Labor Market Effects of Global Supply Chain Disruptions*

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We examine the labor market consequences of global supply chain disruptions. Specifically, we consider the effect of a temporary increase in international trade costs similar to the one observed during the COVID-19 pandemic and analyze its effects on labor market outcomes using a quantitative trade model with downward nominal wage rigidities. The increase in trade costs leads to a temporary but prolonged decline in U.S. labor force participation. However, there is a temporary increase in manufacturing employment as the United States is a net importer of manufactured goods, which become costlier to obtain from abroad. By contrast, service and agricultural employment experience temporary declines. Nominal frictions lead to temporary unemployment when the shock dissipates, but this depends on the degree of monetary accommodation. Overall, the shock results in a 0.14% welfare loss for the United States. The impact on labor force participation and welfare across countries varies depending on the initial degree of openness and sectoral deficits.

JEL codes: F10, F11, F16, F40, F66.

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1 Introduction

Global supply chain disruptions can have serious economic consequences, reverberating across sectors and regions worldwide. Such disruptions, often stemming from unforeseen events such as pandemics, earthquakes, extreme weather events, nuclear accidents, or geopolitical tensions, can lead to strained trade flows due to port closures, reduced shipping capacity, congested trade routes, or a shortage of shipping containers, among other complications. These challenges, in turn, can cause an increase in the costs of international trade, potentially leading to substantial effects on production, prices, and labor markets, as well as reallocation within and across countries.

This paper quantitatively studies the labor market consequences of a generalized increase in international trade costs. Specifically, we analyze an x% increase in the iceberg trade costs of sending products across countries that reverts after τ years. In our baseline exercise, we analyze a 12% shock that reverts after three years, which approximates the size and duration of the trade-cost shock during the COVID-19 pandemic. However, we also examine how the effects of the shock depend on its size (i.e., $x = 6\%, 18\%$, or 24%) or persistence (i.e., $\tau = 2, 4, 5$, or 6). We place special emphasis on how the shock impacts labor markets within the United States, but turn to cross-country results towards the end of the paper. Importantly, our framework can be easily applied to trade-cost shocks of different size and duration and with different underlying causes.

We make use of the quantitative trade model developed by Rodriguez-Clare, Ulate, and Vasquez (2022, henceforth RUV) but pair it a with a novel exposure measure, novel data, and a focus on analyzing the effects of a trade-cost shock. The model features multiple sectors linked by an input-output structure, sector-level trade that satisfies the gravity equation, downward nominal wage rigidity (henceforth DNWR), and a home-production sector that leads to an upward-sloping labor supply curve. Trade takes place between regions, and workers can move across sectors in a given region subject to mobility costs. Each period, workers draw idiosyncratic shocks to the utility of working in each sector. Based on these draws, the costs of switching sectors, and expected future real income adjusted for unemployment, workers choose which sector to participate in.[1]

We capture DNWR as in Schmitt-Grohe and Uribe (2016). This implies that the nominal wage in any period must be no less than a factor δ times the nominal wage in the previous period and that involuntary unemployment arises when wages are constrained by this lower bound.[2] Given the presence of the DNWR, the model also requires a nominal anchor that prevents nominal wages from rising enough to make the DNWR always non-binding.[3] We assume that world nominal GDP in dollars grows at a constant and exogenous rate γ. This assumption captures the regularity that central banks are unwilling to allow inflation or unemployment to be too high (because of their related costs) while simultaneously keeping our model tractable. While this nominal anchor may not capture all the complexities of the real world, it allows us to incorporate a rich trade structure with multiple countries and sectors, intermediate inputs, and forward-looking mobility decisions into our trade framework while still being able to solve this otherwise-unwieldy model.[4]

In order to assess the susceptibility of a given region to a change in trade costs, we derive a new exposure measure using a first-order approximation to nominal GDP. In particular, we compute the responsiveness of total value added in a region to the change in iceberg trade costs across any two periods through its effects on labor demand. This formula resembles the one in Adao et al. (2020, henceforth AAE), but it incorporates new elements given the structure of our model. Specifically, besides considering the direct impact of the trade cost shock, it also incorporates the associated change in marginal costs due to input-output linkages. We use this exposure measure to compare how nominal GDP responds to the COVID-19-induced trade shock across U.S. states in the data with how the same response occurs within the model.

[1]Our baseline model does not feature movement between regions in a given country, but one of our extensions incorporates this feature. The consequences of allowing migration across regions are fairly small.

[2]See Dickens et al. (2007), Grigsby et al. (2019), and Hazell and Taska (2019) for papers that have found support for the presence of DNWR in the data. Labor-market frictions in the real world might go significantly beyond DNWR, but our model uses this modeling device as a parsimonious way to capture such frictions in a rich dynamic quantitative trade model.

[3]Our baseline analysis also assumes flexible exchange rates between the U.S. dollar and other countries' currencies. However, we have also conducted an alternative analysis with fixed exchange rates, and the implications for the United States are similar. The results of this analysis are available upon request.

[4]Introducing other types of nominal anchors prevents us from using the efficient Alvarez-and-Lucas type algorithm developed in RUV to deal with the DNWR, increasing the computation time by several orders of magnitude. Implementing more realistic nominal anchors is left for future research.

We assemble a new dataset for sector-level input-output flows as well as trade flows across all pairs of U.S. states and other countries in our sample. The final dataset combines multiple sources, a set of proportionality assumptions, and implications from a gravity model to construct sector-level trade flows across all region pairs in our sample. The resulting dataset contains 87 regions (50 U.S. states, 36 additional countries, and an aggregate rest of the world region) and 15 sectors (home production, 12 manufacturing sectors, services, and agriculture) for our base year of 2019.

We quantify the effects of the shock in our model using the dynamic "exact-hat algebra" approach to counterfactual analysis (c.f., Caliendo et al., 2019). This methodology ensures that our model perfectly matches sector-level production, trade, and reallocation patterns in the base year. We then introduce an unexpected increase in trade costs that reverts after a certain number of years. It is important to note that while we consider a uniform increase in the iceberg trade costs of international trade (i.e., the shock is the same for all region-sectors), these units of analysis certainly have differential exposures to the shock. This is due to the fact that region-sectors differ on many relevant aspects like their reliance on trade for consumption, sourcing of intermediate inputs, or selling of their production.

Besides the myriad parameters implicitly calibrated by the exact hat algebra approach using data from the base year (2019), we only require an explicit calibration of four parameters. Namely: the DNWR parameter δ, the growth in world nominal GDP in dollars γ, the inverse elasticity of mobility across sectors ν, and the trade elasticity $1-\sigma$. We normalize δ to one, indicating that nominal wages cannot fall, without loss of generality. We then set γ to 4%, in line with the relatively high nominal growth rate observed in recent years, but we explore the robustness of our results to different values (i.e., $\gamma = 2\%$, 3%, 5%, or 6%). Finally, we obtain ν directly from RUV, and take σ from the trade literature.

