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Covid-19 Shocking Global Value Chains

Abstract

In early 2020, the disease Covid-19 caused a drastic lockdown of the Chinese economy. We use a quantitative trade model with input-output linkages to gauge the effects of this adverse supply shock in China on the global economy through international trade and global value chains (GVCs). We find moderate welfare losses in most countries outside of China, while a few countries even gain from the shock due to trade diversion. As a key methodological contribution, we quantify the role of GVCs (in contrast to final goods trade) in transmitting the shock. In a hypothetical world without GVCs, the welfare loss due to the Covid-19 shock in China is reduced by 40% in the median country. In several other countries, the effects are magnified or reversed for several countries. Had the U.S. unilaterally repatriated GVCs, the country would have incurred a substantial welfare loss while its exposure to the shock would have barely changed.

JEL-Codes: F110, F120, F140, F170, F620.

Keywords: Covid-19, quantitative trade model, input-output linkages, global value chains, supply chain contagion, shock transmission.

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1 INTRODUCTION

The disease Covid-19, caused by a novel coronavirus (SARS-CoV-2), was first diagnosed in December 2019 in China's Hubei province. Within weeks the outbreak turned into an epidemic, and by mid-February 2020 most Chinese provinces were under complete or partial lockdown. Even before the virus infected millions of people worldwide, this major shock to Chinese production and consumption affected the global economy through 'supply chain contagion' (Baldwin and Tomiura, 2020, and Gerschel et al., 2020). As early as February 2020, firms around the world began experiencing disruptions of their production processes due to a lack of intermediate inputs from China.[1] Soon thereafter, newspapers around the world were filled with speculations on the global economic repercussions of the Covid-19 shock in China (see, e.g., Reuters, 2020, and The Guardian, 2020). These events have fueled a public discourse about the reliance on Chinese inputs, with politicians on both sides of the Atlantic calling for a 'decoupling' or 'repatriation' of global value chains (GVCs), in particular those involving China (Irwin, 2020, and Baldwin and Evenett, 2020).

This paper informs the ongoing debate by providing the following three contributions. First, we present a model-based quantification of the global repercussions of Covid-19 via international trade and GVCs. Given the importance of China as a pivotal hub in GVCs, we focus on the well-defined *initial* Covid-19 shock in China in January–February 2020, i.e., before the disease turned into a pandemic.[2] Second, and most importantly, we quantify the relevance of GVCs in the shock transmission by reconsidering the same Covid-19 shock in China occurring in a counterfactual world in which intermediate goods trade via GVCs has been shut down. Notably, our counterfactual world still permits international trade in final goods and the existence of sectoral linkages in domestic value chains. Third, and related, we study the repercussions of the shock after the U.S. has unilaterally decoupled from global (or Chinese) value chains, as recently discussed in policy circles.

The framework we use for our analysis is a generalization of the quantitative Ricardian trade model with multiple sectors and input-output (I-O) linkages. Three key features of the model make it particularly suited for our purpose: First, it includes both domestic and international I-O linkages (as in Caliendo and Parro, 2015), and hence describes how sectors are affected directly and indirectly through GVCs. Second, it distinguishes trade costs for intermediate inputs and final goods (as in Antràs and Chor, 2018), which allows us to isolate the role of GVCs. Third, we allow

[1] Between February 1 and March 5, 2020, the majority of the global top 5000 multinational enterprises (MNEs) revised their earnings forecasts for fiscal year 2020 and more than two thirds of the top 100 MNEs issued statements on the impact of Covid-19 on their business (UNCTAD, 2020). See also individual reports on Apple Inc. and Airbus SE in New York Times (2020) and The Economist (2020).

[2] Until the end of February, Covid-19 infections were still predominantly confined to China (see Dong et al., 2020, and the discussion in Section 3.2).

for imperfect intersectoral mobility of labor (similar to Galle et al., 2018).

We use the model and Chinese administrative data to back out the sectoral labor supply shocks caused by Covid-19. To achieve this, we estimate the initial output drop in Chinese sectors from monthly time series. Related to the methodology in Allen et al. (2020), this initial output drop is conceptualized as the 'zeroth degree' effect of the shock in China, i.e., before any response by the rest of the world. By inverting the model for the 0^{th} degree effect, we recover the underlying shocks to efficient labor supply by sector from the output drop. We calibrate the model based on the World Input-Output Database (WIOD, Timmer et al., 2015) to study the global repercussions of the Covid-19 shock in China in a range of counterfactual scenarios. These scenarios are best thought of as answering the question of how the world economy would have responded if Covid-19 had permanently reduced production in China but had not spread internationally.[3]

Our three main findings are as follows: First, our baseline scenario predicts the effects of the Covid-19 shock in China on welfare and real sectoral output for 43 countries (and the rest of the world) in 2014, the most recent year covered in the WIOD. We find that, in the new general equilibrium, China experiences a welfare loss of roughly -30%. At the same time, our model predicts moderate spillovers of this shock to all other countries, with welfare effects ranging from -0.75% in Russia to +0.12% in Turkey. Interestingly, nine (mostly European) countries experience a moderate welfare gain from the shock due to trade diversion.

Second, we isolate the role of GVCs in transmitting the shock. To this end, we shut down GVCs by setting the cost of international trade in intermediate goods to infinity. Importantly, our approach differs from the shutting down of all I-O linkages (as simulated in the seminal paper by Caliendo and Parro, 2015) in allowing for domestic input trade. It also differs from a (gradual) return to autarky (as simulated in the contemporaneous studies by Bonadio et al., 2020, and Sforza and Steininger, 2020) in allowing for final goods trade. This counterfactual analysis corresponds to a full repatriation of input provision of the type that is currently being discussed in some countries. We then compare the shock transmission in this 'no-GVCs' scenario to our baseline predictions. We find that shutting down GVCs reduces the welfare loss due to the Covid-19 shock in China by 40% for the median country, with pronounced heterogeneity across countries. Interestingly, in the world without GVCs, the welfare losses are magnified for several countries, including Germany, while they are reversed for other countries. Further analyses reveal that these results are mainly driven by a decoupling from China and less from reduced GVC trade among all other countries. The cross-country patterns are similar when GVCs are shut down only partially (rather than entirely).

[3]Notably, the main goal of these exercises is not to explain the actual global developments during the Covid-19 crisis in 2020, but to shed light on the global transmission of a major supply shock in China in a world economy that is less integrated via GVCs.

Finally, we consider two policy scenarios of the U.S. repatriating value chains (i) from all other countries or (ii) only from China, and then revisit the international transmission of the Covid-19 shock in China after the policy change. We find that fully repatriating U.S. value chains causes a welfare loss of around 1.56% in the U.S. but hardly reduces U.S. exposure to the shock in China. Furthermore, even if the U.S. could anticipate that the next adverse shock were to come from China, and even if it could fully eliminate any imports of inputs from China, the U.S. welfare loss due to the Covid-19 shock in China would be reduced merely from -0.11% to -0.08%. The reduction in shock exposure must be evaluated against the direct welfare cost to the U.S. from repatriating value chains from China, which amounts to -0.12%. We obtain similar qualitative conclusions when considering less extreme scenarios of increasing trade barriers by 10% or 100%. These analyses inform the ongoing debate, in the U.S. but also in the European Union and other economies, about the costs and benefits of repatriating value chains. Our findings suggest that, even in the face of large and long-lasting shocks abroad, repatriating value chains can hardly be an optimal policy from an economic welfare perspective.

The Covid-19 pandemic has given rise to a fast growing literature studying the economic impact of the disease and policy responses. The macroeconomic effects of the pandemic have been assessed in several important contributions, including Baqaee and Farhi (2020a,b), Eichenbaum et al. (2020), Fornaro and Wolf (2020), Guerrieri et al. (2020), and McKibbin and Fernando (2020). Our paper is most closely related to the contemporaneous papers by Bonadio et al. (2020) and Sforza and Steininger (2020), who consider GVCs in the context of Covid-19. These papers aim at quantifying the impact of quarantine and social distancing measures taken in many countries around the world, while we focus on the initial shock in China. Moreover, in our analysis, we can distinctly pin down the contribution of GVCs (as opposed to trade in general) to the transmission of the Covid-19 shock. Barrot et al. (2020), Bodenstein et al. (2020), and Inoue and Todo (2020) (among others) study the role of domestic supply chains in a closed economy setup.

More broadly, our paper relates to the theoretical and empirical literature on the role of production networks in shaping economic outcomes (see Carvalho and Tahbaz-Salehi, 2019, for a recent overview). The propagation of shocks through supply chains has been studied extensively both theoretically (see, e.g., Acemoglu et al., 2012, and Acemoglu and Tahbaz-Salehi, 2020) and empirically in the context of natural disasters (see, e.g., Barrot and Sauvagnat, 2016, and Carvalho et al., 2016, and Boehm et al., 2019). We complement these studies with a quantitative exercise demonstrating that, for some countries, the Covid-19 shock in China might have been exacerbated (rather than mitigated) in the absence of GVCs.

The paper is organized as follows. We present the model in Section 2. Section 3 describes the data and empirical methodology. Section 4 presents and discusses the simulation results. Finally, we draw some conclusions in Section 5.

2 The model

Our baseline model is strongly related to Antràs and Chor (2018), who extend the multi-sector Eaton-Kortum model by Caliendo and Parro (2015) to allow for varying trade costs for intermediates and final goods, thus being able to exactly match each entry in multi-country I-O tables (i.e., each flow by country-sector and country-use category). A new element that we introduce into this framework is heterogeneity of workers in terms of the efficient labor they can provide to different sectors. This approach has two important advantages for our application. First, it adds realism by acknowledging the imperfect mobility of labor across sectors that seems appropriate in our setting. Second, it allows us to analyze the reductions in efficient labor supply by sector that are at the heart of the Covid-19 shock.

2.1 Endowments

We consider a world economy consisting of J countries indexed by j and i, in which S sectors indexed by s and r can be active. Each country is endowed with an aggregate mass of worker-consumers L_j, with each individual inelastically supplying one unit of raw labor. Workers are immobile across countries and we consider different scenarios concerning their mobility across sectors, ranging from immobility in the short run over imperfect mobility in the medium run and perfect mobility in the long run. In the latter two cases the number of workers L_{js} in each country-sector is endogenous in equilibrium, while it is exogenous in the case of immobility.

2.2 Preferences and sector choice

Preferences. All consumers in country j draw utility from the consumption of a Cobb-Douglas compound good, which itself consists of CES compound goods from each of the sectors $s \in \{1, ..., S\}$. Aggregate consumption C_j in country j is given by

$$C_j = \prod_{s=1}^{S} C_{js}^{\alpha_{js}}, \quad \text{where} \quad \sum_{s=1}^{S} \alpha_{js} = 1, \tag{1}$$

and α_{js} denotes expenditure shares on sectoral compound goods C_{js}. Each C_{js} is a CES aggregate over a continuum of individual varieties $\omega \in [0, 1]$ produced within each sector:

$$C_{js} = \left[\int_0^1 x_{js}(\omega)^{\frac{\sigma_s - 1}{\sigma_s}} \, d\omega \right]^{\frac{\sigma_s}{\sigma_s - 1}}, \tag{2}$$

where $x_{js}(\omega)$ is total final consumption in country j of variety ω from sector s, and $\sigma_s > 1$ is the elasticity of substitution across varieties.

