by the quarterly employment levels, thereby yielding a measure of the quarterly real wage. The world's real wages are indeed the employment-weighted average of real wages across countries.



(a)



(b)

Figure 2: Model Fit in Trade Flows during the Pandemic

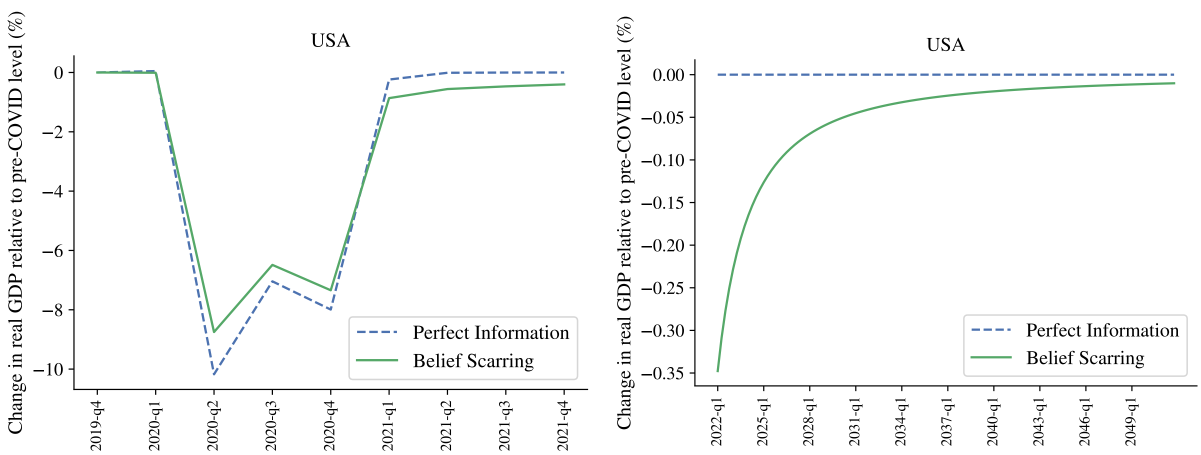
importance of the pandemic shocks. This is because trade costs and technology parameters (the Fréchet scaling parameters) are estimated by the pre-COVID data (2014 WIOD), and the simulated changes in the trade flows during the pandemic are purely due to the pandemic shocks. However, the trade flows in the data are likely affected by potential changes in trade costs and technology parameters, in addition to the pandemic shocks and among other factors.

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. We also conduct a series of robustness checks, extend the model to incorporate information friction on pandemic shocks, and discuss what may occur if downward wage rigidity is incorporated.

4.1 The Long-Run Economic After-Effects

Let $W_{i,t} = \left(r_{i,t}K_i + \sum_{j=1}^{J} w_{i,t}^j L_{i,t}^j\right)/P_{i,t}$ be country i's real income at quarter t. Figure 3a 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 the year 2022. Here, it is clearly seen that the equilibrium with the belief-scarring mechanism reacts to the shocks slower than the perfect-information equilibrium, and hence, it also recovers slower when the shocks are reduced. Upon the elimination of containment measures in the first quarter of 2022, the US still suffers a 0.35% 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



(a) Paths of real income during pandemic

(b) Post-COVID paths of real income

Figure 3: Paths of Real Income

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 back to the pre-COVID level upon eliminating containment measures.[6]

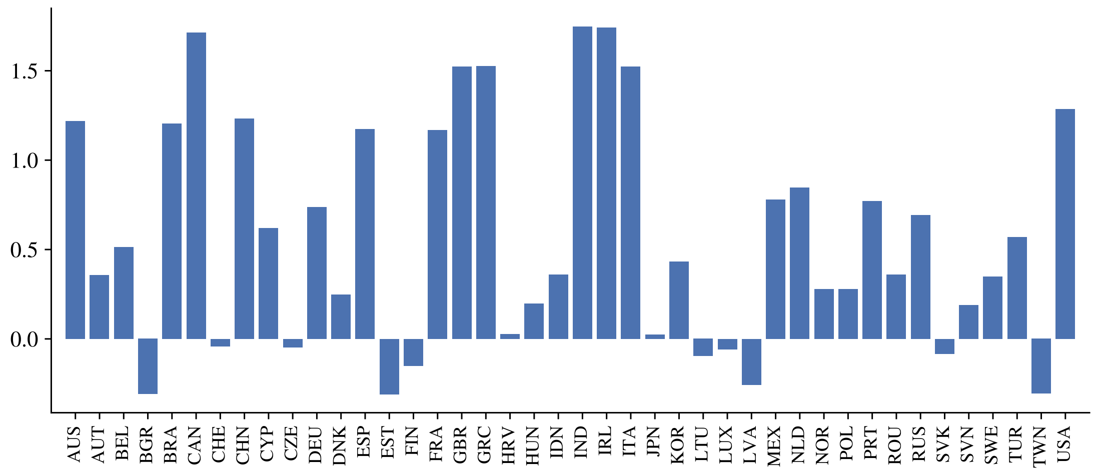
As we simulate the post-COVID economy for 30 years from 2022, Figure 3b shows the US' paths of the percentage changes in real income during the 30 years from 2022 for both the belief-scarring and perfect-information equilibria. Under the perfect-information equilibrium, the US real income stays at the 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 3b.

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

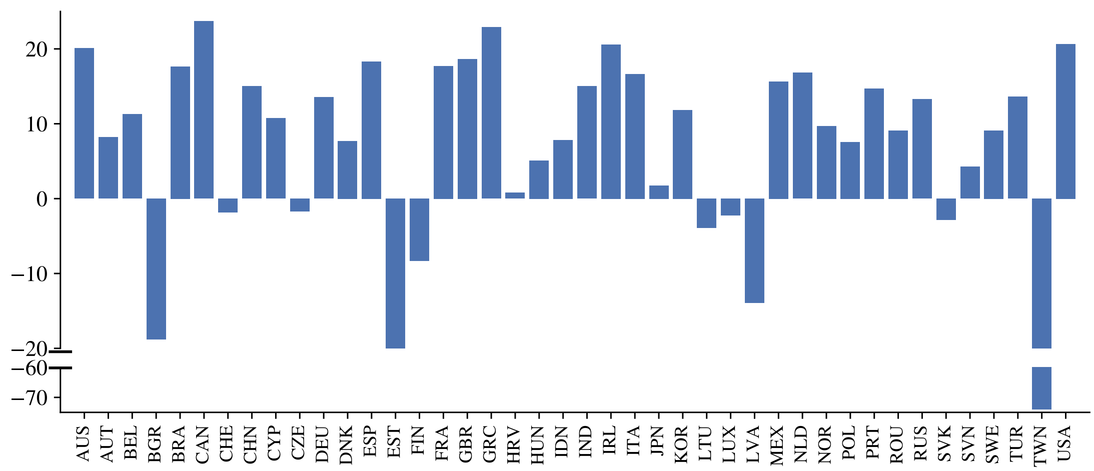
$$\frac{\sum_{t \geq t^*} \rho^{t-t^*} \left(W_{i,t}^{\text{perfect}} - W_{i,t}^{\text{scarred}} \right)}{W_i^{\text{pre-COVID}}} \times \frac{1}{4} \times 100\%,$$

where $t^* = 9$ is the time when the containment measures are lifted. Figure 4a summarizes the BCL in the pre-COVID annual real income (the numbers are reported in the first column of Ap-

[6] 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 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 4: Post-Pandemic Losses (Belief-Scarring Cumulative Losses)

pendix Table C.3). Across countries, this varies from -0.31% to 1.75%. Like the US, the majority of countries (32 out of 42) suffer post-COVID losses due to scarred beliefs, while ten countries turn out to enjoy post-COVID gains. These gains are relatively small as the (unweighted) average of the BCL remains positive at 0.57%. Moreover, when these post-COVID losses and gains are combined globally, the global BCL accounts for 0.69% of the pre-COVID global annual real income.[7] Why do some countries enjoy post-COVID gains? We will answer this question shortly after more information is gathered from further analyses.