Our model-based analysis shows a temporary yet long-lasting decrease in U.S. labor force participation due to the shock. During the high trade cost period, engaging in the home production sector (which provides a constant utility flow) becomes more appealing, resulting in a decline in labor force participation. Once the shock dissipates, there is negative pressure on nominal wages as the economy adjusts to the lower trade costs, which in the presence of DNWR can generate unemployment. The impact of the trade cost shock on the labor market varies by sector. There is a temporary employment increase in manufacturing, a sector that is very tradable and where the United States is a net importer. By contrast, the service and agricultural sectors experience temporary employment reductions. The manufacturing sector, where wages increase the most during the high trade cost period, experiences the most unemployment when the shock dissipates.

We also find that the effect of the shock varies by state. States with larger service sectors (such as Alaska, Nevada, and Hawaii) tend to experience a more significant decline in labor force participation than those with larger manufacturing sectors (such as Ohio, Pennsylvania, and Wisconsin), but additional factors such as the exposure to other countries and states also play an important role in determining the extent of the impact. To test the model predictions, we collect information on nominal GDP at the state level and correlate its change with our exposure measure, finding a negative and significant relationship. The coefficient for the effect of exposure on nominal GDP observed in the data and the one predicted by the model are remarkably similar, suggesting an adequate fit between the model and the data. This approach serves to isolate the effects of the trade cost shock on GDP from other economic shocks that affected GDP during the pandemic period that we intend to abstract from (i.e., health shocks, domestic lockdowns, demand shocks, etc.).

We also investigate how different assumptions affect our conclusions. To do so, we consider alternative specifications where we vary the persistence of the shock, the size of the shock, or the nominal growth rate of world GDP in dollars. In addition, we examine how allowing for migration between U.S. states and varying the elasticity of moving across sectors change our results. Our conclusions are qualitatively robust across these different specifications. Quantitatively, one of the key lessons is that more monetary accommodation in the form of a higher γ can mitigate the unemployment impacts of the shock.

Turning to cross-country results, the consequences of the shock for labor force participation vary internationally and depend on size and trade openness. On the one hand, countries like China, the United States, Brazil, and India, which are relatively large and less reliant on international trade, experience a smaller decrease in labor force participation. On the other hand, small and open economies like Ireland, Estonia, Slovakia, and Cyprus, which rely heavily on foreign intermediate inputs and importing/exporting, experience a more significant decline in labor force participation. Furthermore, countries that are net importers in a given sector tend to increase their participation relatively more in that sector due to a cross-country expenditure-switching effect.

It is important to highlight that our model does not intend to fully explain the labor market effects of the COVID-19 pandemic. In particular, our model does not account for health-related concerns that could also affect participation decisions at the same time as the supply chain disruptions, among other pandemic-related forces that affected employment or wages. Instead, our exercise is useful for isolating the specific effects of an international trade-cost shock and provides insights into the relevant economic mechanisms that would be at play more generally during episodes of global supply chain disruptions.

Our paper contributes to the literature studying the causes and consequences of disruptions in global supply chains. While there are some papers studying the effects of weather-related disruptions (e.g., Castro-Vincenzi, 2023; Balboni et al., 2023), or geopolitical events (Feyrer, 2021), most recent papers have focused on the relationship between the COVID-19 pandemic and global supply chains. This literature has highlighted supply disruptions as one of the main factors explaining the decline in output and increase in inflation. For instance, Bonadio et al. (2021) investigate the role of global supply chains on growth during the pandemic and find that disruptions explain one-quarter of the GDP decline. Meier and Pinto (2020) analyze the impact of Chinese lockdowns on the U.S. economy, finding that sectors with higher exposure to inputs from China experienced larger decreases in output and employment. LaBelle and Santacreu (2022) exploit cross-industry variation in sourcing patterns and find that exposure to supply-chain disruptions is associated with larger increases in the producer price index. Sforza and Steininger (2020) develop a multi-sector model to show that global linkages amplified the pandemic shock.

Additionally, Alessandria et al. (2023) show in a two-country setting that inventory management by firms can smooth the impact of delayed deliveries and thus affect the magnitude and timing of labor demand shocks. Uncertainty regarding aggregate shocks (as in, Handley and Limão, 2017) could also matter. While we abstract from useful elements that other papers in this literature have studied (explicit lockdown measures, inventories, capital investment, shipping networks, uncertainty, etc), we are the first to analyze the effect of global supply disruptions on labor markets using a dynamic trade model that incorporates both costs of moving between sectors (and potentially regions) and unemployment. These two features, plus input-output linkages and forward looking agents, already deliver a rich model with important implications for the impacts of supply chain disruptions.

Our paper also relates to the vast literature that studies the impacts of trade on local labor markets using quantitative trade models. Most recent papers have focused on the effects of the rise of China's prevalence in international trade (RUV, Caliendo et al., 2019; Galle et al., 2020; Adao et al., 2020), but other quantitative papers also examine migration shocks (Caliendo et al., 2021, 2022) or automation (Galle and Lorentzen, 2022).[5] Among these papers, RUV is the closest to our work. They present a dynamic quantitative trade model with DNWR and use it to rationalize the empirical findings from the China-Shock literature. The shock itself is modeled as an increase in productivity in China from 2000 to 2007 that varies across sectors. In contrast, our paper uses a quantitative framework similar to the one in RUV to study the labor market effects of the recent global supply chain disruptions, modeled as an unexpected increase in international trade costs.[6]

Open-economy papers such as Gali and Monacelli (2005, 2008) or Clarida et al. (2002) have incorporated nominal rigidities into macro models with a simplified trade structure. Schmitt-Grohe and Uribe (2016) studies optimal policies in the presence of DNWR in a small open economy and Guerrieri et al. (2021) analyzes monetary policy after pandemic-induced sectoral shocks in a model with DNWR and a nominal anchor similar to ours. Our contribution relative to this literature is to incorporate a hint of these important nominal elements into a rich quantitative trade model to assess the impact of trade cost shocks.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the model. Section 3 describes our data construction and baseline calibration. Section 4 presents the results of our baseline analysis for U.S. states. Section 5 investigates the sensitivity of our results to changes in some of the key assumptions. Section 6 focuses on how the results vary across countries and Section 7 concludes.

[5]This list is by no means exhaustive. Other recent papers study the impacts of trade shocks with unemployment effects generated via search and matching instead of DNWR (e.g. Kim and Vogel, 2020a,b; Dix-Carneiro et al., 2020; Carrere et al., 2020).

[6]Our paper also adds to the rapidly growing literature in trade that discusses or incorporates nominal elements (see RUV, Comin and Johnson, 2020; Costinot et al., 2022; Ahn et al., 2022; Fadinger et al., 2022).

2 Model Environment

In order to study the effects of increases in international trade costs, we use a dynamic multi-sector quantitative trade model with nominal wage rigidities and an input-output structure similar to the one in RUV. In this section, we discuss the main features of the model, relegating further mathematical details to appendix A.