SECTORAL MOBILITY. We assume that if individual Ω in country j decides to work in sector s, the efficient labor in this country-sector increases by $\delta_{js}(\Omega)$. Intuitively, these values 'translating' raw into efficient labor reflect both the applicability of a worker's skills and training to a particular sector and switching costs to this sector. The efficiency of labor $\delta_{js}(\Omega)$ is drawn by each individual from sector- and country-specific Fréchet distributions with means $\delta_{js} > 0$ and shape parameter $\varphi > 1$, such that the cumulative density function becomes

$$\Pr\left[\delta_{js}(\Omega) \leq \delta\right] = e^{-\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\delta^{-\varphi}},$$

where $\Gamma(\cdot)$ denotes the gamma function. The normalization of the scale parameter ensures that the mean of $\delta_{js}(\Omega)$ for sector s across all workers in country j is exactly equal to δ_{js} and independent of our choice of φ. The parameter δ_{js} will turn out to be our key shock parameter. A reduction in δ_{js} reduces the supply of efficient labor in the economy, as all workers draw on average lower values $\delta_{js}(\Omega)$ for country-sector js. This drop captures the essence of the Covid-19 shock in China, as workers are held back from going to work or operate under time-consuming or efficiency-reducing constraints, such as additional hygiene measures or the requirement to work from home.

As explained above, we consider several scenarios with regard to worker mobility across sectors. Under sectoral mobility, workers pick sector s if it offers them the highest compensation. Therefore, given all compensations per unit of efficient labor w_{js} in all sectors s in country j we can derive the number of workers L_{js} who pick sector s as their workplace as

$$L_{js} = L_j \frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}. \tag{3}$$

Notice that our approach implies that wages per efficiency unit do not need to equalize across sectors in equilibrium. More specifically, a sector increasing its wages will, on average, attract workers that provide less efficient labor to this sector than those already working there.

Using the properties of the Fréchet distribution it is easy to show that the average wage w_j paid to each worker, i.e., the ex-ante expected wage, is the same in each sector in country j and given by

$$w_j = \left(\sum_{s=1}^{S} \delta_{js}^{\varphi} w_{js}^{\varphi}\right)^{\frac{1}{\varphi}}. \tag{4}$$

2.3 PRODUCTION

PRODUCTION. On the production side we assume that, in each country j, each sector s potentially produces a continuum of varieties $\omega \in [0, 1]$ under perfect competition and with constant returns to scale. As in Caliendo and Parro (2015), production uses labor and CES compound goods from potentially all sectors as intermediate goods.

More specifically, producers of variety ω in country j and sector s combine efficient labor units $l_{js}(\omega)$ and intermediate goods $m_{jrs}(\omega)$ from all sectors $r \in \{1, ..., S\}$ in a Cobb-Douglas fashion:

$$q_{js}(\omega) = z_{js}(\omega)\, l_{js}(\omega)^{\gamma_{js}} \left(\prod_{r=1}^{S} m_{jrs}(\omega)^{\gamma_{jrs}} \right), \tag{5}$$

where $\gamma_{js}, \gamma_{jrs} \in [0, 1]$ are the cost shares of labor and intermediates from each sector in production, and where $\gamma_{js} + \sum_{r=1}^{S} \gamma_{jrs} = 1$. Following Eaton and Kortum (2002), exogenous productivities $z_{js}(\omega)$ are drawn from country- and sector-specific Fréchet distributions with the cumulative distribution functions $\Pr[z_{js}(\omega) \leq z] = e^{-T_{js} z^{-\varepsilon_s}}$, where T_{js} determines the average productivities in each country j and sector s, and ε_s measures their dispersion across countries, which we assume to satisfy $\varepsilon_s > \sigma_s - 1$. The compound intermediate goods $m_{jrs}(\omega)$ are produced from individual varieties ω using the same CES aggregator as specified in equation (2).

PRICES. Production technologies of all varieties within sector s and country j differ only with respect to productivities. Perfect competition, therefore, implies that all producers in sector s and country j face the same marginal production costs per efficiency unit c_{js} and set mill prices of $p_{js}(\omega) = \frac{c_{js}}{z_{js}(\omega)}$.

All varieties can be traded subject to iceberg trade costs between any two countries i and j. Following Antràs and Chor (2018), we assume that these trade costs depend not only on the country pair ij and sector r of the traded good, but also on the use category $u \in \{1, \ldots, S+1\}$, which can be one of the S sectors using the variety as an intermediate or it can be final demand. Thus, $\tau_{ijru} \geq 1$ units have to be shipped from country i and sector r for one unit to arrive in country j and use category u. The resulting price at which variety ω from sector r in country i is offered to use category u in country j can be expressed as

$$p_{ijru}(\omega) \equiv p_{ir}(\omega)\, \tau_{ijru} = \frac{c_{ir} \tau_{ijru}}{z_{ir}(\omega)}. \tag{6}$$

As prices depend on productivities, they inherit their stochastic nature. In particular, under the assumption that variety ω from sector s is homogeneous across all possible producing countries, firms and consumers buy them from the cheapest source, implying a price of $\min\{p_{ijru}; i \in J\}$. Using the properties of the Fréchet distribution and following Eaton and Kortum (2002), we can derive both the price P_{jru} of sector r compound goods paid in country j and use category u as well as the share π_{ijru} that country i makes up in use category u's expenditure in country j on sector r:[4]

$$P_{jru} = \Gamma\left(\frac{\varepsilon_r + 1 - \sigma_r}{\varepsilon_r}\right)^{\frac{1}{1-\sigma_r}} \left[\sum_{i=1}^{J} T_{ir}\left(c_{ir}\tau_{ijru}\right)^{-\varepsilon_r}\right]^{-1/\varepsilon_r} \tag{7}$$

and

$$\pi_{ijru} = \frac{T_{ir}\left[\tau_{ijru}c_{ir}\right]^{-\varepsilon_r}}{\sum_{k=1}^{J} T_{kr}\left[\tau_{kjru}c_{kr}\right]^{-\varepsilon_r}} \ . \tag{8}$$

COSTS. Firms' profit maximization and the Cobb-Douglas production structure imply that the total expenditure E_{jrs} by sector s in country j on intermediates from sector r and its expenditure on labor are given by

$$E_{jrs} = \gamma_{jrs}R_{js} \quad \text{and} \quad L_{js}w_j = \gamma_{js}R_{js} \ , \tag{9}$$

where R_{js} denotes the total revenue of sector s in country j. Moreover, using the price indices (7), the input bundle cost per efficient unit of output becomes

$$c_{js} = \chi_{js} w_{js}^{\gamma_{js}} \prod_{r=1}^{S} P_{jrs}^{\gamma_{jrs}} \ , \tag{10}$$

with $\chi_{js} = \gamma_{js}^{-\gamma_{js}} \prod_{r=1}^{S} \gamma_{rjs}^{-\gamma_{rjs}}$ being a country- and sector-specific constant.

2.4 EQUILIBRIUM

EXPENDITURE AND CONSUMPTION. Balanced trade together with factor demands from equation (9), implies that aggregate expenditure $E_{jr(S+1)}$ by consumers in any country j on goods from sector r can be expressed as:

$$E_{jr(S+1)} = \alpha_{jr}\left(\sum_{s=1}^{S} \gamma_{js}R_{js}\right) \ . \tag{11}$$

Subsequently, aggregate consumer welfare or real expenditure can be derived by combining expenditures (11) with the price indices (7) to obtain

$$C_j = \frac{\sum_{r=1}^{S} E_{jr(S+1)}}{\prod_{r=1}^{S} P_{jr(S+1)}^{\alpha_{jr}}} \ . \tag{12}$$

[4] A detailed derivation of the price index and these shares can be found in Appendix A.1.

GOODS MARKET CLEARING. In equilibrium, goods market clearing requires that the value of production in country j and sector s equals the value of world final and intermediate goods demand for that sector:

$$R_{is} = \sum_{j=1}^{J} \sum_{u=1}^{S+1} \pi_{ijsu} E_{jsu} \ . \tag{13}$$

FACTOR MARKET CLEARING. In equilibrium, wages adjust such that factor markets clear. Specifically, combining sectoral labor compensation (9) with the definition of the per capita wage given in (4) and the supply of sectoral labor (3) allows us to solve explicitly for the country- and sector-specific wages per efficiency unit of labor as

$$w_{js} = \frac{(\gamma_{js} R_{js})^{\frac{1}{\varphi}} \left(\sum_{s=1}^{S} \gamma_{js} R_{js} \right)^{\frac{\varphi-1}{\varphi}}}{\delta_{js} L_j} \ . \tag{14}$$

It is instructive to point out two extreme cases. First, as φ approaches infinity, all workers draw the same parameter δ_{js} for sector s in country j, and hence labor becomes perfectly mobile across sectors. In this scenario, which is the standard case in the literature, the sectoral wage per efficiency unit of labor simplifies to w_j/δ_{js}. Second, we will also consider a scenario of worker immobility, in particular when modeling the immediate impact of the Covid-19 shock. In this case, equation (3) no longer holds and L_{js} is given exogenously instead. Also, sectoral per-capita wages no longer equalize but can be obtained directly from sectoral factor market clearing as $\gamma_{js} R_{js} / L_{js}$.[5]

EQUILIBRIUM CONDITIONS. An equilibrium in the model is defined by values of P_{jru} and R_{js} for all countries, sectors and use categories that satisfy the following equilibrium conditions given all preference parameters α_{js} and σ_s, cost shares γ_{js} and γ_{jrs}, sectoral and labor productivity distribution parameters T_{js}, δ_{js}, ε_s and φ, and worker endowments L_j. The first set of equilibrium conditions is obtained from the price index equations (7) after replacing marginal costs using (10) and subsequently factor prices using (14). The second set of equilibrium conditions is obtained from goods market clearing (13) after plugging in expenditures from (11) and (9) as well as trade shares (8) combined with marginal costs (10) and factor prices (14).

EQUILIBRIUM IN CHANGES. Instead of solving the model in levels, we rely on the popular 'exact hat algebra' by Dekle et al. (2007) to solve for counterfactual equilibria in response to a shock in terms of changes. Denoting variables after the shock with a prime and their relative changes with a hat we can restate the equilibrium as follows.

[5] This scenario cannot be captured by letting φ approach 0 since, due to the nature of the Fréchet distribution, the average productivity of workers is not well defined for $\varphi \leq 1$.

Given a shock defined by relative changes in average worker productivity draws $\hat{\delta}_{ir}$, average productivities $\hat{T}_{ir}$, trade costs $\hat{\tau}_{ijru}$ for all countries i, j, sectors r and use categories u, the equilibrium of the model in changes consists of values $\hat{P}_{iru}$ and $\hat{R}_{ir}$ for all countries i, sectors r and use categories u that satisfy the following equilibrium conditions given all α_{ir}, cost shares γ_{ir} and γ_{irs}, distributional parameters ε_r and φ, as well as labor endowments L_i, trade shares π_{ijru}, and revenues R_{ir} in the ex-ante equilibrium:

$$\hat{P}_{jru} = \left[\sum_{i=1}^{J} \pi_{ijru}\hat{T}_{ir}\left(\hat{c}_{ir}\hat{\tau}_{ijru}\right)^{-\varepsilon_r}\right]^{-1/\varepsilon_r} , \tag{15}$$

$$\hat{R}_{ir} = \frac{1}{R_{ir}} \sum_{j=1}^{J} \sum_{u=1}^{S+1} \hat{\pi}_{ijru}\pi_{ijru}E'_{jru} , \tag{16}$$

where we use expenditures from (11) and (9), trade shares (8), marginal costs (10) and factor prices (14), all expressed in changes:

$$E'_{jr(S+1)} = \alpha_{jr}\left(\sum_{s=1}^{S} \gamma_{js}\hat{R}_{js}R_{js}\right) , \tag{17}$$

$$E'_{jru} = \gamma_{jru}\hat{R}_{ju}R_{ju} \quad \forall u \leq S , \tag{18}$$

$$\hat{\pi}_{ijru} = \frac{\hat{T}_{ir}\left(\hat{c}_{ir}\hat{\tau}_{ijru}\right)^{-\varepsilon_r}}{\sum_{k=1}^{J} \pi_{kjru}\hat{T}_{kr}\left(\hat{c}_{kr}\hat{\tau}_{kjru}\right)^{-\varepsilon_r}} , \tag{19}$$

$$\hat{c}_{js} = \hat{w}_{js}^{\gamma_{js}} \prod_{r=1}^{S} \hat{P}_{jrs}^{\gamma_{jrs}} , \tag{20}$$

$$\hat{w}_{js} = \frac{\left(\hat{R}_{js}\right)^{\frac{1}{\varphi}} \left(\frac{\sum_{s=1}^{S}\gamma_{js}\hat{R}_{js}R_{js}}{\sum_{s=1}^{S}\gamma_{js}R_{js}}\right)^{\frac{\varphi-1}{\varphi}}}{\hat{\delta}_{js}} . \tag{21}$$

3 Data and empirical methodology

In this section we first outline how the model is mapped to global data on trade in intermediate and final goods from multi-country I-O tables. We then describe our estimation of the initial impact of Covid-19 on the output of Chinese sectors using administrative data. Finally, we explain how we use the model to back out the sectoral labor supply shocks from the estimated output drop.