Figure 4b shows the BCL relative to the economic losses during the pandemic, which is cal-

[7]Here, the global real income is simply defined by the sum of the real income across countries, $\sum_{i=1}^{I} W_{i,t} = \sum_{i=1}^{I} \left(r_{i,t} K_i + \sum_{j=1}^{J} w_{i,t}^{j} L_{i,t}^{j} \right) / P_{i,t}$; this is indeed proportional to the population-weighted average of real income per capita.

culated by

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

where $t = 1, \ldots, 8$ corresponds to the eight quarters during 2020–2021. Among the countries that suffer from post-COVID losses, the BCLs range from 0.77% (Croatia) to 23.7% (Canada) of the economic losses during the pandemic. Among the countries that enjoy post-COVID gains, their gains range from 1.71% (Switzerland) to 74.05% (Taiwan).[8] When these post-COVID losses and gains are combined globally, they account for 12.4%(=0.686/5.524; see Appendix Table C.3) of the global economic losses during the pandemic. In other words, despite the fact that some countries enjoy post-COVID gains, the globe, overall speaking, still suffers from post-COVID losses, and such losses are substantial relative to the losses during the pandemic.

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 5a plots the BCLs (in the pre-COVID annual real income) against the average pandemic shocks $\bar{B}_i$. Recall 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 (0.88) between BCLs and pandemic shocks. More specifically, Figure 5b plots the BCLs against average containment measures during the pandemic.[9] Indeed, countries that experience the greatest BCLs are also those with more severe containment measures during the pandemic. The countries that enjoy post-COVID gains are clearly those that implement rather lenient containment policies during the pandemic.

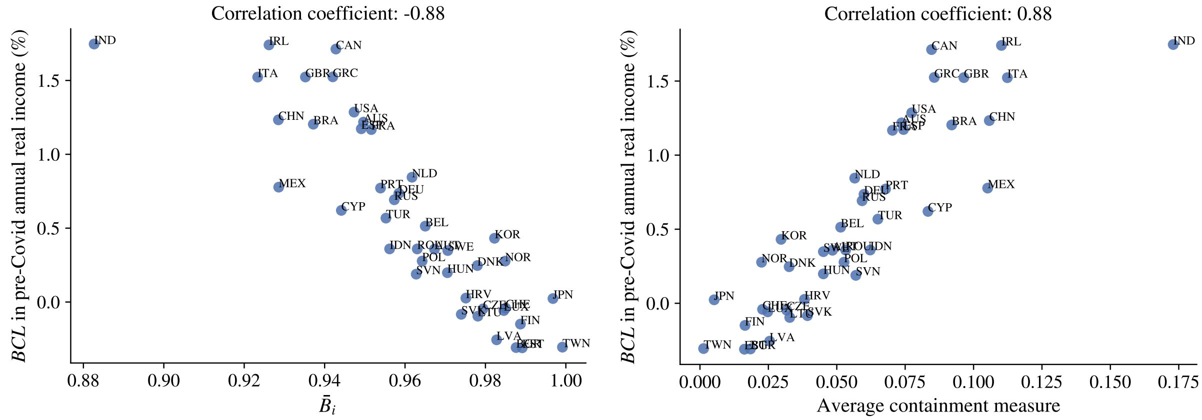
4.2 The Roles of International Trade and Input-Output Linkages

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 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 $1 - \beta_i^{L,j} - \beta_i^{K,j} = 0$ and reapportioning $\beta^{L,j}$ and $\beta^{L,j}$ so that

[8]Note that Taiwan's post-COVID gains account for 0.31% of their annual real income, and such a high number here is because Taiwan's real-income loss during the pandemic is minuscule.

[9]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 5: Pandemic Shocks and the BCLs

they sum to 1 for all j and all i. 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 6a 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 losses for a majority of countries (28 out of 42), but it alleviates the losses for six countries while even turning the losses into gains for eight countries. Because the extra losses under trade are rather substantial for those 28 countries, the global BCL is 50.6% larger under trade than that of under autarky.

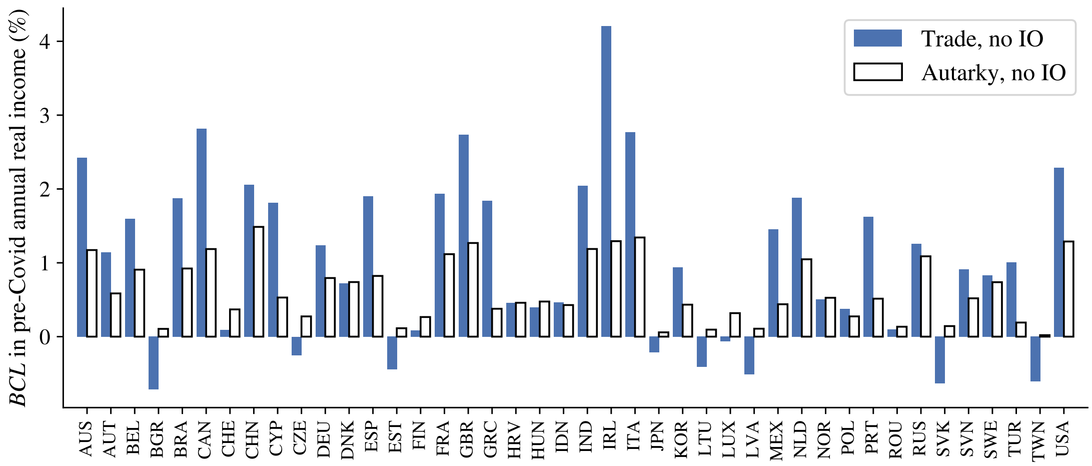
To comprehend these results in Figure 6a, first note that all countries suffer from post-COVID losses in the autarkic world. In an alternative model where capital is not required in the production process (the results not shown here), all countries but four suffer larger losses under trade than under autarky, and two countries enjoy minuscule post-COVID gains. Thus, the interaction between capital and trade is what drives the result that some countries enjoy post-COVID gains (note, however, that the main result that the whole globe, on average, suffers greater post-COVID losses under trade is robust to whether capital is incorporated or not). Therefore, we shall focus on the role of labor first. The reason for the main result is that the stakes of efficient allocation of labor across sectors according to comparative advantages are 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 (2023) 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 between information friction and trade can be harmful.

Fundamentally, a terms-of-trade effect dictates why some countries suffer less post-COVID losses or even enjoy post-COVID gains under trade than under autarky; capital must have played an important role. In particular, Figure 5 clearly shows that the countries that enjoy post-COVID gains are those with lenient containment measures. Examining the simulation results in detail, we find that the real wages in these countries jump upward sharply right after COVID and converge slowly to the pre-COVID level, whereas the real rental prices of capital fall modestly right after COVID and converge slowly to the pre-COVID level. Thus, what happens here is a combination of the Stolper–Samuelson mechanism, containment measures, and the above-mentioned labor misallocation. The heavily locked-down countries are shocked more during the pandemic, and the labor misallocation effects after COVID are stronger for these countries. In other words, scarred beliefs lead these countries to restrain their labor supply in some heavily impacted sectors more than they should. Seizing the opportunities, the less locked-down countries expand their specialization and labor demand in these sectors, causing real wages to increase there. The presence of capital serves as leverage such that the increases in real wages of these countries are sharper than those increases in the case where capital is not required. The above discussion also answers why some countries enjoy post-COVID gains in the benchmark result in Figure 4.