The model incorporates a total number of I regions ($I = 87$, formed of 50 U.S. states, 36 other countries, and an aggregate rest of the world region) and S sectors ($S = 15$, specifically home production, 12 manufacturing sectors, services, and agriculture). The "home production" sector is meant to capture useful activities conducted at home (e.g., taking care of family members, cooking, cleaning, enjoying leisure) that are not remunerated as work. In the baseline model, we assume that there is no mobility across countries or across states of the U.S. In an extension, we allow for migration across U.S. states, but this makes fairly little difference for our results.

Total consumption in the model is a Cobb-Douglas aggregate of consumption across all the market sectors with given time-invariant expenditure shares.[7] As in a multi-sector Armington trade model, consumption within a given market sector (denoted with s) is a CES aggregate of the good produced by each of the regions, with an elasticity of substitution denoted by σ_s. In principle, each region can produce the goods in all of the sectors, but they might have very low productivity in some of these sectors.

We denote the region i, sector s, and time t triad as (i, s, t). Production uses labor and intermediate inputs, but no capital. Specifically, production of the final good in (i, s, t) takes the following Cobb-Douglas form:

$$Y_{i,s,t} = A_{i,s,t} L_{i,s,t}^{\phi_{i,s}} \prod_{k=1}^{S} M_{i,ks,t}^{\phi_{i,ks}},$$

where $A_{i,s,t}$ is total factor productivity in (i, s, t), $L_{i,s,t}$ is employment in (i, s, t), $M_{i,ks,t}$ is the quantity of intermediate inputs of sector k used in (i, s, t), $\phi_{i,s}$ is the time-invariant labor

[7] This assumption is made for tractability and does not capture changes in consumption patterns that might have occurred during the pandemic, which we intentionally abstract from.

share in (i,s), and $\phi_{i,ks}$ is the share of inputs that sector s uses from sector k in region i. Production has constant returns to scale, i.e. $\phi_{i,s} + \sum_k \phi_{i,ks} = 1$.

There are iceberg trade costs $\tau_{ij,s,t} \geq 1$ for sending the product of sector s from region i to region j at time t. These τ's will play an important role because they are the ones getting shocked when the economy faces an increase in trade costs generating the supply chain disruptions.

There is perfect competition in production. Letting $W_{i,s,t}$ denote the wage in dollars in (i,s,t) and $P_{i,k,t}$ denote the dollar price of the composite good of sector k, in region i, at time t, then the dollar price in region j of the (i,s,t) good is:

$$p_{ij,s,t} = \tau_{ij,s,t} A_{i,s,t}^{-1} W_{i,s,t}^{\phi_{i,s}} \prod_{k=1}^{S} P_{i,k,t}^{\phi_{i,ks}}.$$

This expression describes all four factors affecting the price of sending the individual good of sector s from region i to region j at time t; namely: iceberg trade costs, technology at the sector-region of origin, the wage at the sector-region of origin, and intermediate input prices (in all sectors) at the origin location.

We denote the number of agents participating in (i,s,t) by $\ell_{i,s,t}$, whose behavior is described below. In a standard trade model, employment in a sector-region has to equal labor supply in that sector-region, i.e. $L_{i,s,t} = \ell_{i,s,t}$. We depart from this assumption and instead follow Schmitt-Grohe and Uribe (2016) by allowing for a downward nominal wage rigidity (DNWR) specifying that the nominal wage in (i,s,t) has to be greater than δ times the nominal wage in $(i,s,t-1)$, that is:

$$W_{i,s,t} \geq \delta W_{i,s,t-1}.$$

Given this rigidity, employment does not necessarily has to equal labor supply, it could be strictly below it.[8] This is captured by the following weak inequality:

$$L_{i,s,t} \leq \ell_{i,s,t}.$$

[8]Formally, the DNWR applies in the local currency units of region i, which need to be converted into U.S. dollars using an appropriate exchange rate. This is described formally in appendix A.

Importantly, there can only be unemployment if the wage is at its lower bound. Therefore, the previous two inequalities are augmented by a complementary slackness condition indicating that at least one of them always has to hold with equality:

$$(\ell_{i,s,t} - L_{i,s,t})(W_{i,s,t} - \delta W_{i,s,t-1}) = 0.$$

The previous equation says that wage and employment are determined by supply and demand when the wage is away from its lower bound. By contrast, when the wage lower bound is binding, the market does not clear, and there is rationing (i.e., unemployment).

Returning to the determination of $\ell_{i,s,t}$, agents in the model can either engage in home production (sector zero) or look for work in the labor market (sectors 1 through S). Participating in home production results in an exogenous and time-invariant real level of consumption which does not depend on labor market conditions. By contrast, a given market sector $s > 0$ yields a real level of consumption $c_{i,s,t}$ which is endogenous.

Given the existence of downward nominal wage rigidity, agents must take into account the possibility of unemployment when deciding which sector to participate in. To simplify the analysis, we assume a representative agent in each sector-region.[9] Since a fraction $L_{i,s,t}/\ell_{i,s,t}$ of agents is actually employed in (i, s, t), and employed agents obtain a nominal wage of $W_{i,s,t}$, the real level of consumption $c_{i,s,t}$ from participating in market sector s is given by:

$$c_{i,s,t} = \frac{W_{i,s,t}}{P_{i,t}} \cdot \frac{L_{i,s,t}}{\ell_{i,s,t}},$$

where $P_{i,t}$ is the aggregate price index in region i.

Agents choose their sector while facing idiosyncratic preference shocks, switching costs, and incorporating into their decision the expected future income in all sectors (i.e., the $c_{i,s,t}$'s) with perfect foresight. The idiosyncratic preference shocks are assumed to have a Gumbel distribution, making the participation decision tractable and allowing for closed-form expressions (see appendix A for additional details on the derivations). Importantly,

[9] This is equivalent to assuming that the income generated in a sector-region is equally shared between all agents in that sector-region.

there is an elasticity $1/\nu$ of moving across different sectors within any given region.

Since the model contains nominal elements (namely the DNWR) it is also important to introduce a "nominal anchor", preventing nominal wages from rising so much in each period as to make the DNWR always non-binding. We implement a nominal rule that captures the idea that central banks are unwilling to allow inflation or unemployment to be too high (because of their related costs which, in the case of inflation, are outside of the model) while at the same time being amenable for quantification.[10] Specifically, we assume that world nominal GDP in dollars grows at a constant rate γ across years:

$$\sum_{i=1}^{I}\sum_{s=1}^{S} W_{i,s,t}L_{i,s,t} = (1+\gamma)\sum_{i=1}^{I}\sum_{s=1}^{S} W_{i,s,t-1}L_{i,s,t-1}.$$

Although this assumption is useful to solve the model, it has limitations and might not reflect the optimal monetary policy of any given country. This implies that the nominal implications of the model are to be taken with a grain of salt. Consequently, we will refrain from discussing the implications of the trade-cost shock for inflation since the model is not well suited to study this aspect. Nevertheless, the model can provide valuable insights into the behavior of relative prices, which we discuss in our results section.