3.1 Mapping the model to the data

Our main data source is the most recent release of the WIOD, which provides annual time-series of the world input-ouput tables from 2000 to 2014. It covers 43 countries, jointly accounting for more than 85% of world GDP, and an artificial 'rest of the world' (see Table A.1 in the Appendix for a list of countries). The input-output data are available at the level of 56 sectors classified according to the International Standard Industrial Classification revision 4 (see Table A.2 in the Appendix for a list of sectors). In our baseline analysis, we use the data from 2014, the latest available year.

We process the original data by applying the following three adjustments. First, we account for the static nature of our model and follow Costinot and Rodriguez-Clare (2014) in recalculating all flows in the WIOD as if positive inventory changes had been consumed and negative inventory changes produced in the current period. Second, to ensure existence of the equilibrium in a counterfactual world without GVCs, we need to ensure that fixed (exogenous) intermediate requirements of different sectors can be met by an equivalent domestic supply when international intermediate trade is shut down. To address this issue, we assume that each sector in each country sources at least 1 USD worth of inputs domestically in all sectors from which it uses any inputs in the data (similar to Antràs and Chor, 2018).[6] Third, to make the WIOD consistent with our theoretical framework, we purge it from aggregate trade imbalances (following the methodology by Dekle et al. (2008) and Costinot and Rodriguez-Clare (2014)) and examine all shocks starting from this counterfactual scenario.

From the WIOD we take initial values for the trade shares (π_{ijru}) and the Cobb-Douglas structure of our model allows us to recover from the same data the values for cost shares (γ_{ir} and γ_{irs}) and expenditure shares (α_{js}).[7]

We take the values for trade elasticities (ε_r) from Felbermayr et al. (2018), who estimate them from a structural gravity model. The sectoral elasticities are reported in column 2 of Table A.3. We set the baseline sectoral labor mobility parameter (φ) to 3 and vary its value in the sensitivity analysis.

3.2 Estimating the initial impact of Covid-19 in Chinese sectors

To estimate the initial output drop in Chinese sectors due to Covid-19, we adopt an event-study approach that is widely used in economics and finance (see MacKinlay, 1997). We exploit sectoral

[6] It should be noted that this treatment of zeros does not significantly affect our baseline results, as the welfare effects in all countries are identical to those reported below to at least 6 digits precision.

[7] Notice that WIOD is the only data base that allows disentangling trade shares according to use category, thereby allowing for use category specific trade costs τ_{ijru}.

time series from the National Bureau of Statistics (NBS) of China over three years before the Covid-19 shock (the 'estimation window') to predict the counterfactual output in the absence of the shock in January and February 2020 (the 'event window'). The difference between observed and predicted output in the event window is our estimate of the initial Covid-19 impact by sector.

Our choice of the event window in January–February 2020 exploits the exact timing of the Covid-19 crisis. The first official, public mentioning of the disease dates from December 31, 2019 (when the cases were few), so the earliest economic impact can be expected in January 2020. Most containment measures in China were then implemented over the course of the subsequent two months. Notably, the spread of the virus was almost exclusively confined to China until late February. More specifically, data from Dong et al. (2020) show that on February 29, 92% of all globally confirmed Covid-19 cases were recorded in China, with only 6,655 cases confirmed outside of China (mostly concentrated in South Korea, Italy, and Iran). One week earlier, on February 22, China's share was at 98%, with only 1,578 infections confirmed outside of China (of which 634 were recorded on he cruise ship 'Diamond Princess'). Not before March 11 did the WHO declare Covid-19 a pandemic. While certain containment measures in China remained effective into March and beyond, the disease had by then spread internationally. Hence, we cannot exclude the possibility that the output data in these later months reflect also a response to international infections or to international repercussions of the initial shock in China. It is the latter channel that we investigate in detail in our main analysis, but we want to rule it out in our estimate of the initial shock. Thus, we do not consider data after February 2020 in this exercise.

We use monthly sector-level data on output (or more broadly, performance) from the NBS of China. The NBS reports only cumulative numbers for the first two months of each year (not for January and February separately), due to the Chinese spring festival. Hence, we construct bi-monthly time series by sector. For the industrial sector (which encompasses mining, manufacturing, and utilities), we use data on operating revenues of industrial enterprises, deflated by the sectoral producer price index (PPI). These data are reported for 41 sectors, which can be mapped directly into 23 WIOD sectors, accounting for 57% of total Chinese output in the 2014 WIOD. For the tertiary sector, we use different time series measuring performance (mostly revenues, appropriately deflated) in specific services, corresponding to 17 WIOD sectors (including retail trade, telecommunications, and transport). We complement these data with the aggregate index of service production in sectors for which more disaggregate data are unavailable (corresponding to 14% of total Chinese output). Since monthly data for the Chinese primary sector are unavailable, we use data from the industry 'processing of food from agricultural products' for this sector. Table A.2 in the Appendix provides the details on the selected time series and a concordance table of NBS and WIOD sectors (both following the International Standard Industrial Classification Rev. 4).

We denote the output of sector s in 2-month period t by Y_{st} and define the annual (6-period) difference in output as $\Delta Y_{st} \equiv Y_{st} - Y_{s(t-6)}$. Our goal is to estimate the impact of the Covid-19 shock as the difference between the observed and expected output change in the first period of 2020 (i.e., the so-called 'abnormal return' in the event study literature):

$$\textit{Covid-19 impact}_{st} = \Delta Y_{st} - E[\Delta Y_{st}]. \tag{22}$$

Our preferred estimator $\widehat{\Delta Y_{st}}$ for the expected output change $E[\Delta Y_{st}]$ is the seasonally differenced model with a first-order autoregressive AR(1) disturbance:

$$\Delta Y_{st} = u_{st}\ , \qquad \text{with} \qquad u_{st} = \rho u_{s(t-1)} + e_{st}\ , \tag{23}$$

where u_{st} is the AR(1) disturbance, ρ is the autocorrelation parameter, and e_{st} is the i.i.d., mean-zero, and normally distributed error term. This estimator is chosen to purge the bi-monthly time series of sector-specific seasonality while taking into account the serial correlation present in the data.[8] Notably, equation (23) is estimated from bi-monthly time series over the pre-shock years 2017 to 2019, as is customary to ensure that the estimates are unaffected by the event itself, and it is then used to predict $\widehat{\Delta Y_{it}}$ for the first period of 2020.

Figure A.1 summarizes the estimates. It shows for each sector: the differenced time series, the prediction of the differenced AR(1) model, and the predicted abnormal return in the first period of 2020 – our estimate of the initial impact of Covid-19.[9] The estimates show that the impact was dramatic. The average sectoral output declined by 30% compared to its expected value. The most affected sector (textiles) experienced a drop of almost 60%, while output in land transport and several other manufacturing sectors dropped by around 50% due to the virus and the lockdown. Only few sectors experienced no significant drop or even a slight increase in output, in particular the oil extraction and telecommunication services sectors. The latter example points the relevance of I-O linkages for the estimated output drop, highlighting the need for backing out the underlying sectoral labor supply shocks from the estimated output drop, which is what we do in the next subsection.

The estimated effects are mapped to WIOD sectors according to Table A.2 and aggregated at the level of WIOD sectors, weighted by initial values in January–February 2019. Table A.3 reports in column 2 the estimated drop in output caused by Covid-19 for each WIOD sector in China.

[8] The size of the estimated impact by sector hardly changes at all if we include a constant term in equation (23) to allow for a trend in the growth rate. This model, as well as alternative models of the ARIMA class (adding, e.g., moving averages, or autoregressive disturbances of higher order) turn out to be inferior to the AR(1) model in most sectors by the Akaike and Bayesian information criteria.

[9] The autocorrelation plots for the AR(1) model residuals, depicted in Figure A.2, demonstrate that there is no significant autocorrelation pattern remaining.

3.3 BACKING OUT LABOR SUPPLY SHOCKS

The estimated output drop in Chinese sectors due to Covid-19 reflects not only the underlying labor supply shock in a given sector, but also an equilibrium response to the shock in other sectors linked via I-O relationships. For instance, output in the Chinese steel sector might drop not only because steel workers are forced to stay at home, but also because other sectors, such as the machinery, auto, and construction sectors use less steel. Given the short time frame of only two months (between the very first announcement of the outbreak and the end of our event window), and in view of lengthy international shipping times and firms' inventory holdings, any second-round feedback effect to China from an early response in other countries is likely to be negligible. Thus, it seems suitable to interpret the estimated output drop as a short-term response of the Chinese economy to its domestic Covid-19 shock in January–February 2020.

Conceptually, this approach is related to Allen et al. (2020), who formally demonstrate in a broad class of gravity trade models that the full general equilibrium response to a shock can be decomposed into a 'zeroth-degree' effect (occurring only in the directly affected countries) and higher-order effects (starting with the immediate effect on affected countries' trading partners, followed by the feedback effects on all trading partners' trading partners, and so forth until the general equilibrium is reached). In this spirit, we define the 'zeroth degree' effect in the current application focused on output drops in January-Februrary 2020 as adjustments in China only, disregarding any response in the rest of the world or feedback effects thereof on China. Moreover, in consideration of warehousing, transportation times and binding contracts driving real world economies we take intermediate and final good prices to be fixed in our short term exercise. Finally, we assume that the short term view also restricts workers to be (sectorally) immobile. Under these assumptions, the estimated output drop in China can immediately be translated into changes in Chinese final and intermediate goods expenditures using equations (17) and (18). With third-country import shares and intermediate goods prices fixed in the short run, we can combine equation (19), and (20) to derive the underlying sectoral labor efficiency shocks in China given that sectorally immobile labor implies $\hat{w}_{ir} = \hat{R}_{ir}/\hat{\delta}_{ir}$. [10] Thus,

$$\hat{\delta}_{CHN,r} = \left(\frac{\hat{R}_{CHN,r} - \frac{1}{R_{CHN,r}} \sum_{j \neq CHN}^{J} \sum_{u=1}^{S+1} \pi_{CHN,jru} E_{jru}}{\frac{1}{R_{CHN,r}} \sum_{u=1}^{S+1} \pi_{CHN,CHN,ru} E'_{CHN,ru} \hat{R}_{CHN,r}^{-\gamma_{CHN,r}\varepsilon_r}} \right)^{\frac{1}{\gamma_{CHN,r}\varepsilon_r}}. \tag{24}$$

Table A.3 reports in column 3 the labor supply shocks by sector in China. These shocks do not correspond one to one to the estimated revenue changes (in column 2), as they reflect, firstly, Chinese firms substituting workers for intermediates (as labor becomes less efficient), secondly, changes in Chinese firms' reliance on imported versus domestic intermediate goods and, thirdly,

[10] For the full derivation see appendix A.1.3.