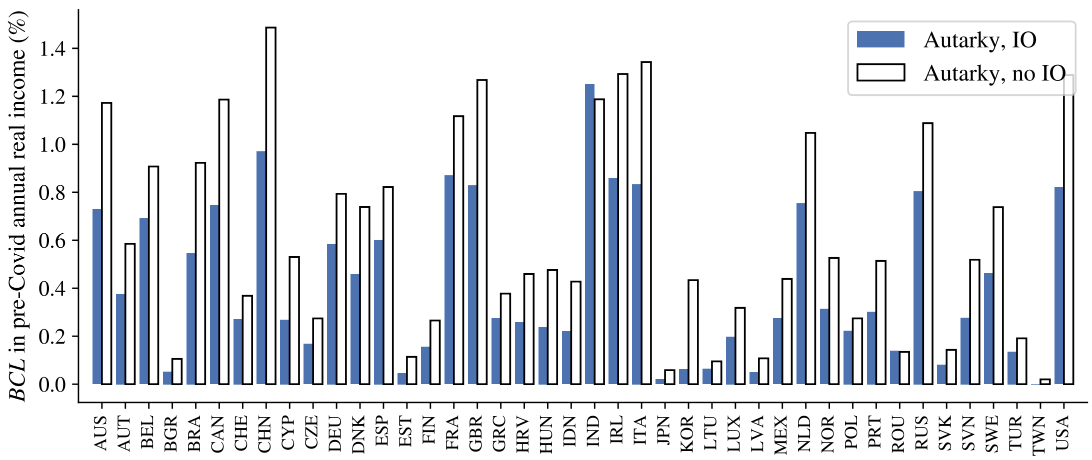
Next, to highlight the role of input-output linkages, we compare two autarkic worlds in which each country is an autarky, one with such linkages and one without. The BCLs in the pre-COVID annual real income are presented in Figure 6b. The existence of domestic input-output linkages mitigates post-pandemic losses for all but two countries. For many countries, the reductions in losses when input-output linkages are present are substantial. The global BCL is 30.8% smaller than that 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 BCL under trade and under autarky when input-output linkages are present. The result is summarized in Figure 7. When input-output linkages are present, international trade exacerbates the losses for a majority of countries (23 out of 42), and it alleviates the losses for 11 countries while even turning the losses into gains for eight countries. Recall



(a) Comparison of BCLs between Trade and Autarky, without Input-Output Linkages



(b) Comparison of BCLs with and without Input-Output Linkages, under Autarky

Figure 6: The Roles of International Trade and Input-Output Linkages

that the same numbers when input-output linkages are absent are 28, 6, and 8, respectively. This suggests that input-output linkages mitigate the negative effects of international trade on post-pandemic losses, consistent with the messages from Figure 6b. However, this mitigation is only slight because the global BCL is 48.5% larger under trade than that of under autarky while the same number when input-output linkages are absent is 50.6%.

To understand why the presence of input-output linkages does not substantially mitigate the adverse effect of trade on the global post-pandemic loss, it is useful to dissect the various countervailing forces here. As we have seen from Figure 6a, 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 that in Figure 6a because using intermediate inputs lowers labor's importance in the production process. In contrast, trade can amplify the above-mentioned

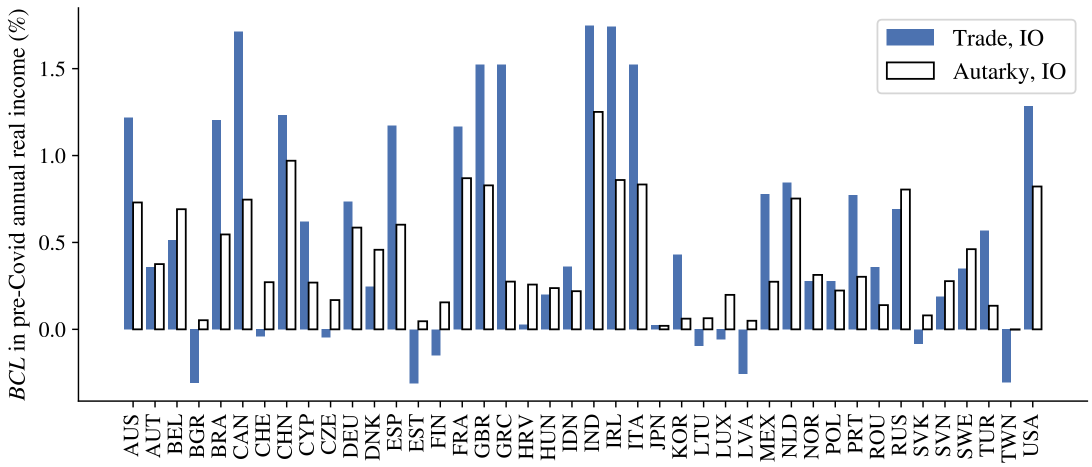


Figure 7: The Role of International Trade When Input-Output Linkages are Present

sourcing benefits because the opportunities to source from the best input suppliers worldwide enhance 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*. Moreover, the combination of international trade and input-output linkages gives rise to a third and negative effect from the interaction between labor misallocation and international sourcing because the existence of global supply chains amplifies the stake of efficient allocation according to comparative advantages. The two effects due to input-output linkages counteract each other, rendering a similar effect of trade to the case without such linkages.

Note that if COVID shocks were absent, the long-run welfare would be proportional to the pre-COVID global real income, as the former is simply a discounted sum of repeated values of the latter. Thus, the global BCL as a percentage loss in terms of pre-COVID global real income can also be read as a percentage loss in terms of long-run welfare. Given that the global BCL as a percentage loss in terms of long-run welfare is larger under trade than that under autarky, one might wonder if this would lead to a lower long-run welfare level under trade than that under autarky despite the fact that the long-run welfare under trade is higher than that under autarky when COVID shocks are absent. We thus compare the long-run welfare levels when COVID shocks are present between the two scenarios. In particular, we calculate the ratio of global long-run welfare under trade to that under autarky:

$$\frac{\sum_{i=1}^{I}\sum_{t=1}^{\infty}\rho^t W_{i,t}^{\text{trade}}}{\sum_{i=1}^{I}\sum_{t=1}^{\infty}\rho^t W_{i,t}^{\text{autarky}}},$$

where we let time start from 1, the first quarter of 2020 when the COVID shocks started. This ratio is 1.8929 under our benchmark value for $\rho = 0.9898$ (which corresponds to an annual discount factor of 0.96). When the annual discount factor is changed to 0.8 and 0.9999, this ratio is changed to 1.8945 and 1.8927, respectively. Namely, under reasonable discount factor values, the equilibrium under trade is always more efficient than that under autarky despite the finding that trade worsens the post-COVID losses.

4.3 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.,

$$\sigma_i^2(\chi) = \frac{\left(\sigma_i^2\right)^{\text{benchmark}}}{\chi}. \tag{14}$$

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 baseline 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.

For the comparative statics of the learning rate χ, the global BCLs are 7.7% smaller and 26.8% smaller for $\chi = 10$ and $\chi = 0.1$, respectively, in comparison to the baseline scenario. Thus, the global BCL is not monotonic in the learning rate χ. The two countervailing forces are as follows. First, a larger χ (a faster learning rate) implies faster recovery compared with the perfect-information equilibrium, and this implies smaller post-pandemic losses. Second, a faster learning rate also implies that COVID shocks the real income to a larger degree during the pandemic period, and the post-pandemic losses due to scarred beliefs are therefore larger because both the beliefs and the economy are more scarred to begin with.