As mentioned above, the main objective of the paper is to examine the effects of an unanticipated trade-cost shock. To do so in a computationally tractable way, we employ a technique known as "dynamic exact hat algebra", which allows the model to implicitly match production, trade, and reallocation patterns in a given base year. By doing so, one can then introduce a percentage change in any of the model's fundamentals, such as trade costs, without knowing the initial levels of these fundamentals, and study the economy's dynamic response to such a shock.

To analyze the effects of the trade cost shock, we assume that the base year is 2019. At that point, the shock has not hit the economy and the model perfectly matches production, trade, and sectoral flow patterns as they occurred in the real world. Then, the shock is introduced in 2020, and the agents in the model learn the full path of the shock (recall that

[10]The tractability of this nominal anchor allows us to solve our model using a fast contraction mapping algorithm in the spirit of Alvarez and Lucas (2007) developed in RUV to deal with the complementary slackness condition implied by the DNWR. A similar nominal anchor is used in Guerrieri et al. (2021).

the agents in the model have "perfect foresight"). As the shock hits, employment, prices, production, and trade respond accordingly.

2.1 Regional Exposure Measure

We are also interested in assessing how different regions are exposed to trade cost shocks. To this end, we use the labor demand equation from our model and a first-order approximation to construct a regional exposure measure that tracks how the change in trade costs impacts regional value added (which is equivalent to nominal GDP). The derivation details are in Appendix B. This formula can be understood as a comparative statics exercise that tells us how much demand across regions (and, therefore, countries) shifts in response to trade cost shocks. This measure is somewhat similar to the one in Adao, Arkolakis, and Esposito (2020) but it includes new elements due to the presence of intermediate inputs in our model.[11] As discussed in the appendix, the exposure formula for region i after a change in the vector of trade costs $\hat{\tau}$ is given by:

$$\hat{\eta}_i(\hat{\tau}) \;=\; \sum_{s=1}^{S}(1-\sigma_s)\omega_{i,s,0}\theta_{i,s}(\hat{\tau}).$$

In the previous expression, $(1-\sigma_s)$ is the trade elasticity in sector s, $\omega_{i,s,0}$ is the share of the wage bill in market i that goes to sector s in the base year (denoted with a zero even though in our implementation it will be the year 2019), and $\theta_{i,s}(\hat{\tau})$ is the shift in demand for the sector s good of region i:

$$\theta_{i,s}(\hat{\tau}) \;=\; \sum_{j=1}^{I} r_{ij,s,0}\left(\hat{\tau}_{ij,s}+\widehat{mc}_{i,s}-\sum_{q=1}^{I}\lambda_{qj,s,0}(\hat{\tau}_{qj,s}+\widehat{mc}_{q,s})\right).$$

The variable $r_{ij,s,0}$ denotes the share of market i's sales in sector s that go to market j in the base year, $\lambda_{qj,s,0}$ denotes the share of market j's purchases in sector s that come from market q in the base year, $\hat{\tau}_{ij,s} = \ln(\tau_{ij,s,2022}) - \ln(\tau_{ij,s,2019})$ denotes the log difference in the iceberg trade costs between the base year and the high-trade-cost years, and $\widehat{mc}_{i,s} =$

[11] In the case of AAE, their model adds labor force participation to a classic trade model but does not incorporate intermediate inputs via an input-output structure.

$\ln(mc_{i,s,2022}) - \ln(mc_{i,s,2019})$ denotes the log difference in the marginal cost between the base year and the high-trade-cost years.[12] The changes in marginal costs $\widehat{mc}$, can themselves be expressed as a function of the change in trade costs, as discussed in Appendix B, and they appear in the previous formula due to the presence of intermediate inputs. If labor was the only factor of production, then the $\widehat{mc}$'s would disappear from the previous expression, and our formula would more closely resemble equation (17) of AAE.

$\hat{\eta}_i(\hat{\tau})$ represents market i's "revenue shock exposure". It is the sum across sectors of the shock to the demand for the good of region i in each sector, $\theta_{i,s}(\hat{\tau})$, weighted by that sector's share in i's wage bill in the base year $\omega_{i,s,0}$. The sector-level demand shock, $\theta_{i,s}(\hat{\tau})$, is itself the sum across destinations j of the impact of market i's own trade shock (including the effects via the marginal cost) on the demand for its good minus the demand shift caused by competitors' trade shocks (including the effects via the marginal cost) in that sector, weighted by the revenue importance of each destination in the base year $r_{ij,s,0}$. Note that all components of $\hat{\eta}_i(\hat{\tau})$ can be computed with information on bilateral trade flows in the base year plus measures of the bilateral trade shocks. In our quantitative implementation, $\hat{\tau}_{ij,s} \approx 12\%$ if i and j are regions located in different countries, while $\hat{\tau}_{ij,s} = 0$ if $i = j$ or if i and j are regions of the same country (e.g., two U.S. states).

The previous exposure measure provides a useful way to assess the impact of shocks on a given region by taking into account how it competes with all other regions in all possible destination markets, including its own. If a region is in autarky, a change in the τ's has no effect and $\theta_{i,s}(\hat{\tau}) = 0$ for all s, resulting in $\hat{\eta}_i(\hat{\tau}) = 0$. Regions that are more open or have higher wage-bill shares in open sectors are more exposed to trade cost shocks.

3 Data, Calibration, and Shocks

3.1 Data Construction

We put together a combination of datasets to create a matrix of sector-by-region bilateral trade flows for all U.S. states and countries. Our data construction follows steps

[12] Recall that in our baseline quantitative implementation the high trade costs will start in 2020, persist during 2021 and 2022, and revert back to their 2019-levels in 2023.

that are related to those in RUV, but setting the base year to 2019 (as opposed to 2000 as in RUV) requires incorporating new data sources such as the OECD's Inter-Country Input-Output Database (ICIO) since the World Input-Output Database (WIOD) is not available after 2014. A summary of the data-construction process is provided here, with additional details available in Appendix C.

Labor, input, and consumption shares: Data from the BEA (for U.S. states) and from the ICIO are used to compute the value-added share in gross output (which is used as the labor share in the model) and the input-output coefficients for each region. Consumption shares can be inferred based on trade flows, labor shares, and intermediate input shares.

Bilateral flows: The model requires bilateral trade flows in all sectors between any pair of regions in the sample. These are constructed in four steps, which we briefly describe below, relegating additional details to Appendix C.2.

In the first step, we use sector-level bilateral trade data among countries directly from the ICIO database. In the second step, we compute bilateral trade flows in the manufacturing sector across U.S. states. This involves combining the ICIO database with the Commodity Flow Survey (CFS). Initially, we determine bilateral expenditure shares for states and sectors based on CFS. Subsequently, employing a proportionality assumption, we allocate the total U.S. domestic sales from ICIO according to these bilateral shares. This step ensures alignment between the trade flows within the bilateral trade matrix for the 50 U.S. states and the total U.S. internal sales from ICIO within each sector.