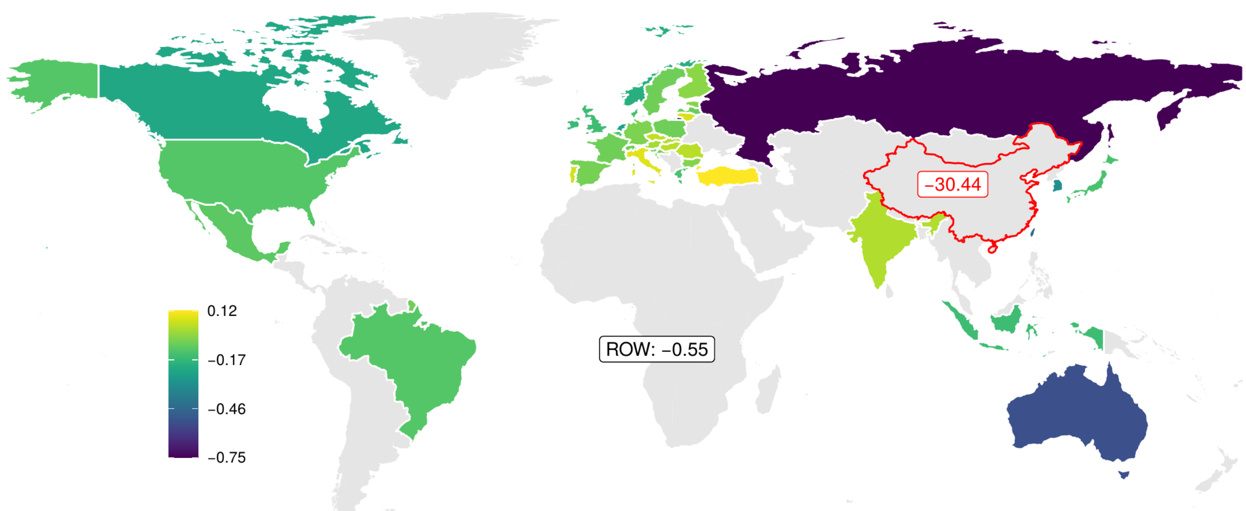
changes in Chinese expenditure on intermediate and final goods. Nevertheless, the ranking of labor supply shocks is similar to that of the estimated output changes, with a correlation of 0.92.

4 SIMULATION RESULTS

4.1 GLOBAL REPERCUSSIONS OF THE COVID-19 SHOCK IN CHINA

Figure 1 illustrates how welfare of all countries in our data is affected by the Covid-19 shock in China. Our main simulation results show a welfare loss of -30.4% for China in the new general equilibrium. The welfare effects for all other countries are moderate and range from -0.75% for Russia to +0.12% in Turkey. The most negatively affected countries (including Russia, Australia, and Taiwan) are in relatively close geographic proximity and have strong trade linkages to China. The US (-0.11%) and Germany (-0.05%) experience small negative effects. Interestingly, nine countries experience moderate welfare gains due to the adverse supply shock in China. Besides Turkey, these are mostly European countries (e.g. Italy, Portugal, and the Czech Republic). Apparently, these countries gain from trade diversion as importers around the world switch away from Chinese suppliers.

Figure 1: World map of welfare effects in baseline scenario



To assess the sensitivity of our counterfactual predictions to various auxiliary modeling assumptions and the specific shock magnitudes considered so far, we conduct a range of robustness exercises. The results are briefly summarized below and discussed in detail in Appendix A.3. First, our main conclusions do not change if we model trade deficits as exogenous transfers held constant instead of eliminating them in the initial equilibrium. Second, varying our assumptions on intersectoral labor mobility delivers welfare effects that are highly correlated to our baseline scenario across countries. For most countries the effects (both positive and negative) are somewhat magnified if labor is immobile, while they tend to be mitigated if we allow for perfect mobility. Third, to illustrate the relevance of our backing out of the labor supply shocks ($\hat{\delta}_{CHN,r}$), we contrast our results with a set-up in which we ignore any cross-sectoral spillovers in China in January-February 2020 and treat the estimated output drop as sectoral supply shocks (productivity shocks). While the predicted cross-country pattern of welfare effects is again similar, this alternative treatment of shocks overpredicts the welfare losses for the vast majority of countries relative to our baseline setting. Fourth, to assess how our findings depend on the specific sectoral structure of the Covid-19 shock, we compare them to a set-up in which efficient labor supply is reduced by a uniform 20% in all Chinese sectors. We find a cross-country correlation of 88% with our baseline results, suggesting that our main insights generalize to other negative supply shocks in China.

4.2 A WORLD WITHOUT GVCS

In this section, we shut down international trade in intermediate goods to study the effect of the same Covid-19 shock as in the previous section occurring in a world without global value chains. We simulate such a counterfactual world by raising the barriers to intermediate goods trade (τ_{ijru}) to infinity among all country pairs ij, for all producing sectors r, and for all use categories u except for final demand. Thus, this 'no GVCs' scenario reflects the complete repatriation of all value chains by all countries, while still allowing for final goods trade and domestic input-output linkages. We will consider less extreme scenarios further below.

Figure 2 displays the welfare effects of the Covid-19 shock by country for the no GVCs scenario and compares them to our baseline predictions. The magnitudes are shown in Figure 2(a), while Figure 2(b) displays the ratio of the effects in a no-GVCs world relative to the baseline results. We find that the welfare effects of the Covid-19 shock are more favorable for most countries in the absence of GVCs. In particular, among the countries experiencing welfare losses, these losses are smaller in a world without GVCs, by 40% of the initial value for the median country. The reductions are much greater for Indonesia, Brazil, and the Rest of the World. Notably, there are seven countries for which the losses are aggravated – including Germany, Slovenia, and Austria.[11] In all countries that stand to gain from the shock in China, these gains are reduced in a world without GVCs. Moreover, in four countries the effects are even reversed, resulting in welfare losses for the Czech Republic, Hungary, Slovakia, and India.

SHUTDOWN OF GVCS INVOLVING CHINA. To what extent are the changes due to the shutdown of GVCs driven by a decoupling of the world from China – where the shock happened – or driven

[11] These are the countries with effect ratios exceeding one in Figure 2(b), where Austria is omitted in the interest of readability because its very small baseline loss increases by a factor of 32.

Figure 2: Welfare effects in a world with GVCs vs. without GVCs in 2014

by the inability of other countries to trade intermediate goods between themselves? To see this, we examine a shutdown of only those GVCs that involve China, by raising trade barriers to infinity on intermediate goods imports to and exports from China. Figure A.7 shows the welfare effects of the Covid-19 shock after a decoupling from China. The predictions resemble those in the no GVCs world for most countries, so the direct decoupling from China plays the predominant role for our analysis. However, the welfare effects are more favorable for almost all countries after decoupling from China than after a complete shutdown of GVCs. This is intuitive, since allowing for intermediate goods trade among all other countries provides them with an additional margin of adjustment when responding to the shock. Interesting patterns arise for Estonia, Slovenia, and Belgium, where shutting down all GVCs aggravates the welfare losses, while shutting down only Chinese GVCs mitigates the losses due to the shock. This can be rationalized by the fact that these countries are deeply integrated into European GVCs, but much less engaged in intermediate goods trade directly with China.

STEPWISE SHUTDOWN OF GVCS. Instead of closing down GVCs altogether, we can also consider less extreme scenarios of higher (but not prohibitively high) barriers to intermediate goods trade. To assess the effects of the Covid-19 shock in such a world with hampered GVCs, we alternatively raise intermediate goods trade barriers in the initial (counterfactual) equilibrium by 10%, 50%, 100%, or 200% respectively. The left panel of Figure A.8 illustrates the predicted welfare effects of the Covid-19 shock in these alternative setups alongside those for the baseline. We find that, as intermediate goods trade barriers are increased step by step, the welfare effects adjust smoothly from the baseline to the no-GVCs world for the vast majority of countries. Especially among the countries that experience the greatest welfare losses, increasingly inhibiting GVCs seems to monotonically reduce their losses from the shock. Where the shutdown of GVCs has increased losses, this magnification also seems to be smooth (e.g. Slovenia or Estonia), while we see some non-monotonicities among the countries with positive welfare effects (e.g. Portugal or Lithuania).

SHUTDOWN OF ALL TRADE. To contrast our findings with a scenario in which all trade barriers (on both intermediate and final goods) are raised simultaneously, we stepwise raise trade barriers in the initial equilibrium by 10%, 50%, 100%, or 200% respectively. The right panel of Figure A.8 illustrates the welfare effects of the Covid-19 shock in China in each of these scenarios. Obviously, if all trade barriers (on intermediate and final goods) were set to infinity, we would reach the extensively studied case of autarky, and the international transmission of the shock would converge to zero. The effects approach this limiting case step by step, they are reduced at a much faster rate compared to the shutdown of GVCs, and there are hardly any non-monotonicities.

EATON-KORTUM WORLD Finally, we contrast our findings with an alternative way of shutting down GVCs, akin to Cappariello et al. (2020). In this exercise we ignore the input-output structure in the WIOD, assuming that production uses only labor and all trade is in final goods. Hence, the model boils down to a multi-sector Eaton and Kortum (2002, EK) model. As the Covid-19 shock hits the EK world economy, it can only affect other countries through final goods trade – as in our 'no GVCs' world – but we pretend that all observed trade were final goods trade. Major differences arise between our main analysis and this exercise. The strong regional pattern discussed earlier is not visible anymore and many countries are predicted to benefit from the shock, most of all Germany. This illustrates the need for taking into account the factual pattern of intermediates vs. final goods trade when thinking about the role of GVCs in international shock transmission.

4.3 U.S. REPATRIATING VALUE CHAINS

The complete shutdown of GVCs studied in the previous section is an interesting benchmark, but it is also an extreme scenario and unattainable by any individual country's trade policy. To bring the analysis closer to the ongoing debate on the repatriating of value chains, we investigate in this section more realistic policy scenarios, with a focus on the U.S. repatriating value chains. More precisely, we ask the following questions: What would be the welfare effects of the U.S. repatriating either (i) its input production from all other countries or (ii) only its GVCs from China? And how would the effects of the Covid-19 shock in China on U.S. welfare be different in such a world with repatriated value chains?