In terms of the role of trade, we find that trade worsens the global BCL by 46.2% and 81.9% for $\chi = 10$ and $\chi = 0.1$, respectively. Recall that the same number in the baseline scenario is 48.5%. The sharp increase in the effect of trade under $\chi = 0.1$ compared with the baseline scenario is likely due to the fact that trade amplifies the labor misallocation effect. That is, when the learning rate is slower, the labor misallocation effect lingers longer because the misperceived information that distorts comparative advantages becomes more persistent. However, despite the differences in magnitude, the qualitative prediction that trade worsens the long-run economic losses due to scarred beliefs still remains.

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 by 44.1% and 24.8% for $\phi = 3$ and $\phi = 1.2$, respectively. Compared with the baseline value of 48.5% under $\phi = 5.34$, this suggests that trade worsens the global BCL by a lesser degree when the sectoral labor supply elasticity is lower. When the sectoral labor supply becomes less elastic, the labor misallocation effect is dampened.

4.4 Extension: Dual Information Frictions

In the baseline model, we assume that workers do not know the full workings of the economy and form their forecasts about sectoral real wages for their sectoral choices through a Bayesian learning process. However, this might not be the only important information friction in an economy that faces pandemic shocks. Specifically, it is plausible to assume that workers also do not fully understand how governments decide their containment policies and hence the pandemic shocks. In this subsection, we extend the model to incorporate additional information friction such that workers also form forecasts about the pandemic shocks through a Bayesian learning process.

4.4.1 Revised Model

Recall from Section 2.4 that it is the firms who absorb the pandemic shocks, $B^j_{i,t} = 1 - \eta_{i,t}(1 - \mu^j_i)$, so that when the fraction $\eta_{i,t}(1 - \mu^j_i)$ of workers are locked away, the firms still pay them full wages, instead of laying them off. This assumption was made for tractability but is now modified to incorporate the additional information friction. That is, we now assume that it is the workers who shoulder the pandemic shocks directly so that they are not paid when locked away. In other words, containment measures adjusted for WFH capacities form a direct constraint on workers' labor supply, similar to unemployment. When workers make their sectoral choices in period $t - 1$, they must anticipate the likelihood that their labor can actually be supplied. Thus, the expected real wages for a sector-j worker becomes $B^j_{i,t}\omega^j_{i,t}$. Here, workers must form forecasts on both the sectoral pandemic shocks and real wages.

Following the same procedure and given forecasts on sectoral pandemic shocks and real wage $\bar{B}^j_{i,t}$ and $\bar{\omega}^j_{i,t}$, the sectoral employment share is given by

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

The Bayesian learning process for the pandemic shocks is modeled in the same way as that for real wages. At period 0, workers in country i have initial prior beliefs about the pandemic shock for each sector j given by

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

At the end of period $t-1$, workers receive a signal which is the observed realization of pandemic shocks $\{B^j_{i,t-1}\}^J_{j=1}$. Workers interpret this signal as an unbiased piece of data about $\ln(\widetilde{B}^j_{i,t-1})$ with precision $1/(\sigma^B_i)^2$. Namely,

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

where $\varepsilon^{B,j}_{i,t-1} \sim N\left(0, (\sigma^B_i)^2\right)$. With the new signal/data $\{B^j_{i,t-1}\}^J_{j=1}$, workers then update their beliefs using Bayes' rule:

$$\ln(\bar{B}^j_{i,t}) = \frac{\frac{1}{(\widetilde{\sigma}^{B,j}_{i,t-1})^2} \times \ln(\bar{B}^j_{i,t-1}) + \frac{1}{(\sigma^B_i)^2} \times \ln\left(B^j_{i,t-1}\right)}{\frac{1}{(\widetilde{\sigma}^{B,j}_{i,t-1})^2} + \frac{1}{(\sigma^B_i)^2}}$$

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

In contrast to (4), the pandemic shocks $B^j_{i,t}$ no longer appear in the expression of unit cost because it is now the workers directly absorbing the pandemic shocks, not the firms. That is,

$$c^j_{i,t} = \left(w^j_{i,t}\right)^{\beta^{L,j}_i} (r_{i,t})^{\beta^{K,j}_i} \left(P^{M,j}_{i,t}\right)^{1-\beta^{L,j}_i-\beta^{K,j}_i}.$$

The sectoral labor supply is now $B^j_{i,t}L^j_{i,t}$, instead of $L^j_{i,t}$ in the baseline model. Thus, the goods and labor market-clearing conditions are revised as follows:

$$X^j_{i,t} = \alpha^j_i \left[\sum_{k=1}^{J} w^k_{i,t} B^k_{i,t} L^k_{i,t} + r_{i,t} K_{i,t}\right] + \sum_{l=1}^{J} \gamma^{l,j}_i (1 - \beta^{L,l}_i - \beta^{K,l}_i) \sum_{n=1}^{I} \pi^l_{i,n,t} X^l_{n,t}$$

$$w^j_{i,t} \times (B^j_{i,t} L^j_{i,t}) = \beta^{L,j}_i \sum_{n=1}^{I} \pi^j_{i,n,t} X^j_{n,t},$$

where the number of workers choosing to work in sector j is given by

$$L^j_{i,t} = \ell^j_{i,t} L_i.$$

4.4.2 Parameterization

All of the economic parameters remain the same as in the baseline model. All of the pandemic parameters remain the same except that the scaling parameters for obtaining effective containment measures, δ_1 and δ_2, are recalibrated to fit the percentage reduction in world real GDP.

As there is no historical data on pandemic shocks,[10] the information parameters for pandemic shocks are calibrated using the data from 2020–2021. First, the means of the initial prior distributions of sectoral pandemic shocks $\left\{\bar{B}_{i,0}^{j}\right\}_{i,j}$ are assumed to be unity, in which all workers are expected to get paid in the pre-COVID era. Second, using the recalculated $\{\eta_{i,t}\}_{t=2020q1,\ldots,2021q4}$ (as δ_1 and δ_2 have been changed), the sectoral pandemic shocks $B_{i,t}^{j} = 1 - \eta_{i,t}(1 - \mu_i^j)$ are recalculated. The inverse measures for the precision of initial prior belief and that of signals, $\left(\widetilde{\sigma}_{i,0}^{B,j}\right)^2$ and $(\sigma_i^B)^2$, are then set to be the following sample variances:

$$(\widetilde{\sigma}_{i,0}^{B,j})^2 = s^2\left(\{\ln B_{i,t}^{j}\}_{t=2020q1,\ldots,2021q4}\right)$$
$$(\sigma_i^B)^2 = s^2\left(\{\ln B_{i,t}^{j}\}_{t=2020q1,\ldots,2021q4}^{j=1,\ldots,J}\right),$$

where the first sample variance is taken over the quarters during the pandemic for each country-sector pair, and the second is taken over sectors and quarters for each country.

4.4.3 Quantitative Results

We conduct similar quantitative exercises to those in the baseline model, and the results are summarized in Table C.6. When the post-COVID losses are combined globally, they account for 11.6%(=0.602/5.21; see Table C.6) of the global economic loss during the pandemic. Trade (without input-output linkages) amplifies the global BCL by 45.7%, while input-output linkages (under autarky) remove 38.8% of the global BCL. When input-output linkages are considered, trade worsens the global BCL by 54.0%. Recall the same numbers in the baseline model are 12.4%, 50.6%, 30.8%, and 48.5%, respectively. Thus, the results under the model with dual information frictions are similar to the baseline model.