Moving to the third step, we use data from the Import and Export Merchandise Trade Statistics from the U.S. Census to compute sector-level bilateral trade flows in manufacturing and agriculture between individual U.S. states and other countries in our sample for 2018. To maintain coherence, we employ the same proportionality assumption for bilateral trade flows between U.S. states and other countries, aligning these flows with the aggregated sectoral trade figures between the U.S. and other nations, according to the ICIO.

In the final step, we use data on production and expenditure in services from the Regional Economic Accounts of BEA, alongside ICIO data and bilateral distance between regions, to construct the trade flows in services between regions consistent with a gravity structure. Similarly, we combine data with a gravity-based approach for trade flows in agriculture, drawing from data sourced from the Agricultural Census, the National Marine Fisheries Service Census, and ICIO. Through this gravity approach, the bilateral trade flows in services and agriculture coincide with the overall trade aggregates in these sectors between all countries, according to ICIO.

Labor flows across sectors and regions: Data for intersectoral mobility for each U.S. state is obtained from the Current Population Survey (CPS), while frictionless mobility is assumed for other countries. In the extension allowing for migration within the U.S., data for interstate mobility is obtained from the American Community Survey (ACS).

Labor supply: Data on employment by sector (including home production) comes from the WIOD Socio Economic Accounts, the International Labor Organization, the U.S. Census, and the ACS. As in RUV, only observations for people aged between 25 and 65 are kept. Labor force participation is measured as the share of individuals in that age group who are either employed or unemployed.

Nominal GDP across U.S. states: We also collect information on the nominal GDP of each U.S. state between 2019 and 2022 from the Federal Bank of St. Louis' FRED. We use these data to test how the relationship between nominal value added and exposure to the trade cost shock compares between the model and the data.

3.2 Parameter Calibration

Table 1 describes the parameters used in the baseline specification. Notice that γ (the nominal growth rate of world GDP in U.S. dollars) and δ (the downward nominal wage rigidity parameter) are not separately identified. For a given δ, if γ is higher, then the DNWR is less likely to bind. Likewise, for a given γ, if δ is lower, then the DNWR is less likely to bind. Therefore, we require a normalization and set $\delta = 1$, indicating that nominal wages in dollars cannot fall, and putting the burden of the nominal adjustment on γ.

We set $\gamma = 4\%$, due to the high nominal growth rate in the post-pandemic period. We discuss the implications of different γ's (between 2% and 6%) in Section 5. The implications go in the direction expected, the higher the γ, the less binding the DNWR is, and the less unemployment is generated in the model. For a high γ of 6% or higher, the model has essentially the same behavior as the model without DNWR. The outcomes of the model

Table 1: Parameter values used

Parameter	Value	Description	Source
δ	1	Lower bound in DNWR	Normalization
γ	4%	Growth rate of world nominal GDP in $	Suggestive
ν	0.55	Inverse elasticity of moving across sectors	RUV
σ	6	Trade elasticity	Trade Literature

Notes: This table contains the parameter values used in the baseline specification, together with their description and the source where they are taken from.

unrelated to unemployment are slightly affected by the choice of γ.

Parameter ν for the inverse elasticity of moving across sectors is taken directly from RUV and set to 0.55. In that paper, the inverse elasticity of moving across sectors is set to match the evidence shown in Autor et al. (2013) on how more exposure to the China shock across U.S. commuting zones affects labor force participation. As we will discuss in Section 5, our results do not change substantially when using other reasonable values of ν. Finally, we set σ_s to 6 in all sectors, which implies a trade elasticity of -5, consistent with the trade literature (see, e.g., Costinot and Rodriguez-Clare, 2014).[13]

3.3 Trade Shock

As indicated in the introduction, the baseline exercise examines a 12% increase in the iceberg trade costs of sending products across countries that reverts after three years. We also explore, in alternative exercises described in Section 5, how the effects of the shock depend on its size (i.e., 6%, 18%, or 24% instead of 12%) or persistence (i.e., 2, 4, 5, or 6 years instead of 3).[14]

The choice of a 12% magnitude for the increase in trade costs in our baseline specification is motivated by the behavior of the producer price index for deep sea freight transportation services, depicted in figure 1. This index increased by approximately 12% from

[13] We abstract from the fact that the elasticity of substitution σ can be lower in the short-run vs. the long-run as documented in Atalay (2017) and Boehm et al. (2019). A lower σ would imply stronger responses in labor demand.

[14] While we model a general shock to all regions and sectors (as opposed to estimating which regions and sectors of the world were subject to a more severe shock due to shipping networks as in Ganapati et al., 2021), different regions and sectors are still differentially exposed to the shock due to their differential trade exposure.

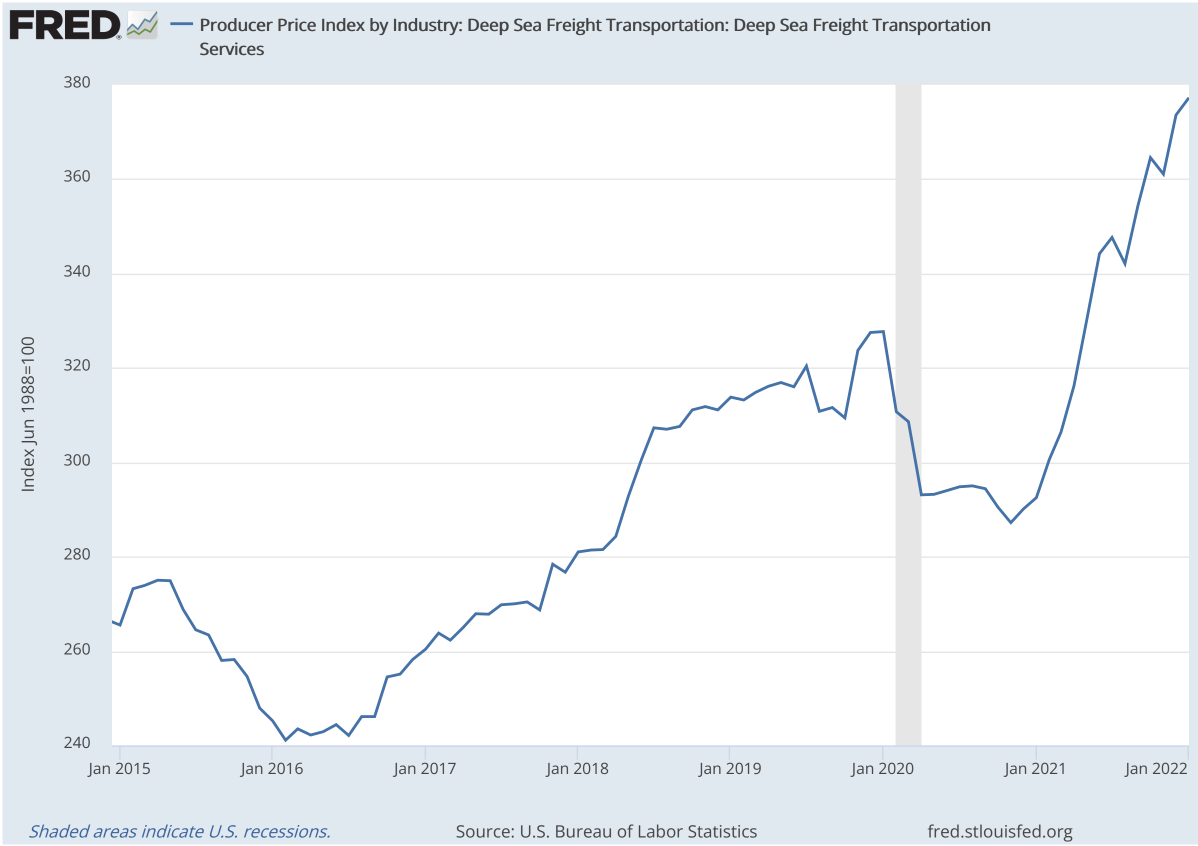

Figure 1: PPI for deep sea freight transportation services between January 2015 and January 2022, taken directly from FRED.

its pre-pandemic level of 330 to around 370 in December 2021.