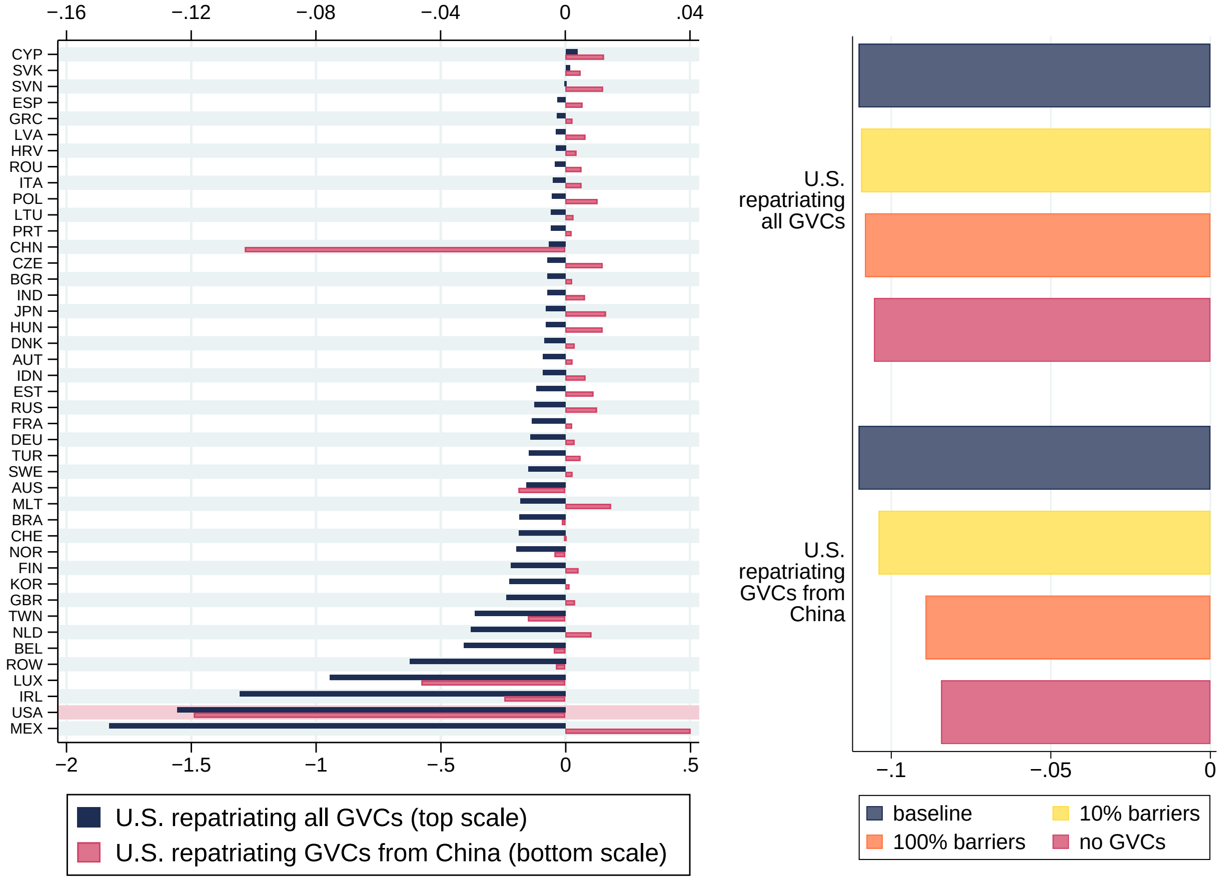
To address these questions, we proceed in two steps: In the first step, we implement a policy change that mirrors the repatriation of value chains by increasing trade barriers on U.S. imports of intermediate inputs (but not on final goods). In practice, policy makers seeking to repatriate value chains would face the challenge of distinguishing intermediate inputs from final goods. While this distinction is not clear cut for every product, we would argue that such a policy could approximately be implemented by increasing trade barriers within each sector for typical inputs like fertilizer, heavy machinery, or trucks (as opposed to consumer goods like shampoo, game consoles, or sport cars). In our analysis, we shut down U.S. GVCs step by step, increasing trade barriers by 10%, 100%, and eventually to infinity (as we did in our no-GVCs scenario for the whole world). And we consider alternatively (i) U.S. imports of intermediates from all other countries, or (ii) only U.S. imports of intermediates from China. In the second step, we then reconsider the international transmission of the Covid-19 shock in China after the U.S. has repatriated its value chains.

The results from our two-step analysis are illustrated in Figure 3. Figure 3(a) presents the global welfare effects of the policy changes themselves for the case of infinite trade barriers. Fully repatriating all value chains and inhibiting any imports of intermediate goods reduces U.S. welfare by 1.56%. Only Mexico would suffer even more from such a policy due to its strong GVC ties with the U.S. It should be noted that almost all other countries would lose from this policy as well (though the the effects are mostly much smaller), suggesting that U.S. GVC participation is beneficial to the world. If the U.S. withdraws input production only from China, welfare drops by 0.12% in the U.S. and by 0.10% in China. In this case, the majority of all other countries benefit from the policy, among other reasons because value chains are in fact not repatriated to the U.S. but instead shifted to other countries. This effect is most clearly visible for Mexico, which experiences welfare gains of 0.04% due to U.S. protectionism against its Asian competitor.

Can the welfare losses in the U.S. due to the repatriation of value chains be justified by a reduced exposure to adverse shocks from abroad, in particular from China? Figure 3(b) sheds some light on this question. It reconsiders the effects of the Covid-19 shock in China on U.S. welfare in the situation *after* U.S. value chains have been repatriated from all countries (top panel)

Figure 3: U.S. repatriating value chains

(a) Global welfare effects of U.S. repatriating value chains (b) Effects of Covid-19 shock in China on U.S. welfare



or only from China (bottom panel). We begin by focusing on the bottom (red) bars in each panel of Figure 3(b), which represent the scenarios of a complete shutdown of U.S. GVCs (overall or from China), and which correspond to the policy changes depicted in Figure 3(a). It is immediately obvious that shutting down all GVCs hardly reduces the U.S. exposure to the Covid-19 shock in China. If only GVCs from China are repatriated, the U.S. welfare loss due to shock is reduced from 0.11% to 0.08%. However, contrasting this reduction with the welfare loss due to the policy itself (0.12%), it becomes clear that repatriating value chains does not enhance welfare even if the U.S. were to face a large and long-lasting adverse supply shock in China with certainty. In the more moderate policy scenarios of increasing U.S. import barriers on intermediate inputs by 10% or 100%, the reduction in shock transmission is naturally smaller, as the middle (yellow and orange) bars show, and we continue to find that this reduction cannot justify the welfare loss induced by repatriating value chains.

5 Conclusion

When the disease Covid-19 hit China in early 2020, managers and politicians around the world feared major disruptions of global value chains (GVCs). We quantify these repercussions using a multi-country multi-sector trade model that features input-output linkages, different trade costs for final and intermediate goods, and imperfect sectoral mobility of labor. We find substantial welfare losses in China in excess of 30%, but only moderate welfare effects in other countries, ranging from -0.75% to +0.12%.

As a key methodological contribution, we leverage the flexibility of our model to isolate the role of GVCs in the international transmission of the shock. To achieve this, we reconsider the effects of the shock in a world without GVCs, where we set trade barriers for intermediate goods trade to a prohibitively high level. We find that the welfare losses due to the Covid-19 shock in China are lower by 40% for most countries in a world without GVCs. Interestingly, for a few countries shutting down GVCs can magnify or even reverse the effects of the shock. We hope that our approach of isolating the role of GVCs will prove useful also in related applications, studying trade policy or the international transmission of other shocks.

The Covid-19 crisis has fueled criticism of GVCs in many countries, questioning the dependence on intermediate inputs from China. The U.S. and several EU governments have started or furthered their considerations to 'repatriate' or 'renationalize' supply chains with the goal of reducing their dependence on China or their vulnerability to foreign shocks. To assess these concerns, we focus on the U.S. and examine the effects of the Covid-19 shock in China in a situation after the U.S. has unilaterally repatriated value chains from abroad. We find that repatriating supply chains hardly mitigates the U.S. welfare losses caused by the shock in China, but the policy itself comes at a substantial welfare cost. In light of these results, repatriating GVCs appears to be a costly and ineffective way to reduce vulnerability to foreign shocks.

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Appendix:

Covid-19 Shocking Global Value Chains

A.1 Theory Appendix

A.1.1 Sectoral Mobility

The probability that a given worker Ω draws a productivity for working in country j and country s that is no larger than δ is given by:

$$\Pr\left[\delta_{js}(\Omega) \leq \delta\right] = e^{-\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\delta^{-\varphi}}.$$

Then the distribution of potential compensation of a worker in country j and sector s is

$$\mathbb{G}_{js}\left(w\right) = \Pr\left[\delta_{js}\left(\Omega\right)w_{js} \leq w\right] = e^{-\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{js}}\right)^{-\varphi}},$$

$$\frac{d\mathbb{G}_{js}\left(w\right)}{dw} = e^{-\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{js}}\right)^{-\varphi}}\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\varphi w_{js}^{\varphi}w^{-\varphi-1}.$$

The probability of any worker having the highest compensation in sector s is:

$$\Pr\left[\delta_{js}\left(\Omega\right)w_{js} \geq \max_{s\neq r}\delta_{jr}\left(\Omega\right)w_{jr}\right] = \int_0^{\infty}\Pr\left[\max_{s\neq r}\delta_{jr}\left(\Omega\right)w_{jr} \leq w\right]\frac{d\mathbb{G}_{js}\left(w\right)}{dw}dw$$

$$= \int_0^{\infty}\prod_{s\neq r}\Pr\left[\delta_{jr}\left(\Omega\right)w_{jr} \leq w\right]e^{-\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{js}}\right)^{-\varphi}}\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\varphi w_{js}^{\varphi}w^{-\varphi-1}dw$$

$$= \int_0^{\infty}\prod_{s\neq r}e^{-\frac{\delta_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{jr}}\right)^{-\varphi}}e^{-\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{js}}\right)^{-\varphi}}\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\varphi w_{js}^{\varphi}w^{-\varphi-1}dw$$

$$= \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}w_{js}^{\varphi}\int_0^{\infty}e^{-\sum_{r=1}^{S}\frac{\delta_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{jr}}\right)^{-\varphi}}\varphi w^{-\varphi-1}dw$$

$$= \frac{\delta_{js}^{\varphi}w_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}\sum_{r=1}^{S}\frac{\delta_{jr}^{\varphi}w_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}}\int_0^{\infty}\left(\sum_{r=1}^{S}\frac{\delta_{jr}^{\varphi}w_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\right)e^{-\sum_{r=1}^{S}\frac{\delta_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{jr}}\right)^{-\varphi}}\varphi w^{-\varphi-1}dw$$

$$= \frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}} \int_0^{\infty} \left(\sum_{r=1}^{S} \frac{\delta_{jr}^{\varphi} w_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \right) e^{-\sum_{r=1}^{S} \frac{\delta_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{w}{w_{jr}}\right)^{-\varphi}} \varphi w^{-\varphi-1} dw$$

$$= \frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}} \left[e^{-\sum_{r=1}^{S} \frac{\delta_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{w}{w_{jr}}\right)^{-\varphi}} \right]_0^{\infty} = \frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}} \equiv \frac{L_{js}}{L_j},$$

which is equivalent to equation 3. The CDF of the compensation of workers that actually move to sector s is:

$$\Pr\left[w_{js}\delta_{js}(\Omega) < w | w_{js}\delta_{js}(\Omega) \geq \max_{s \neq r} w_{jr}\delta_{jr}(\Omega) \right]$$

$$= \frac{1}{\frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}} \int_0^{w} \Pr\left[\max_{s \neq r} w_{jr}\delta_{jr}(\Omega) < x \right] \frac{d\mathbb{G}_{js}(x)}{dx} dx$$

$$= \frac{1}{\frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}} \int_0^{w} \prod_{s \neq r} \Pr\left[w_{jr}\delta_{jr}(\Omega) \leq x \right] e^{-\frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{x}{w_{js}}\right)^{-\varphi}} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \varphi w_{js}^{\varphi} x^{-\varphi-1} dx$$

$$= \frac{1}{\frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}} \int_0^{w} e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{x}{w_{js}}\right)^{-\varphi}} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \varphi w_{js}^{\varphi} x^{-\varphi-1} dx$$

$$= \frac{1}{\frac{\delta_{js}^{\varphi} w_{js}^{\varphi}}{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}} \int_0^{w} e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{x}{w_{js}}\right)^{-\varphi}} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \varphi w_{js}^{\varphi} x^{-\varphi-1} dx$$

$$= \int_0^{w} \left(\frac{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \right) e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{x}{w_{js}}\right)^{-\varphi}} \varphi x^{-\varphi-1} dx$$

$$= \left[e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{x}{w_{js}}\right)^{-\varphi}} \right]_0^{w} = e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{w}{w_{js}}\right)^{-\varphi}}.$$