4.5 Discussion

As this study concerns labor market changes when the economy faces a negative shock, one relevant question is what occurs if downward wage rigidity is considered. Downward wage rigidity is a salient phenomenon that is widely documented and studied, e.g., Abbritti and Fahr (2013), Elsby, Shin and Solon (2016), Rodríguez-Clare, Ulate and Vasquez (2020), and Baqaee and Farhi (2022). However, it is difficult to incorporate into the model explicitly because if agents did take the downward wage rigidity into account, the distribution of the prior belief of the real wages would become truncated, and hence, the tractability of the belief-updating process vanishes. Although modeling downward wage rigidity is beyond the scope of the current paper,

[10] The last pandemic on a similar scale was the Spanish flu during 1917–1919, but there is no available historical data on the containment measures and WFH capacities across countries for the Spanish flu.

we offer a discussion below to surmise the potential effects when downward wage rigidity is incorporated.

First, note that by assuming that the workers shoulder the pandemic shocks directly in the extended model (Section 4.4), instead of the firms in the baseline model, the extended model already captures the unemployment effect to some extent. More specifically, the pandemic shocks $B_{i,t}^{j}$ form a constraint on workers' labor supply because a worker can, on average, supply only $B_{i,t}^{j} \leq 1$ fraction of their labor. This can also be interpreted as the fraction of workers keeping their jobs. Moreover, when they make their sectoral choices, they form forecasts on $B_{i,t}^{j}\omega_{i,t}^{j}$ instead of just on the real wages $\omega_{i,t}^{j}$ in the baseline model. If wages are difficult to adjust downward during a pandemic, this implies that more unemployment will be observed and the effects of the pandemic shocks will be more severe. This implies that greater belief-scarring losses will be observed if downward wage rigidity is incorporated.

Thus, despite not modeling downward wage rigidity directly, we carry out two exercises that artificially intensify the pandemic shocks $B_{i,t}^{j}$ to surmise the potential effect of incorporating the downward wage rigidity. Specifically, we choose a scaling parameter $\lambda > 1$ such that the artificial pandemic shocks are set to be $\widetilde{B}_{i,t}^{j} = \left(B_{i,t}^{j}\right)^{\lambda}$, where $B_{i,t}^{j}$ are the same as those in the extended model. We tried two values for λ: 1.5 and 2.

As conjectured, the post-pandemic losses increase when the pandemic shocks are more severe. When $\lambda = 1.5$ and $\lambda = 2$, the global BCLs are 0.90% and 1.21% of the global annual real income, which is up from 0.60% in the extended model; these amount to 50% and 102% increases, respectively. The quantitative magnitudes of other main results remain remarkably similar. When $\lambda = 1.5$, the global BCL is 11.4% in terms of the economic losses during the pandemic. Trade (without input-output linkages) amplifies the global BCL by 45.8%, while input-output linkages (under autarky) remove 38.6% of the global BCL. When input-output linkages are considered, trade worsens the global BCL by 53.9%. When $\lambda = 2$, the same numbers are 11.7%, 46.1%, 38.7%, 54.1%, respectively. Recall that the same numbers in Section 4.4 are 11.6%, 45.7%, 38.8%, and 54.0%, respectively.

In short, downward wage rigidity is likely to amplify the quantitative implications of our model, but the roles played by trade and input-output linkages might remain similar.

5 Conclusion

This paper studies how the interaction between information friction 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 vary substantially across countries and that when these post-COVID losses are combined globally, they are 12.4% of the global economic loss during the pandemic, indicating a significant effect due to this mechanism. 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 is rather unique relative to the trade literature in the sense that whereas most trade theories assume perfect information, we show that with imperfect information, trade may negatively affect economic outcomes due to misperceived comparative advantages. As a result, the negative effect of trade on the long-run economic outcomes is contrary to the findings in recent studies on the interaction between trade and the pandemic. Moreover, even though input-output linkages alone tend to dampen such losses, such linkages can amplify the negative effect of trade when they work in an open-economy environment.

Appendix

A Equilibrium Algorithm

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

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

which can be represented by a system of linear equations with consumption as intercepts. Let $JI \times 1$ vector $\mathbf{X_t} \equiv \{X_{i,t}^j\}$ be ordered as $(j=1, i=1), (j=1, i=2), \ldots, (j=2, i=1), (j=2, i=2), \ldots, (j=J, i=I)$. The system can be expressed as

$$\underset{JI\times 1}{\mathbf{b_t}} = \underset{JI\times JI}{\mathbf{A_t}} \times \underset{JI\times 1}{\mathbf{X_t}}, \tag{15}$$

where the element of each term is

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

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

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

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

A.1 Equilibrium Prices

Given $L_{i,t}$, sectoral employment 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 $\xi = 0, 1, 2, \ldots$. For $\xi = 0$, start with an initial guess of wages and rental prices of capital $\{w_i^j(0), r_i(0)\}$ such that it lies in a simplex (as in Alvarez and Lucas (2007)), i.e.,

$$r_i(0) K_i + \sum_{j=1}^J \sum_{i=1}^I w_i^j(0) L_i^j = 1.$$

The equilibrium is computed by the following algorithm.

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

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

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

   (b) Update the price index of the intermediate-input bundle:

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

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

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

   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:

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

2. By definition of X_i^j,

$$
X_i^j(\xi) = \alpha_i^j \left[r_i(\xi) K_i + \sum_{k=1}^J w_i^k(\xi) \ell_i^k L_i \right] + \sum_{l=1}^J \gamma_i^{l,j} (1 - \beta_i^{L,l} - \beta_i^{K,l}) \sum_{n=1}^I \pi_{i,n}^l(r) X_n^l(r),
$$

which entails a linear system of equations written as

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

where

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

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

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

$$\begin{aligned}Z_i^{L,j}(\xi) &\equiv \frac{1}{w_i^j(\xi)} \left[\sum_{n=1}^{I} \beta_i^{L,j}\pi_{i,n}^j(\xi)X_n^j(\xi) - w_i^j(\xi)\ell_i^j L_i \right]\\ Z_i^K(\xi) &\equiv \frac{1}{r_i(\xi)} \left[\sum_{j=1}^{J}\sum_{n=1}^{I} \beta_i^{K,j}\pi_{i,n}^j(\xi)X_n^j(\xi) - r_i(\xi)K_i \right].\end{aligned}$$

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

$$\begin{aligned}w_i^j(\xi+1) &= w_i^j(\xi)\left[1+\psi\frac{Z_i^{L,j}(\xi)}{\ell_i^j L_i}\right]\\ r_i(\xi+1) &= r_i(\xi)\left[1+\psi\frac{Z_i^{K,j}(\xi)}{K_i}\right],\end{aligned}$$

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

4. Stop iterations if

$$\max_i \left\{ \max\left\{ |Z_i^{L,j}(\xi)|, |Z_i^K(\xi)| \right\} \right\} < \text{tolerance}.$$

Otherwise, go back to Step 1.

Given the equilibrium wages and the rental prices of capital $\{w_i^j, r_i\}$, the equilibrium price indices can be calculated accordingly.

A.2 Equilibrium Sectoral Labor Supply with Perfect Foresight

In this subsection, we present the procedure to find the sectoral employment shares. Workers make decisions regarding their sectoral choices in period t at the end of period $t-1$. Assume that they have perfect foresight about future containment policies $\eta_{i,t}$. Recall from Section 2.3 that real capital income does not matter for workers' sectoral choices.

We use an iterative procedure to solve the equilibrium sectoral employment shares $\ell_{i,t}^{j}$:

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

2. Use $\ell_{i,t}^{j}(\xi)$ and future of containment measures $\widetilde{\eta}_{i,t}$ to compute real wages $\widetilde{\omega}_{i,t}^{j}(\xi) = \frac{w_{i,t}^{j}(\xi)}{P_{i,t}(\xi)}$ for each country i and each sector j.