It is worth noting that the aforementioned producer price index may not capture the full increase in the cost of cross-border trade, as other trade cost components could have also risen. Nevertheless, iceberg trade costs in trade models also include non-physical factors such as marketing or research costs for entry into a foreign country, which may not have risen as much as physical costs. Overall, we view the 12% increase in the iceberg trade cost as a suggestive benchmark and assess the sensitivity of our results to different values of this parameter.

The choice of a 3-year duration for the shock is based on current evidence suggesting that global supply chain disruptions have largely subsided by early 2023. Thus, we assume that high trade costs are in effect for 2020, 2021, and 2022, but then dissipate by 2023. In Section 5, we examine how different shock duration impacts the results. We find that longer-lasting shocks lead to more severe outcomes because, given the costs of switching sectors, it makes more sense to pay the cost for more extended shocks than it does for more transitory ones.

4 Baseline Results

This section investigates the effects of a 12% increase in the iceberg trade costs of sending products across countries on labor outcomes for the United States.

Our baseline exercise uses a model where there is no migration across U.S. states, world nominal GDP in dollars grows at 4% per year, and the trade cost shock lasts for 3 years (2020-2022). We discuss the effects on labor force participation, employment, and unemployment in the aggregate, as well as on labor supply to the broad sectors of manufacturing, services, and agriculture. We also assess how these effects vary across different U.S. states. Importantly, we also compare how nominal GDP in the data reacted to the trade cost shock (through the lens of our exposure measure) with how this occurs in the model. Cross-country results are discussed in Section 6.

Figure 2 displays the effects of the shock on model-implied employment-related outcomes for the United States as a whole. The blue line depicts the cumulative percentage change in employment since 2019, the green line shows the cumulative percentage change in labor supply since 2019, and the red line shows the level of unemployment (in percent).

We find that aggregate U.S. labor supply in the model decreases during the years when the trade shock is active, with the largest cumulative decline of 0.7% occurring in 2022. The fall in labor supply occurs because, while trade costs are high, participating in the home-production sector (which offers a constant real utility flow) temporarily becomes more attractive than participating in the market sectors. This is due to the fact that high trade costs make the market sectors less productive because intermediate inputs from other countries are more expensive, which is akin to a fall in productivity. Although aggregate nominal wages increase at a faster-than-normal pace during the period of high trade costs, aggregate prices increase even faster, resulting in a decrease in real wages (see appendix figure D.1), which is what causes some individuals to exit the labor force.

The recovery of labor supply once the shock disappears is slow, by 2027 labor supply

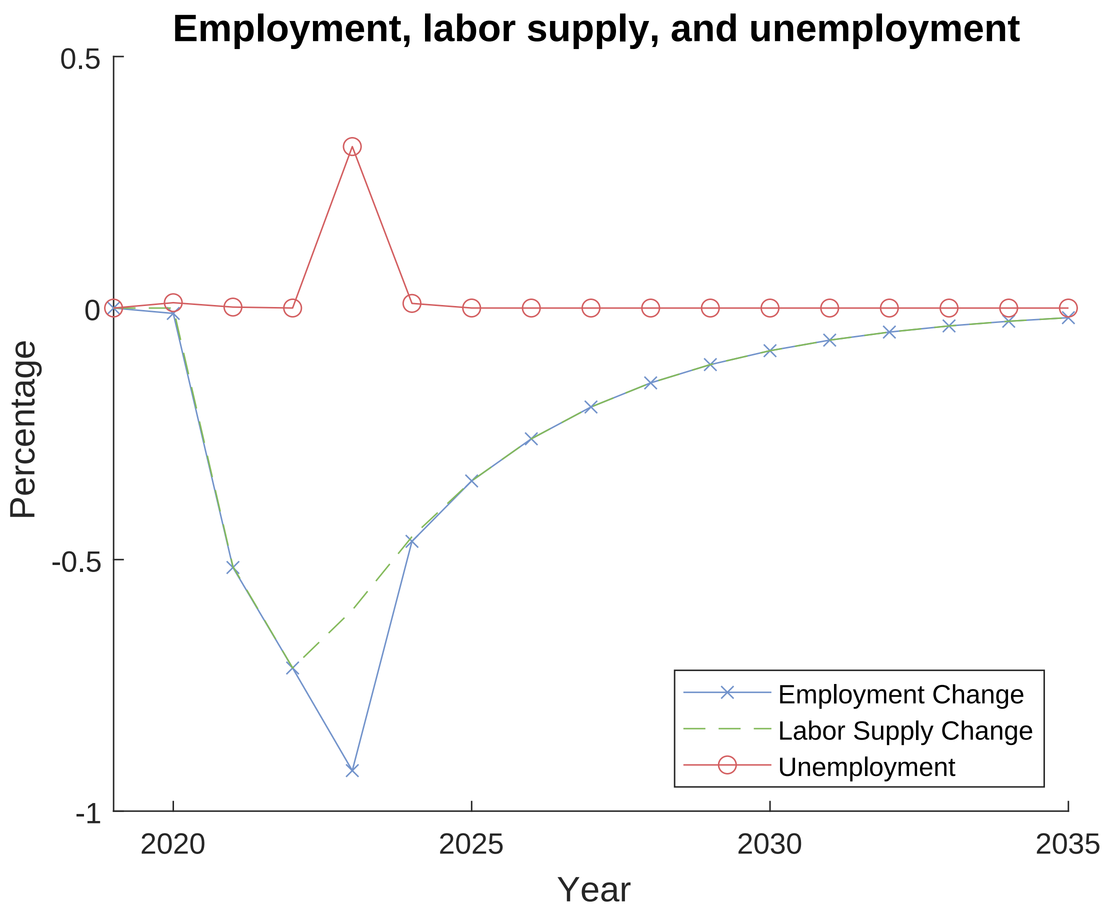

Figure 2: Paths of relevant variables for the U.S. on aggregate. The cumulative percentage change in employment since 2019 is in blue, the cumulative percentage change in labor supply since 2019 is in green, and the level of unemployment (in percent) is in red. The years in the x-axis go from 2019 until 2035.

is still 0.2% lower than pre-shock. In the model, the costs of switching between market sectors and the costs of entering/exiting the labor force are calibrated based on pre-pandemic mobility patterns. These patterns suggest that there are substantial costs associated with reallocating across sectors, which explains why agents return to the labor force gradually. Although the pandemic may have altered the costs of switching between sectors, the model does not account for such changes.[15]

[15] Another limitation of our model is that it does not feature an income effect on labor supply, because the agents do not have a level of wealth or assets that enters their labor decision. Agents simply compare their real consumption of participating in home production (which is constant) against the real consumption they obtain from participating in a given market sector (which is given by the real wage in that sector adjusted for unemployment). Moreover, the agents cannot choose their level of employment (or their "hours"); they simply choose their sector and supply all their units of labor inelastically to that sector.