This shows that the distribution of the compensation of workers is the same in each sector and for the economy of country j as a whole. The PDF is:

$$\frac{de^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{w}{w_{js}}\right)^{-\varphi}}}{dw} = \left(\frac{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \right) e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} \left(\frac{w}{w_{js}}\right)^{-\varphi}} \varphi w^{-\varphi-1}.$$

. These results allow to derive the average or ex-ante expected wage of a worker conditional on working in any sector s:

$$w_j = \int_0^\infty w \frac{d\left(e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{js}}\right)^{-\varphi}}\right)}{dw} dw$$

$$= \int_0^\infty \left(\frac{\sum_{r=1}^{S} \delta_{jr}^{\varphi} w_{jr}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\right) e^{-\sum_{s=1}^{S} \frac{\delta_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\left(\frac{w}{w_{js}}\right)^{-\varphi}} \varphi w^{-\varphi} dw.$$

Define $x\left(w\right) = w^{-\varphi} \frac{\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}$ and thus $dx/dw = -\varphi w^{-\varphi-1} \frac{\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}} = -\varphi \frac{x}{w}$ and $w = \left(\frac{x\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}{\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}}\right)^{-\frac{1}{\varphi}}$, yielding $\frac{dw}{dx} x = -\frac{1}{\varphi}\left(\frac{x\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}{\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}}\right)^{-\frac{1}{\varphi}}$ to transform the above into

$$\int_0^\infty e^{-x} \varphi x dw$$

$$= \varphi \int_{x(0)}^{x(\infty)} e^{-x} x \frac{dw}{dx} dx$$

$$= -\left(\frac{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}{\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}}\right)^{-\frac{1}{\varphi}} \int_\infty^0 e^{-x} x^{-\frac{1}{\varphi}} dx$$

$$= \left(\frac{\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\right)^{\frac{1}{\varphi}} \int_0^\infty e^{-x} x^{-\frac{1}{\varphi}} dx$$

$$= \left(\frac{\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}}{\Gamma\left(1-\frac{1}{\varphi}\right)^{\varphi}}\right)^{\frac{1}{\varphi}} \Gamma\left(1-\frac{1}{\varphi}\right)$$

$$= \left(\sum_s \delta_{js}^{\varphi} w_{js}^{\varphi}\right)^{\frac{1}{\varphi}} \equiv w_j,$$

which is equivalent to the wage described by equation (4).

A.1.2 DERIVATION OF PRICES

Productivity is identically and independently distributed Fréchet on a sector region level. The cumulative distribution function of productivities is given by:

$$\Pr[z_{ir}(\omega) \leq z] = e^{-T_{ir} z^{\varepsilon_r}}.$$

This functional form implies that the prices that sector r in region i offers sector u in region j are also distributed Fréchet with the CDF $\mathbb{F}_{ijru}(p)$ given by:

$$\begin{aligned}
\mathbb{F}_{ijru}(p) = \Pr[p_{ijru}(\omega) \leq p] &= \Pr\left[\frac{c_{ir}\tau_{ijru}}{z_{ir}(\omega)} \leq p\right] = \Pr\left[\frac{c_{ir}\tau_{ijru}}{p} \leq z_{ir}(\omega)\right] \\
&= 1 - \Pr\left[z_{ir}(\omega) \leq \frac{c_{ir}\tau_{ijru}}{p}\right] = 1 - e^{-T_{ir}\left(\frac{c_{ir}\tau_{ijru}}{p}\right)^{-\varepsilon_r}}.
\end{aligned}$$

The equilibrium price in sector u in region j for variety (ω) in sector r is given by $p_{jru}(\omega) \equiv \underset{i}{min}\ p_{ijru}(\omega)$. Let us denote the probability $\mathbb{F}_{jru}(p)$ that this lowest price is below some price p as follows:

$$\begin{aligned}
\mathbb{F}_{jru}(p) &= \Pr\left[\min_i p_{ijru}(\omega) \leq p\right] = 1 - \Pr\left[\min_i p_{ijru}(\omega) > p\right] \\
&= 1 - \prod_{i=1}^{J} \Pr\left[p_{ijru}(\omega) > p\right] = 1 - \prod_{i=1}^{J} \left(1 - \mathbb{F}_{ijru}(p)\right) \\
&= 1 - \prod_{i=1}^{J} \left(1 - \left(1 - e^{-T_{ir}\left(\frac{c_{ir}\tau_{ijru}}{p}\right)^{-\varepsilon_r}}\right)\right) = 1 - \prod_{i=1}^{J} e^{-T_{ir}\left(\frac{c_{ir}\tau_{ijru}}{p}\right)^{-\varepsilon_r}} \\
&= 1 - e^{\sum_{i=1}^{J} -T_{ir}\left(\frac{c_{ir}\tau_{ijru}}{p}\right)^{-\varepsilon_r}} = e^{-p^{\varepsilon_r} - T_{ir}\left(\frac{c_{ir}\tau_{ijru}}{p}\right)^{-\varepsilon_r}} \\
&= 1 - e^{-p^{\varepsilon_r \Phi_{jru}}}
\end{aligned}$$

with $\Phi_{jru} \equiv \sum_{i=1}^{J} T_{ir}(c_{ir}\tau_{ijru})^{-\varepsilon_r}$. The CES price index of sector r compound goods paid in country j and use category u can then be derived in the following way:

$$\begin{aligned}
P_{jru} &= \left(\int_0^1 p_{jru}(\omega)^{1-\sigma_r} d\omega\right)^{\frac{1}{1-\sigma_r}} \\
\Rightarrow P_{jru}^{1-\sigma_r} = \left(\int_0^1 p_{jru}(\omega)^{1-\sigma_r} d\omega\right) &= \int_0^\infty p^{1-\sigma_r} \frac{d\mathbb{F}_{jru}(p)}{dp} dp \\
&= \int_0^\infty p^{1-\sigma_r} \varepsilon_r \Phi_{jru} p^{\varepsilon_r - 1} e^{-p^{\varepsilon_r}\Phi_{jru}} dp.
\end{aligned}$$

Defining $x \equiv p^{\varepsilon_r} \Phi_{jru}$ we get:

$$P_{jru}^{1-\sigma_r} = \int_0^\infty \left(\frac{x}{\Phi_{jru}}\right)^{\frac{1-\sigma_r}{\varepsilon_r}} \frac{dx}{dp} e^{-x} dp = \int_0^\infty \left(\frac{x}{\Phi_{jru}}\right)^{\frac{1-\sigma_r}{\varepsilon_r}} e^{-x} dx$$
$$= \Phi_{jru}^{-\frac{1-\sigma_r}{\theta_r}} \int_0^\infty x^{\frac{1-\sigma_r}{\varepsilon_r}} e^{-x} dx = \; = \Phi_{jru}^{-\frac{1-\sigma_r}{\varepsilon_r}} \Gamma\left(\frac{\varepsilon_r + 1 - \sigma_r}{\varepsilon_r}\right),$$

where $\Gamma(t) \equiv \int_0^\infty x^{t-1} e^{-x} dx$ is the gamma function. Consequently:

$$P_{jru} = \Phi_{jru}^{-1/\varepsilon_r} \Gamma\left(\frac{\varepsilon_r + 1 - \sigma_r}{\varepsilon_r}\right)^{\frac{1}{1-\sigma_r}} = \Gamma\left(\frac{\varepsilon_r + 1 - \sigma_r}{\varepsilon_r}\right)^{\frac{1}{1-\sigma_r}} \left(\sum_{j=1}^{J} T_{ir} (c_{ir} \tau_{ijru})^{-\varepsilon_r}\right)^{-1/\varepsilon_r}.$$

A.1.3 Derivation of labor supply shocks

We begin with equation (16) applied to the Chinese sectors ($i = CHN$) subject to the labor efficiency shock. Plugging in equations (19) and (20) gives

$$\hat{R}_{CHN,r} = \frac{1}{R_{CHN,r}} \sum_{j=1}^{J} \sum_{u=1}^{S+1} \frac{\left(\hat{w}_{CHN,r}^{\gamma_{CHN,r}} \prod_{s=1}^{S} \hat{P}_{CHN,sr}^{\gamma_{CHN,sr}}\right)^{-\varepsilon_r}}{\hat{P}_{jru}^{-\varepsilon_r}} \pi_{CHN,jru} E'_{jru}.$$

Under our assumption of intermediate and final use prices remaining constant in the short term, we have $\hat{P}_{jru} = 1$ for all j, r and u. Moreover, with sectoral labor immobility relative wage changes depend only on changes in the relative sectoral revenue (of which a constant share is paid to workers) and changes in labor efficiency ($\hat{w}_{js} = \hat{R}_{js}/\hat{\delta}_{js}$). Finally, foreign imports and thus expenditure shares from China are also fixed in the zeroth-degree world, implying that we can rewrite the above equation as

$$\hat{R}_{CHN,r} = \frac{1}{R_{CHN,r}} \sum_{j \neq CHN}^{J} \sum_{u=1}^{S+1} \pi_{CHN,jru} E_{jru} + \frac{1}{R_{CHN,r}} \sum_{u=1}^{S+1} \pi_{CHN,CHN,ru} E'_{CHN,ru} \left(\frac{\hat{R}_{CHN,r}}{\hat{\delta}_{CHN,r}}\right)^{-\gamma_{CHN,r}\varepsilon_r}.$$

Solving this expression for $\hat{\delta}_{CHN,r}$ yields equation (24) in the main text.