3. Use the new sectoral real income to update the sectoral labor supply

$$\ell_{i,t}^{j}(\xi+1) = \frac{\exp\left(\widetilde{\omega}_{i,t}^{j}(\xi)\right)^{1/\phi}}{\sum_{k=1}^{J} \exp\left(\widetilde{\omega}_{i,t}^{k}(\xi)\right)^{1/\phi}}.$$

4. Stop the iterative procedure if

$$\max_{(j,i)}\{|\ell_{i}^{j}(\xi+1) - \ell_{i}^{j}(\xi)|\} < \text{tolerance}.$$

   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 rely 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, total capital compensation, employment (in terms of the total number of persons engaged for each industry), and nominal capital stock for each country and each sector. These allow for calculating country-sector-specific wages and country-specific rental prices of capital. 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)[11] for reference.

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 $\{\nu^j, D_i^{j,exp}\}$.

[11] https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

B.2.2 Uncover Technological Parameters

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

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

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

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

where $c^j_i = (w^j_i)^{\beta^{L,j}_i}(r_i)^{\beta^{K,j}_i}(P^{M,j}_i)^{1-\beta^{L,j}_i-\beta^{K,j}_i}$ is the unit cost of production. As mentioned in Appendix B.1.1, from the Social Economic Account in the WIOD, wages w^j_i are calculated by dividing the total labor compensation of (j, i) by the number of people employed in (j, i); similarly, the rental price of capital r_i is calculated by dividing the total capital compensation by the nominal capital stock. Hence,

$$\hat{T}^j_i = \exp(\hat{D}^{j,exp}_i) \times [(w^{j,data}_i)^{\beta^{L,j}_i}(r^{data}_i)^{\beta^{K,j}_i}(\hat{P}^{M,j}_i)^{1-\beta^{L,j}_i-\beta^{K,j}_i}]^\theta \tag{16}$$

$$\hat{P}^{M,j}_i = \prod_{l=1}^{J}(\hat{P}^l_i)^{\gamma^{j,l}_i} \tag{17}$$

$$\hat{P}^j_i = \Gamma\left(\frac{\theta - 1 + \kappa}{\theta}\right)\left(\sum_{k=1}^{K}\hat{T}^j_k[(w^{j,data}_i)^{\beta^{L,j}_i}(r^{data}_i)^{\beta^{K,j}_i}(\hat{P}^{M,j}_i)^{1-\beta^{L,j}_i-\beta^{K,j}_i}\hat{\tau}^j_{i,k}]^{-\theta}\right)^{-\frac{1}{\theta}}. \tag{18}$$

The following procedure is used to solve for $\{T^j_i\}$, as in Fieler (2011) and Ravikumar, Santacreu and Sposi (2019). Let ξ index the rounds of iterations, and start with an initial guess of $\{\hat{P}^{M,j}_i(0)\}$.

1. Update productivity:

$$\hat{T}^j_i(\xi) = \exp(\hat{D}^{j,exp}_i) \times [(w^{j,data}_i)^{\beta^{L,j}_i}(r^{data}_i)^{\beta^{K,j}_i}\hat{P}^{M,j}_i(\xi)^{1-\beta^{L,j}_i-\beta^{K,j}_i}]^\theta.$$

2. Update sectoral price indices:

$$\hat{P}^j_i(\xi) = \Gamma\left(\frac{\theta - 1 + \kappa}{\theta}\right)\left[\sum_{k=1}^{I}\hat{T}^j_k(r)[(w^{j,data}_i)^{\beta^{L,j}_i}(r^{data}_i)^{\beta^{K,j}_i}\hat{P}^{M,j}_i(\xi)^{1-\beta^{L,j}_i-\beta^{K,j}_i}\hat{\tau}^j_{i,k}]^{-\theta}\right]^{-\frac{1}{\theta}}.$$

3. Update the price indices of the intermediate-input bundle:

$$\hat{P}^{M,j}_i(\xi+1) = \prod_{l=1}^{J}[\hat{P}^l_i(\xi)]^{\gamma^{j,l}_i}.$$

4. Stop the iterations if

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

   Otherwise, go back to Step 1.

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

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 (%)

	With IO linkages		Without IO linkages	
Country	Open economy	Autarky	Open economy	Autarky
AUS	1.218	0.730	2.424	1.173
AUT	0.358	0.375	1.139	0.586
BEL	0.514	0.691	1.596	0.907
BGR	-0.308	0.053	-0.715	0.105
BRA	1.204	0.546	1.871	0.923
CAN	1.713	0.746	2.816	1.186
CHE	-0.041	0.271	0.093	0.369
CHN	1.233	0.970	2.061	1.486
CYP	0.620	0.269	1.817	0.530
CZE	-0.046	0.168	-0.250	0.274
DEU	0.736	0.585	1.239	0.794
DNK	0.247	0.458	0.722	0.739
ESP	1.173	0.602	1.902	0.822
EST	-0.310	0.047	-0.446	0.114
FIN	-0.149	0.155	0.088	0.266
FRA	1.167	0.870	1.935	1.117
GBR	1.523	0.828	2.735	1.268
GRC	1.524	0.275	1.840	0.378
HRV	0.026	0.258	0.459	0.459
HUN	0.199	0.237	0.398	0.476
IDN	0.360	0.220	0.466	0.428
IND	1.747	1.251	2.045	1.187
IRL	1.741	0.859	4.203	1.293
ITA	1.523	0.834	2.770	1.343
JPN	0.023	0.020	-0.210	0.058
KOR	0.431	0.061	0.942	0.433
LTU	-0.096	0.064	-0.407	0.095
LUX	-0.058	0.198	-0.066	0.318
LVA	-0.256	0.049	-0.513	0.108
MEX	0.778	0.274	1.454	0.439
NLD	0.845	0.753	1.880	1.048
NOR	0.277	0.313	0.504	0.527
POL	0.277	0.223	0.378	0.274
PRT	0.771	0.302	1.622	0.514
ROU	0.359	0.139	0.102	0.134
RUS	0.692	0.804	1.255	1.088
SVK	-0.083	0.080	-0.632	0.143
SVN	0.189	0.277	0.912	0.519
SWE	0.348	0.461	0.828	0.738
TUR	0.568	0.136	1.005	0.191
TWN	-0.306	-0.002	-0.608	0.020
USA	1.286	0.822	2.291	1.289
World	0.686	0.462	1.006	0.668
Average	0.572	0.411	1.046	0.623
World (during COVID)	5.524	5.587	5.926	5.914

Note: This table reports the post-COVID belief-scarring cumulative losses (BCLs) relative to the pre-COVID annual real income. The "World" row reports the global sum of the BCLs in the pre-COVID global annual income. The "Average" row reports the simple average of the BCLs across countries. The "World (during COVID)" row reports the global economic losses during COVID relative to the global annual real income. The four columns report the four scenarios according to whether the global economy is open or autarkic and whether input-output linkages are incorporated. The first column is our baseline model.