Unemployment is generated mostly when the shock dissipates, with the peak amount of unemployment of 0.32% occurring in 2023. As mentioned above, during the years with high trade costs nominal wages are increasing faster than usual, so the downward wage rigidity mostly does not bind. By contrast, when the shock dissipates nominal wages need to fall in some region-sectors.[16] Consequently, those locations hit the DNWR and experience some temporary unemployment.

While, at first glance, it might seem counterintuitive that unemployment is generated when the shock dissipates instead of when it first hits, recall that out model is, **intentionally**, not capturing the lockdowns or health disruptions induced by the COVID-19 pandemic. We do this in an attempt to isolate the effects of the increase in international trade costs. As such, it is not surprising that we do not observe a spike in unemployment during 2020 when the pandemic first hit. The amount of unemployment generated depends on the degree of monetary accommodation, as will be discussed further in Section 5.

The blue line in figure 2, which shows the cumulative change in employment since 2019, is essentially the combination of the green and red lines (labor supply and unemployment). Importantly, even though the trough for labor supply occurs in the year 2022, the trough for employment occurs in 2023, due to the additional unemployment generated when the trade-cost shock dissipates.

Figure 3 displays the cumulative percentage change since 2019 of activity (i.e., the number of people engaged) in four different broad sectors for the U.S. as a whole, as implied by the model. Home production is depicted in blue, manufacturing in green, services in red, and agriculture in purple. While home production and manufacturing show an increase during the period when the shock is active, services and agriculture decline.

The rise in home production has already been explained above, so we now focus on the employment changes in the other sectors. Several forces affect employment in each market sector. First, there is a general decrease in demand due to the aggregate fall in em-

[16]While high trade costs are active, agents are flowing out of the labor force, which forces nominal wages to increase faster than usual to attain the γ growth of nominal GDP embedded in the nominal anchor. Once trade costs return to their normal level, agents flow back into the labor force, which implies nominal wages must grow more slowly than usual (or in some cases fall) to satisfy the nominal anchor. This is reminiscent of central banks around the world withdrawing monetary accommodation once the pandemic and supply disruptions subsided and the labor market normalized.

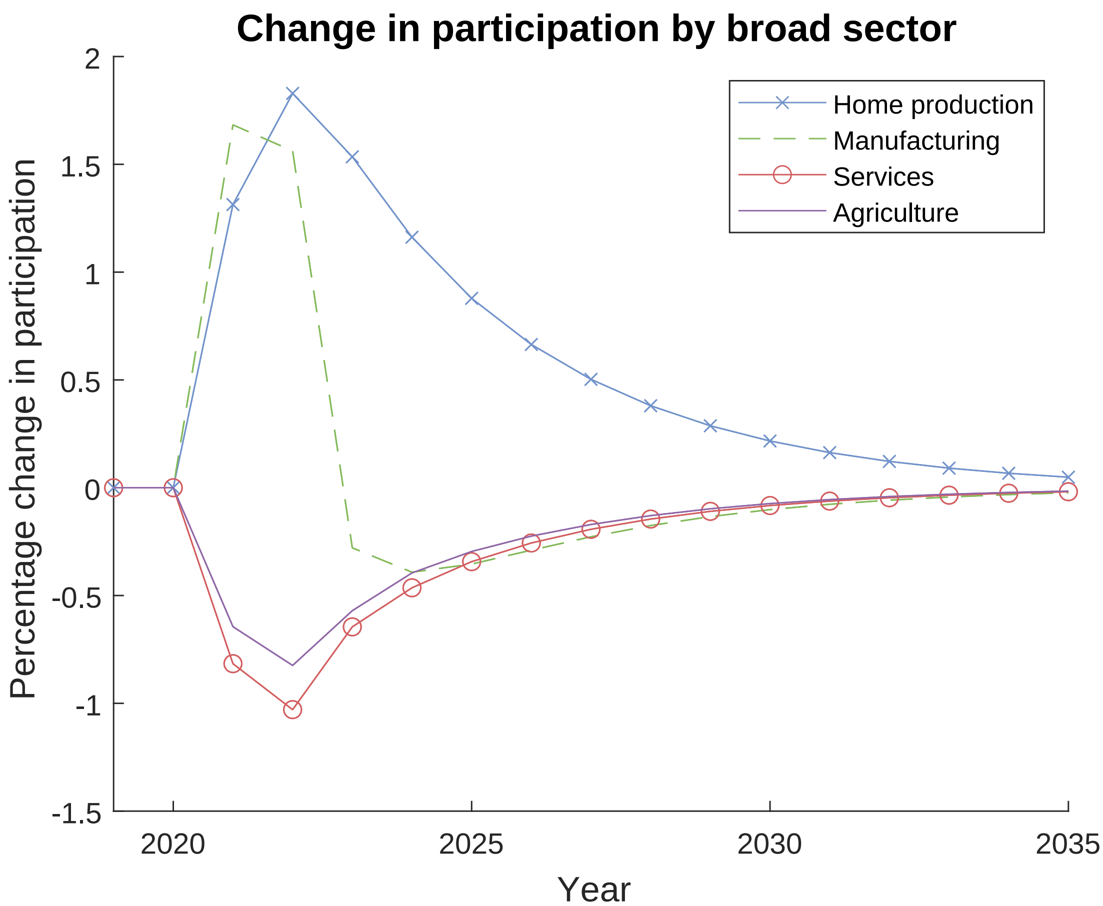

Figure 3: Paths of aggregate participation for different broad sectors in the U.S. The percentage change in home production from the baseline year of 2019 is in blue, the percentage change in labor supply to the manufacturing sector since 2019 is in green, the same concept for the service sector is in red, and for the agricultural sector is in purple.

ployment (with people out of work there is less spending power). Second, intermediate inputs become more expensive, making production less efficient and decreasing labor demand. Third, there is an expenditure-switching effect across countries: imports become more expensive and tend to be substituted with local production, increasing labor demand in net-importing sectors.