A.2 DATA APPENDIX

Table A.1: List of countries in WIOD and country codes

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

Table A.2: Sector correspondence: WIOD and NBS

WIOD sector		Time series from NBS	
1	Crop & animal production, hunting & related service activities	8	Processing of Food from Agricultural Products
2	Forestry & logging	8	Processing of Food from Agricultural Products
3	Fishing & aquaculture	8	Processing of Food from Agricultural Products
4	Mining & quarrying	1	Mining & Washing of Coal
4	Mining & quarrying	2	Extraction of Petroleum & Natural Gas
4	Mining & quarrying	3	Mining & Processing of Ferrous Metal Ores
4	Mining & quarrying	4	Mining & Processing of Non-Ferrous Metal Ores
4	Mining & quarrying	5	Mining & Processing of Nonmetal Ores
4	Mining & quarrying	6	Mining & Support Activities
4	Mining & quarrying	7	Mining of Other Ores
5	Manufacture of food products, beverages & tobacco products	8	Processing of Food from Agricultural Products
5	Manufacture of food products, beverages & tobacco products	9	Foods
5	Manufacture of food products, beverages & tobacco products	10	Wine, Beverages & Refined Tea
5	Manufacture of food products, beverages & tobacco products	11	Tobacco
6	Manufacture of textiles, wearing apparel & leather products	12	Textile
6	Manufacture of textiles, wearing apparel & leather products	13	Textile Wearing Apparel & Clothing
6	Manufacture of textiles, wearing apparel & leather products	14	Leather, Fur, Feather & Related Products
7	Manufacture of wood & of products of wood & cork, except furniture	15	Timber, Manufacture of Wood, Bamboo, Rattan, Palm & Straw Products
8	Manufacture of paper & paper products	17	Paper & Paper Products
9	Printing & reproduction of recorded media	18	Printing, Reproduction of Recording Media
10	Manufacture of coke & refined petroleum products	20	Processing of Petroleum, Coal & Other Fuels
11	Manufacture of chemicals & chemical products	21	Raw Chemical Materials & Chemical Products
11	Manufacture of chemicals & chemical products	23	Chemical Fibers
12	Manufacture of pharmaceutical products	22	Medicines
13	Manufacture of rubber & plastic products	24	Rubber & Plastics
14	Manufacture of other non-metallic mineral products	25	Non-metallic Mineral Products
15	Manufacture of basic metals	26	Smelting & Pressing of Ferrous Metals
15	Manufacture of basic metals	27	Smelting & Pressing of Non-Ferrous Metals
16	Manufacture of fabricated metal products, except machinery & equipment	28	Metal Products
17	Manufacture of computer, electronic & optical products	34	Communication Equipment, Computers & Other Electronic Equipment
17	Manufacture of computer, electronic & optical products	35	Measuring Instruments
18	Manufacture of electrical equipment	33	Electrical Machinery & Equipment
19	Manufacture of machinery & equipment n.e.c.	29	General Purpose Machinery
19	Manufacture of machinery & equipment n.e.c.	30	Special Purpose Machinery
20	Manufacture of motor vehicles, trailers & semi-trailers	31	Automobiles
21	Manufacture of other transport equipment	32	Railway, Shipping, Aerospace & Other Transport
22	Manufacture of furniture; other manufacturing	16	Furniture
22	Manufacture of furniture; other manufacturing	19	Articles for Culture, Education, Art, Sport & Entertainment Activities
22	Manufacture of furniture; other manufacturing	36	Other Manufacturing
23	Repair & installation of machinery & equipment	38	Repair of Metal Products, Machinery & Equipment
24	Electricity, gas, steam & air conditioning supply	39	Production & Supply of Electric Power & Heat Power
24	Electricity, gas, steam & air conditioning supply	40	Production & Supply of Gas
25	Water collection, treatment & supply	41	Production & Supply of Water
26	Sewerage; waste & disposal activities; recycling; etc.	37	Comprehensive Utilization of Waste
27	Construction	70	Investment of Real Estate, Construction
28	Wholesale & retail trade & repair of motor vehicles & motorcycles	42	Total Retail Sales of Consumer Good
29	Wholesale trade, except of motor vehicles & motorcycles	42	Total Retail Sales of Consumer Good
30	Retail trade, except of motor vehicles & motorcycles	42	Total Retail Sales of Consumer Good
31	Land transport & transport via pipelines	61	Railways Passenger Kilometers
31	Land transport & transport via pipelines	62	Highways Passenger Kilometers
31	Land transport & transport via pipelines	65	Railways Freight Ton Kilometers
31	Land transport & transport via pipelines	66	Highways Freight Ton Kilometers
32	Water transport	63	Passenger-Kilometers of Waterways
32	Water transport	67	Freight Ton-Kilometers of Waterways
33	Air transport	64	Civil Aviation Passenger Kilometers
33	Air transport	68	Civil Aviation Freight Ton Kilometers
34	Warehousing & support activities for transportation	400	Index of Service Production (ISP)
35	Postal & courier activities	43	Revenue from Postal Services
36	Accommodation & food service activities	400	Index of Service Production (ISP)
37	Publishing activities	400	Index of Service Production (ISP)
38	Movie, TV, and video production; music publishing; broadcasting	400	Index of Service Production (ISP)
39	Telecommunications	44	Revenue from Telecommunication Services
40	Computer programming, consultancy; information services	45	Software Revenue
41	Financial service activities, except insurance & pension funding	400	Index of Service Production (ISP)
42	Insurance, reinsurance & pension funding, except compulsory social security	400	Index of Service Production (ISP)
43	Activities auxiliary to financial services & insurance activities	400	Index of Service Production (ISP)
44	Real estate activities	46	Development & Sales of Real Estate, Transaction Value of Land
44	Real estate activities	47	Total Sale of Commercialized Buildings Sold
45	Legal & accounting; activities of head offices; management consultancy	400	Index of Service Production (ISP)
46	Architectural & engineering activities; technical testing & analysis	400	Index of Service Production (ISP)
47	Scientific research & development	400	Index of Service Production (ISP)
48	Advertising & market research	400	Index of Service Production (ISP)
49	Other professional, scientific & technical activities; veterinary activities	400	Index of Service Production (ISP)
50	Administrative & support service activities	400	Index of Service Production (ISP)
51	Public administration & defence; compulsory social security	400	Index of Service Production (ISP)
52	Education	400	Index of Service Production (ISP)
53	Human health & social work activities	400	Index of Service Production (ISP)
54	Other service activities	400	Index of Service Production (ISP)
55	Activities of households as employers	400	Index of Service Production (ISP)
56	Activities of extraterritorial organizations & bodies	400	Index of Service Production (ISP)

The table reports the sector correspondence between WIOD and NBS of China and the time series used to measure performance. For NBS sectors 1-41 we use time series of operating revenue deflated by the sector-specific PPI. To deflate the nominal series in the tertiary sector, we use the retail price index for sector 42; the 'Transport & Communication' component of CPI for sectors 43-45; and the 'Residential' component of the CPI in sectors 46, 47, and 70. Sectors 61-68 refer to physical quantities, which need no deflating; here we use the simple mean in aggregating to WIOD sectors. Sector 400 refers to a real performance index, which needs no deflating.

Table A.3: Sectoral trade elasticities, output drop and labor supply shocks in China

(1)	(2)	(3)	(4)	(5)
Sector	Trade elasticity	Output drop (estimated)	Labor supply shock (backed out)	Output response (counterfactual)
1	1.956	-36.1	-41.4	-23.9
2	1.869	-36.1	-25.0	-2.1
3	3.584	-36.1	-40.5	-26.1
4	3.584	-25.5	-28.7	-5.3
5	1.634	-24.8	-19.0	-13.7
6	3.584	-45.8	-62.1	-39.2
7	3.584	-54.9	-68.7	-37.1
8	1.037	-38.1	-55.3	-18.7
9	2.042	-51.8	-78.2	-42.9
10	6.039	-12.0	0.0	2.1
11	3.776	-37.5	-44.0	-13.2
12	7.630	-21.7	-22.4	-9.2
13	2.815	-49.0	-70.0	-32.9
14	1.417	-43.3	-70.6	-30.7
15	4.715	-18.9	-6.5	4.5
16	1.841	-39.7	-64.0	-23.1
17	5.731	-18.1	-21.5	-6.2
18	6.424	-33.4	-42.9	-21.4
19	7.509	-44.1	-52.1	-35.5
20	4.390	-37.6	-44.6	-26.8
21	5.173	-32.1	-37.2	-25.6
22	3.416	-41.5	-56.5	-49.7
23	7.509	-19.1	0.0	109.4
24	5.959	-11.2	0.0	5.8
25	5.959	-15.1	-9.1	-3.4
26	5.959	-33.2	-36.3	-16.8
27	5.959	-26.0	-23.8	-30.8
28	5.959	-27.4	0.0	71.8
29	5.959	-27.4	-27.8	-10.2
30	5.959	-27.4	-27.8	-10.2
31	5.959	-37.7	-40.6	-20.4
32	5.959	-30.5	-33.3	-9.2
33	5.959	-30.3	-36.9	-15.9
34	5.959	-18.6	-12.7	4.2
35	5.959	-25.9	-26.9	-6.9
36	5.959	-18.6	-14.9	-11.6
37	5.959	-18.6	0.0	74.7
38	5.959	-18.6	0.0	86.2
39	5.959	-0.9	0.0	12.7
40	5.959	-20.7	-18.7	-14.9
41	5.959	-18.6	-16.7	4.4
42	5.959	-18.6	-15.0	-2.7
43	5.959	-18.6	0.0	80.1
44	5.959	-37.6	-39.4	-32.1
45	5.959	-18.6	-15.9	0.7
46	5.959	-18.6	0.0	63.1
47	5.959	-18.6	-14.9	-2.2
48	5.959	-18.6	0.0	93.6
49	5.959	-18.6	-14.9	-2.8
50	5.959	-18.6	-15.3	-12.5
51	5.959	-18.6	-15.1	-20.3
52	5.959	-18.6	-15.4	-18.4
53	5.959	-18.6	-12.9	-23.6
54	5.959	-18.6	-15.5	-9.5
55	5.959	-18.6	0.0	47.1
56	5.959	-18.6	0.0	0.0

The table reports for each WIOD sector r the trade elasticity ε_r (in column 2) and (in columns 3-5, respectively, each in percent): the estimated output drop caused by Covid-19 in China (see Section 3.2), the implied labor supply shock $\hat{\delta}_{CHN,r}$ (see Section 3.3), and the real output response predicted by our simulation of the global general equilibrium model.

Figure A.1: Performance of Chinese sectors over time: Data vs. AR(1) model

Seasonally differenced data (green, solid line, dots); seasonally differenced AR(1) model (blue, dashed line, crosses); predicted effect of Covid-19 (red, vertical spike). Data source: NBS. See the text for details.

Figure A.2: Autocorrelation plot of residuals from AR(1) model

Autocorrelations of residuals ($\Delta Y_{it} - \widehat{\Delta Y_{it}}$) from seasonally differenced AR(1) model. Barlett's formula for MA(q) 95% confidence bands. Data source: NBS.

A.3 SENSITIVITY ANALYSIS

In this Appendix, we describe the sensitivity analysis of our main predictions from Section 4.1. First, to assess whether the elimination of trade deficits plays an important role for our findings, we adopt an alternative approach, in which we model trade deficits as exogenous transfers D_j that are positive for deficit countries and negative for surplus countries.[12] The deficit transfers D_j are held constant at the level observed in the data in the simulation. Figure A.3 displays the real wage effects of the Covid-19 shock in this world compared to our baseline analysis. We consider real wage effects, which are identical to welfare effects in the baseline scenario without deficits, and which capture the welfare change that is not due to the transfer in the scenario with deficits. We find that the effects are of almost identical magnitudes with a cross-country correlation of 99%, so our findings are not sensitive to the treatment of deficits.

Second, we find that varying the assumptions on intra-sectoral labor mobility does not substantially change our predictions for the effects of the Covid-19 shock. The welfare loss in China is almost identical to our baseline scenario for the extreme cases of perfect and no mobility and the cross-country pattern in the welfare effects, illustrated in Figure A.4, is highly correlated to our baseline scenario. In most countries the effects (both positive and negative) are somewhat magnified if labor is immobile, while they are mitigated if we allow for perfect mobility.

Third, what is the relevance of our backing out of the labor supply shocks ($\hat{\delta}_{CHN,r}$)? To assess this question, Figure A.5 contrasts our baseline results with the welfare effects predicted by sectoral supply shocks (productivity shocks) that are equal to the estimated output drop, without allowing for any cross-sectoral spillovers in China in January-February 2020. We find that the cross-country pattern of welfare effects is again similar, but for most countries the productivity shock scenario predicts worse welfare effects than our baseline approach.

Fourth, one may also wonder to what extent our findings are limited to the specific Covid-19 shock, which hit different sectors heterogeneously. To examine this, we hit China with a uniform -20% shock to efficient labor supply in all sectors. Figure A.6 demonstrates that the resulting cross-country pattern of the welfare effects is rather similar to our baseline results. Indeed, the cross-sectional correlation between the two scenarios is 88%, though the effects are smaller in magnitude and fewer countries gain from the shock. Overall these results suggest that our main insights from the analysis of the Covid-19 shock generalize to other negative supply shocks in China.

[12] Equation (11) then becomes $E_{jr(S+1)} = \alpha_{jr} \left(\sum_{s=1}^{S} \gamma_{js} R_{js} + D_j \right)$ and the equivalent of equation (17) reads $E'_{jr(S+1)} = \alpha_{jr} \left(\sum_{s=1}^{S} \gamma_{js} \hat{R}_{js} R_{js} + D_j \right)$.