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

	Learning rate $= 10$		Learning rate $= 0.1$	
Country	Open economy	Autarky	Open economy	Autarky
AUS	1.080	0.729	1.150	0.499
AUT	0.321	0.393	0.463	0.324
BEL	0.387	0.677	0.518	0.465
BGR	-0.424	0.055	0.122	0.034
BRA	1.186	0.581	0.763	0.284
CAN	1.665	0.796	1.002	0.359
CHE	-0.151	0.261	0.212	0.233
CHN	1.203	1.003	0.794	0.613
CYP	0.396	0.312	0.352	0.107
CZE	-0.099	0.169	0.144	0.156
DEU	0.678	0.587	0.455	0.381
DNK	0.140	0.422	0.325	0.354
ESP	1.080	0.619	0.869	0.367
EST	-0.417	0.051	0.049	0.025
FIN	-0.244	0.154	0.168	0.133
FRA	1.037	0.859	1.097	0.634
GBR	1.440	0.868	0.792	0.420
GRC	1.447	0.291	1.382	0.177
HRV	-0.207	0.281	0.210	0.125
HUN	0.137	0.224	0.219	0.283
IDN	0.308	0.143	0.250	0.055
IND	1.799	1.295	1.213	0.891
IRL	1.557	0.899	1.556	0.569
ITA	1.425	0.839	1.605	0.738
JPN	-0.045	0.017	0.055	0.023
KOR	0.361	0.056	0.212	0.118
LTU	-0.218	0.070	0.139	0.037
LUX	-0.082	0.202	-0.041	0.093
LVA	-0.342	0.053	0.066	0.031
MEX	0.727	0.277	0.798	0.262
NLD	0.707	0.751	0.816	0.532
NOR	0.160	0.282	0.233	0.241
POL	0.186	0.226	0.420	0.164
PRT	0.649	0.307	1.192	0.261
ROU	0.234	0.144	0.719	0.102
RUS	0.597	0.785	0.768	0.756
SVK	-0.143	0.082	0.221	0.061
SVN	0.092	0.283	0.622	0.224
SWE	0.250	0.429	0.444	0.419
TUR	0.494	0.143	0.672	0.094
TWN	-0.367	-0.003	-0.079	-0.003
USA	1.139	0.794	1.072	0.579
World	0.633	0.433	0.502	0.276
Average	0.480	0.414	0.572	0.291
World (during COVID)	5.590	5.731	5.173	5.464

Note: This table reports the post-COVID belief-scarring cumulative losses (BCLs) relative to the pre-COVID annual real income. The "World" row reports the global sum of the BCLs in the pre-COVID global annual income. The "Average" row reports the simple average of the BCLs across countries. The "World (during COVID)" row reports the global economic losses during COVID relative to the global annual real income. The four columns report the four scenarios according to whether the global economy is open or autarkic and whether input-output linkages are incorporated. The first column is our baseline model.

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
AUS	0.753	0.804	-0.104	0.604
AUT	0.079	0.422	-0.159	0.344
BEL	0.160	0.779	-0.043	0.613
BGR	-0.550	0.076	-0.714	0.112
BRA	1.297	0.704	0.969	0.829
CAN	1.438	0.889	0.242	0.849
CHE	-0.270	0.280	-0.320	0.165
CHN	1.326	1.146	0.921	1.054
CYP	0.214	0.374	-0.112	0.509
CZE	-0.163	0.150	-0.146	0.064
DEU	0.546	0.625	0.207	0.442
DNK	0.008	0.421	0.029	0.185
ESP	0.977	0.735	0.238	0.714
EST	-0.515	0.068	-0.459	0.098
FIN	-0.372	0.182	-0.324	0.164
FRA	0.841	0.935	0.123	0.657
GBR	1.091	0.940	0.087	0.758
GRC	1.417	0.397	0.542	0.581
HRV	-0.324	0.329	-0.488	0.342
HUN	0.156	0.124	0.175	0.003
IDN	0.338	0.113	0.305	0.050
IND	2.192	1.636	2.396	1.831
IRL	1.138	1.067	0.075	1.196
ITA	1.102	0.920	0.099	0.694
JPN	0.061	0.009	0.097	0.001
KOR	0.496	0.001	0.731	-0.006
LTU	-0.294	0.099	-0.568	0.167
LUX	-0.089	0.246	0.129	0.243
LVA	-0.449	0.074	-0.519	0.113
MEX	0.823	0.297	0.577	0.260
NLD	0.481	0.842	-0.084	0.659
NOR	0.115	0.279	0.079	0.118
POL	0.131	0.274	-0.246	0.276
PRT	0.452	0.396	-0.319	0.468
ROU	0.118	0.197	-0.371	0.263
RUS	0.462	0.774	0.054	0.340
SVK	-0.248	0.111	-0.416	0.144
SVN	-0.227	0.360	-0.502	0.400
SWE	0.090	0.406	0.015	0.157
TUR	0.586	0.201	0.452	0.307
TWN	-0.381	-0.003	-0.252	-0.007
USA	1.147	0.875	0.401	0.602
World	0.693	0.481	0.553	0.443
Average	0.385	0.466	0.067	0.413
World (during COVID)	5.461	5.624	5.656	5.764

Note: This table reports the post-COVID belief-scarring cumulative losses (BCLs) relative to the pre-COVID annual real income. The "World" row reports the global sum of the BCLs in the pre-COVID global annual income. The "Average" row reports the simple average of the BCLs across countries. The "World (during COVID)" row reports the global economic losses during COVID relative to the global annual real income. The four columns report the four scenarios according to whether the global economy is open or autarkic and whether input-output linkages are incorporated. The first column is our baseline model.

Table C.6: BCL in Pre-COVID Annual Real Income (%) with Dual Information Frictions

Country	With IO linkages		Without IO linkages	
	Open economy	Autarky	Open economy	Autarky
AUS	1.033	0.725	2.144	1.168
AUT	0.278	0.369	0.676	0.568
BEL	0.376	0.685	1.362	0.917
BGR	-0.497	0.053	-1.212	0.106
BRA	1.295	0.620	1.936	1.055
CAN	1.786	0.838	3.065	1.337
CHE	-0.214	0.255	-0.293	0.353
CHN	1.212	0.997	2.096	1.633
CYP	0.348	0.330	1.520	0.641
CZE	-0.163	0.156	-0.659	0.252
DEU	0.615	0.543	0.909	0.746
DNK	0.088	0.408	0.330	0.690
ESP	1.088	0.629	1.719	0.859
EST	-0.507	0.051	-0.880	0.121
FIN	-0.304	0.148	-0.259	0.254
FRA	1.007	0.853	1.619	1.110
GBR	1.476	0.876	2.922	1.395
GRC	1.151	0.255	1.113	0.346
HRV	-0.262	0.305	0.184	0.495
HUN	0.076	0.224	0.088	0.446
IDN	0.268	0.062	0.474	0.332
IND	1.794	1.267	1.995	1.234
IRL	1.385	0.863	3.567	1.262
ITA	1.334	0.792	2.261	1.272
JPN	-0.099	0.015	-0.459	0.053
KOR	0.274	0.057	0.737	0.422
LTU	-0.295	0.068	-0.868	0.102
LUX	-0.161	0.207	-0.522	0.332
LVA	-0.399	0.052	-0.913	0.108
MEX	0.681	0.290	1.122	0.453
NLD	0.585	0.709	1.438	0.997
NOR	0.082	0.265	0.089	0.474
POL	0.125	0.219	-0.092	0.277
PRT	0.511	0.283	0.983	0.480
ROU	0.157	0.137	-0.510	0.137
RUS	0.574	0.788	0.962	1.075
SVK	-0.216	0.077	-1.067	0.139
SVN	0.020	0.266	0.391	0.506
SWE	0.188	0.415	0.473	0.684
TUR	0.425	0.135	0.629	0.197
TWN	-0.430	-0.005	-0.920	0.016
USA	1.132	0.793	2.184	1.296
World	0.602	0.391	0.931	0.639
Average	0.424	0.407	0.722	0.627
World (during COVID)	5.210	5.496	6.055	5.927

Note: This table reports the post-COVID belief-scarring cumulative losses (BCLs) relative to the pre-COVID annual real income. The "World" row reports the global sum of the BCLs in the pre-COVID global annual income. The "Average" row reports the simple average of the BCLs across countries. The "World (during COVID)" row reports the global economic losses during COVID relative to the global annual real income. The four columns report the four scenarios according to whether the global economy is open or autarkic and whether input-output linkages are incorporated. The first column is our baseline model.

References

Abbritti, Mirko, and Stephan Fahr. 2013. “Downward Wage Rigidity and Business Cycle Asymmetries.” *Journal of Monetary Economics*, 60(7): 871–886.