Figure A.3: No trade deficits vs. constant observed deficits (real wage effects)

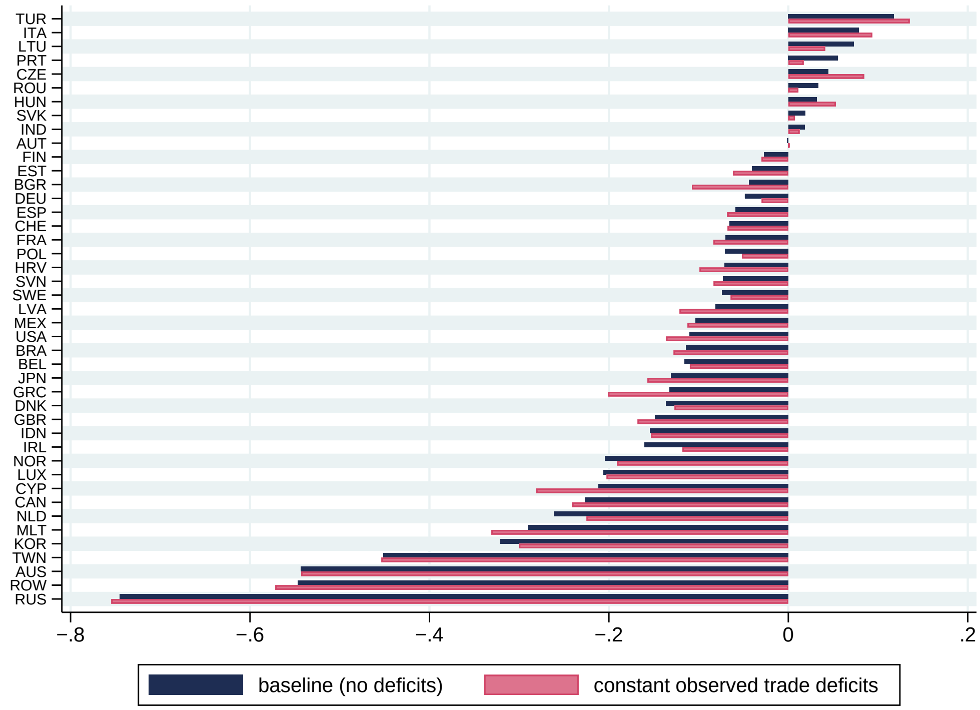


Figure A.4: Welfare effects for varying intersectoral labor mobility

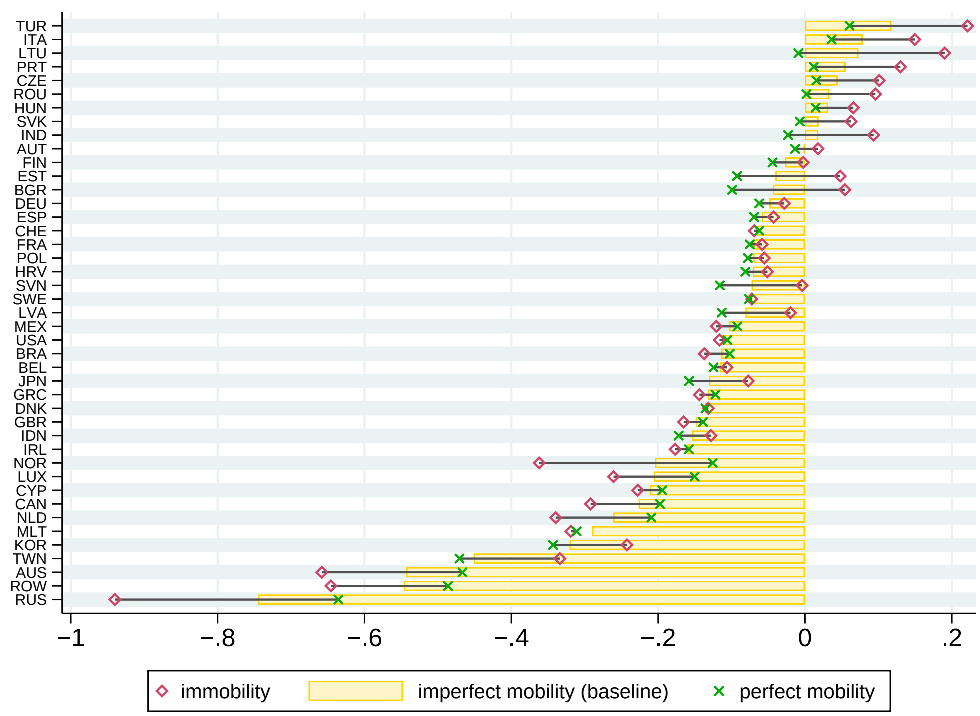


Figure A.5: Labor supply shock vs. productivity shock equal to output drop

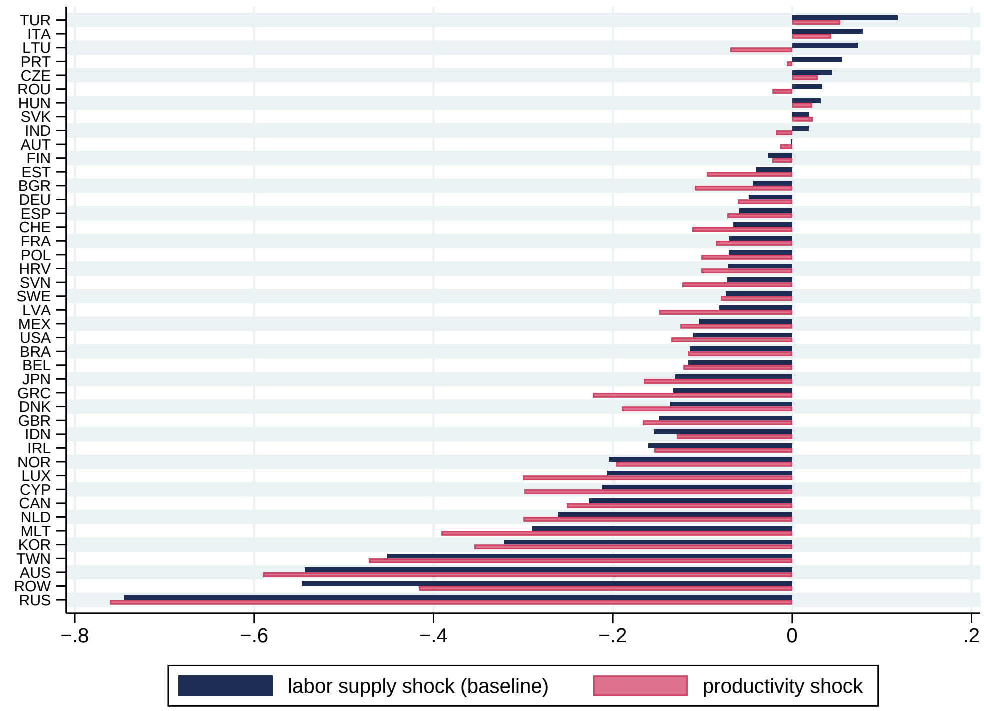
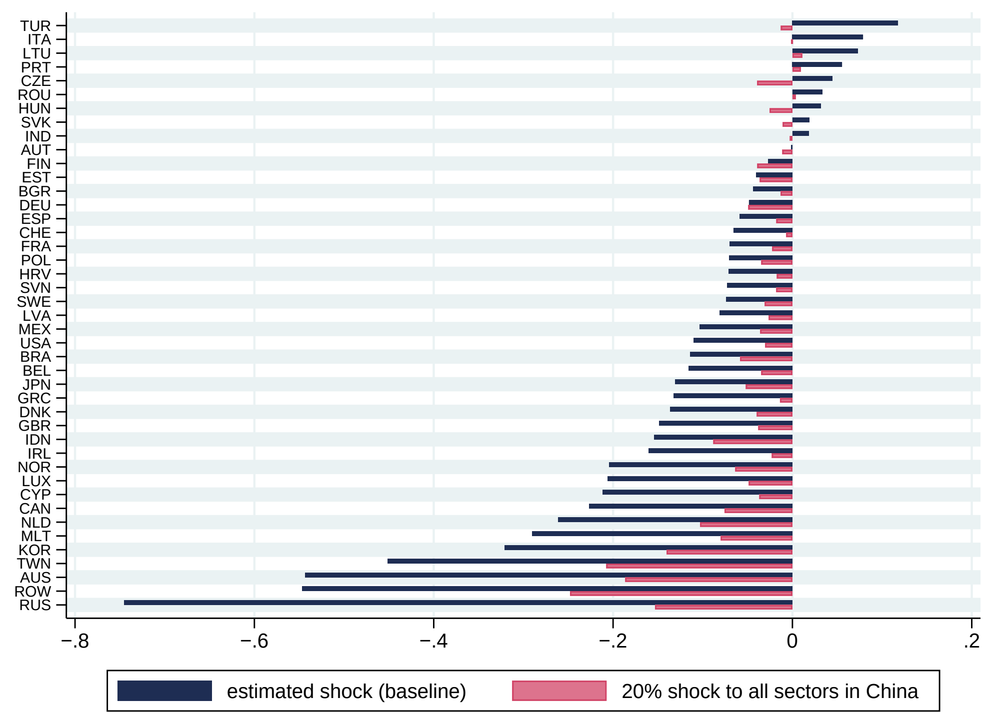


Figure A.6: Covid-19 shock vs. uniform 20% shock to all sectors in China



A.4 Additional results

Figure A.7: Welfare effects in a world with GVCs vs. without GVCs involving China

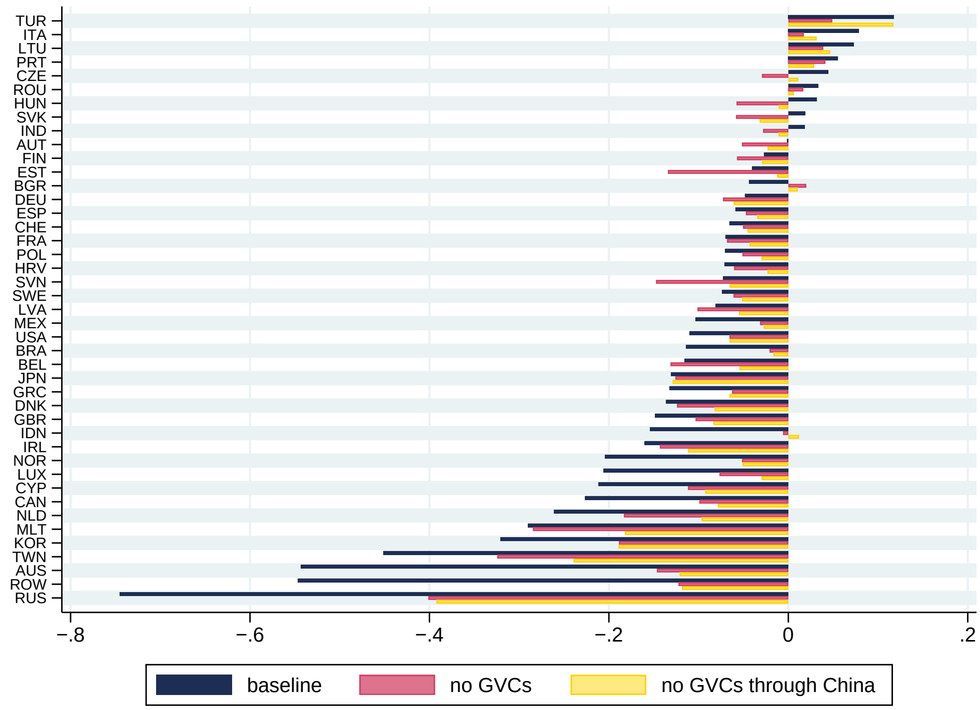


Figure A.8: Welfare effects of stepwise increase of trade barriers