Acemoglu, Daron, Victor Chernozhukov, Iván Werning, and Michael D. Whinston. 2021. “Optimal Targeted Lockdowns in a Multigroup SIR Model.” *American Economic Review: Insights*, 3(4): 487–502.

Alvarez, Fernando, and Robert E. Lucas. 2007. “General Equilibrium Analysis of the Eaton–Kortum model of International Trade.” *Journal of Monetary Economics*, 54(6): 1726–1768.

Alvarez, Fernando, David Argente, and Francesco Lippi. 2021. “A Simple Planning Problem for COVID-19 Lock-Down, Testing, and Tracing.” *American Economic Review: Insights*, 3(3): 367–82.

Antrás, Pol, Stephen J. Redding, and Esteban Rossi-Hansberg. 2020. “Globalization and Pandemics.” NBER Working Paper 27840.

Argente, David, Chang-Tai Hsieh, and Munseob Lee. 2022. “The Cost of Privacy: Welfare Effects of The Disclosure of Covid-19 Cases.” *Review of Economics and Statistics*, 104(1): 176–186.

Atkeson, Andrew. 2020. “What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios.” NBER Working Paper 26867.

Baqaee, David, and Emmanuel Farhi. 2022. “Supply and Demand in Disaggregated Keynesian Economies with an Application to the COVID-19 Crisis.” *American Economic Review*, 112(5): 1397–1436.

Bonadio, Barthélémy, Zhen Huo, Andrei A. Levchenko, and Nitya Pandalai-Nayar. 2021. “Global Supply Chains in the Pandemic.” *Journal of International Economics*, 133: 103534.

Bonatti, Alessandro, Gonzalo Cisternas, and Juuso Toikka. 2017. “Dynamic Oligopoly with Incomplete Information.” *The Review of Economic Studies*, 84(2): 503–546.

Caliendo, Lorenzo, and Fernando Parro. 2015. “Estimates of the Trade and Welfare Effects of NAFTA.” *The Review of Economic Studies*, 82(1): 1–44.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro. 2019. “Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock.” *Econometrica*, 87(3): 741–835.

Cisternas, Gonzalo. 2018. "Two-sided Learning and the Ratchet Principle." *The Review of Economic Studies*, 85(1): 307–351.

Cogley, Timothy, and Thomas J. Sargent. 2008. "The Market Price of Risk and the Equity Premium: A Legacy of the Great Depression?" *Journal of Monetary Economics*, 55(3): 454–476.

Dingel, Jonathan I., and Brent Neiman. 2020. "How Many Jobs Can be Done at Home?" *Journal of Public Economics*, 189: 104235.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica*, 70(5): 1741–1779.

Eichenbaum, Martin S., Sergio Rebelo, and Mathias Trabandt. 2021. "The Macroeconomics of Epidemics." *The Review of Financial Studies*, 34(11): 5149–5187.

Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh. 2022. "Can the Covid Bailouts Save the Economy?" *Economic Policy*. eiac009.

Elsby, Michael WL, Donggyun Shin, and Gary Solon. 2016. "Wage Adjustment in the Great Recession and Other Downturns: Evidence from the United States and Great Britain." *Journal of Labor Economics*, 34(S1): S249–S291.

Fajgelbaum, Pablo D., Amit Khandelwal, Wookun Kim, Cristiano Mantovani, and Edouard Schaal. 2021. "Optimal Lockdown in a Commuting Network." *American Economic Review: Insights*, 3(4): 503–22.

Farboodi, Maryam, Gregor Jarosch, and Robert Shimer. 2021. "Internal and External Effects of Social Distancing in a Pandemic." *Journal of Economic Theory*, 196: 105293.

Fieler, Ana Cecilia. 2011. "Nonhomotheticity and Bilateral Trade: Evidence and a Quantitative Explanation." *Econometrica*, 79(4): 1069–1101.

Fogli, Alessandra, and Laura Veldkamp. 2011. "Nature or Nurture? Learning and the Geography of Female Labor Force Participation." *Econometrica*, 79(4): 1103–1138.

Hale, Thomas, Noam Angrist, Rafael Goldszmidt, Beatriz Kira, Anna Petherick, Toby Phillips, Samuel Webster, Emily Cameron-Blake, Laura Hallas, Saptarshi Majumdar, et al. 2021. "A Global Panel Database of Pandemic Policies (Oxford COVID-19 Government Response Tracker)." *Nature Human Behaviour*, 5(4): 529–538.

Head, Keith. 2014. "Gravity Equations: Workhorse, Toolkit, and Cookbook." *Handbook of International Economics*, 4: 131.

He, Zhiguo, Bin Wei, Jianfeng Yu, and Feng Gao. 2017. "Optimal Long-term Contracting with Learning." *The Review of Financial Studies*, 30(6): 2006–2065.

Hsu, Wen-Tai, Hsuan-Chih (Luke) Lin, and Han Yang. 2023. "Between Lives and Economy: COVID-19 Containment Policy in Open Economies." *European Economic Review*, 157: 104512.

Jones, Callum, Thomas Philippon, and Venky Venkateswaran. 2021. "Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home." *The Review of Financial Studies*, 34(11): 5188–5223.

Kermack, William Ogilvy, A. G. McKendrick, and Gilbert Thomas Walker. 1927. "A Contribution to the Mathematical Theory of Epidemics." *Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character*, 115(772): 700–721.

Kozlowski, Julian, Laura Veldkamp, and Venky Venkateswaran. 2020*a*. "Scarring Body and Mind: The Long-term Belief-scarring Effects of COVID-19." *Jackson Hole Economic Policy Symposium Proceedings*.

Kozlowski, Julian, Laura Veldkamp, and Venky Venkateswaran. 2020*b*. "The Tail that Wags the Economy: Beliefs and Persistent Stagnation." *Journal of Political Economy*, 128(8): 2839–2879.

Krueger, Dirk, Harald Uhlig, and Taojun Xie. 2022. "Macroeconomic Dynamics and Reallocation in an Epidemic: Evaluating the 'Swedish Solution'." *Economic Policy*. eiac010.

LaBelle, Jesse, Fernando Leibovici, and Ana Maria Santacreu. 2021. "Global Value Chains and US Economic Activity during COVID-19." *Federal Reserve Bank of St. Louis Review*. Third Quarter 2021.

Leibovici, Fernando, and Ana Maria Santacreu. 2023. "Shortages of Critical Goods in a Global Economy: Optimal Trade and Industrial Policy." Federal Reserve Bank of St. Louis Working Paper.

Mayer, Thierry, and Soledad Zignago. 2011. "Notes on CEPII's distances measures: The GeoDist database." CEPII Working Papers 2011-25.

Piguillem, Facundo, and Liyan Shi. 2022. "Optimal Covid-19 Quarantine and Testing Policies." *The Economic Journal*. ueac026.

Porcher, Charly. 2022. "Migration with Costly Information." Georgetown University Working Paper.

Ravikumar, B, Ana Maria Santacreu, and Michael Sposi. 2019. "Capital Accumulation and Dynamic Gains from Trade." *Journal of International Economics*, 119: 93–110.

Rodríguez-Clare, Andrés, Mauricio Ulate, and Jose P Vasquez. 2020. "Trade with Nominal Rigidities: Understanding the Unemployment and Welfare Effects of the China Shock." National Bureau of Economic Research Working Paper 27905.

Simonovska, Ina, and Michael E. Waugh. 2014. "The Elasticity of Trade: Estimates and Evidence." *Journal of International Economics*, 92(1): 34–50.

Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen J. De Vries. 2015. "An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production." *Review of International Economics*, 23(3): 575–605.