The United States is a net exporter of services and has balanced trade in agriculture, in these sectors the first two effects mentioned in the previous paragraph dominate, decreasing participation. By contrast, the United States is a net manufacturing importer. In this sector, the expenditure-switching effect dominates and participation increases. Since manufacturing is the sector that experiences an increase in participation (and the highest

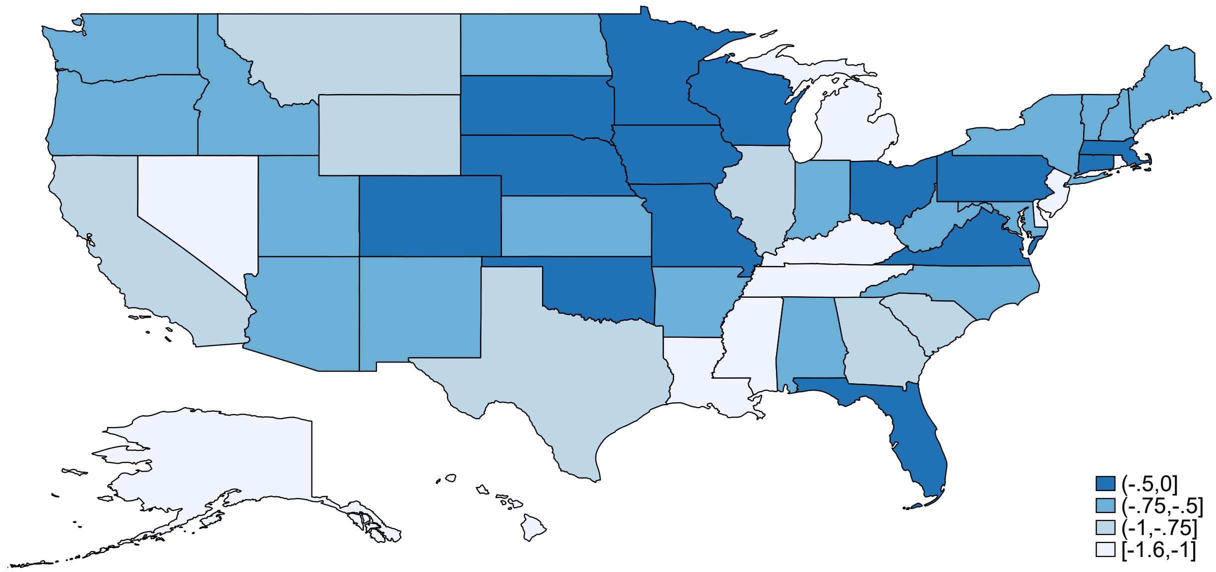

Figure 4: Map for the cumulative percentage change in participation between 2019 and 2022 across U.S. states. Darker shades of blue represent smaller falls in participation.

increase in nominal wages) during the years when the shock is active, it is also the sector that suffers most of the unemployment when the shock dissipates.

Appendix figure D.2 depicts the evolution of relative sectoral prices (nominal sectoral prices divided by the aggregate price index). Manufacturing experiences the highest increase in relative price (up to 4%). Agriculture's relative price increases slightly (up to 1%), while the relative price of services decreases (up to -1%).

Turning to regional results, figure 4 presents a map of the cumulative percentage change in labor force participation between 2019 and 2022 for U.S. states. Some of the states where labor participation falls the most are Alaska, Nevada, and Hawaii, while some states where it falls the least are Pennsylvania, Ohio, and Wisconsin.

While the states where participation falls the most tend to have a relatively large service sector and the ones where participation falls the least tend to have a larger manufacturing sector, the way the shock affects each state is not immediately apparent. This is because the fall in participation and the amount of unemployment generated depend on several factors, such as the distribution of labor across sectors, deficits in the pre-pandemic period, and exposure to trade with other countries and other U.S. states, among others.

4.1 Effects on Nominal GDP in Model and Data

So far, we have exclusively presented and discussed model-generated results. We are now interested in testing the model predictions compare to real-world data. However, there are many shocks unrelated to trade costs impacting real-world outcomes that our model intentionally abstracts from. This would render a direct comparison between model and data pointless. Therefore, our approach to provide model validation is to project the change in nominal GDP across states on our measure of exposure, which is precisely designed to assess the response of nominal GDP to trade cost shocks in a given region.

Specifically, we run the following state-level regression:

$$\Delta GDP_s = \beta_0 + \beta_1 \hat{\eta}_s(\hat{\tau}) + \epsilon_s, \tag{1}$$

where ΔGDP_s corresponds to the percentage change between 2019 and 2022 in the nominal GDP of state s (either in the model or in the real-world data) and $\hat{\eta}_s(\hat{\tau})$ represents the exposure measure to the trade cost shock that we introduced in Section 2.1. The results are presented in table 2.

Notice first that the β_1 coefficient estimated from the model (-2.45) is very similar to the one estimated in the data (-2.53). This shows that nominal GDP across U.S. states in the data responded to exposure in a very similar manner to the one predicted by the model,

Table 2: Change in nominal GDP across states projected on exposure

	Model (1)	Data (2)
β_1	-2.456***	-2.533*
	(0.158)	(1.334)
Number of observations	50	50
R^2	0.764	0.055

Notes: This table presents coefficient β_1 and its standard error (in brackets) estimated from regression (1). In Column (1), the dependent variable is the percentage change between 2019 and 2022 across U.S. states implied by the model, while in column (2) the dependent variable is the percentage change between 2019 and 2022 across U.S. states in the real-world data. Standard errors are robust to heteroskedasticity. Asterisks denote statistical significance: *=10%, **=5%, ***=1%.

indicating that the model has a remarkably good fit. The standard deviation of the exposure variable is 0.429. Thus, a state with a one-standard-deviation higher exposure to the shock suffers a roughly 1 percentage point greater fall in nominal GDP than an otherwise comparable state (both according to the model and the data). While both the significance of the β_1 coefficient and the R^2 of the regression for the model-implied response are higher than those for the data-implied response, this is not surprising given that there are many other economic shocks during this period that affected nominal GDP that our model intentionally abstracts from.

5 Alternative Assumptions

This section explores how our results change if we make different assumptions regarding the persistence or size of the shock or the nominal growth rate of world GDP in dollars. We also touch briefly on the consequences of allowing for migration between U.S. states or changing the elasticity of switching sectors.

To begin, we focus on persistence. Different amounts of persistence are captured by having the shock revert after 2, 4, 5, or 6 years instead of 3 years (which is the baseline assumption). Figure 5 illustrates the cumulative change in participation in the broad sectors of home production, manufacturing, and services (agriculture is excluded for simplicity and because it is a small sector) for different values of persistence.

A higher persistence leads to a greater increase in home production and a more substantial decrease in services. Manufacturing, however, is much less sensitive to changes in persistence. This is due to the fact that, out of the three factors affecting sectoral reallocation (fall in aggregate demand, lower productivity, and expenditure switching), a longer shock exacerbates the fall in aggregate demand without increasing the expenditure switching effect. The amount of unemployment generated across different amounts of persistence is essentially the same (i.e., around 0.32%).

We can also explore the impact of varying the size of the shock. Figure 6 depicts the cumulative change in participation in home production, manufacturing, and services for four different values of the shock: 6%, 12%, 18%, and 24%. A larger shock tends to amplify

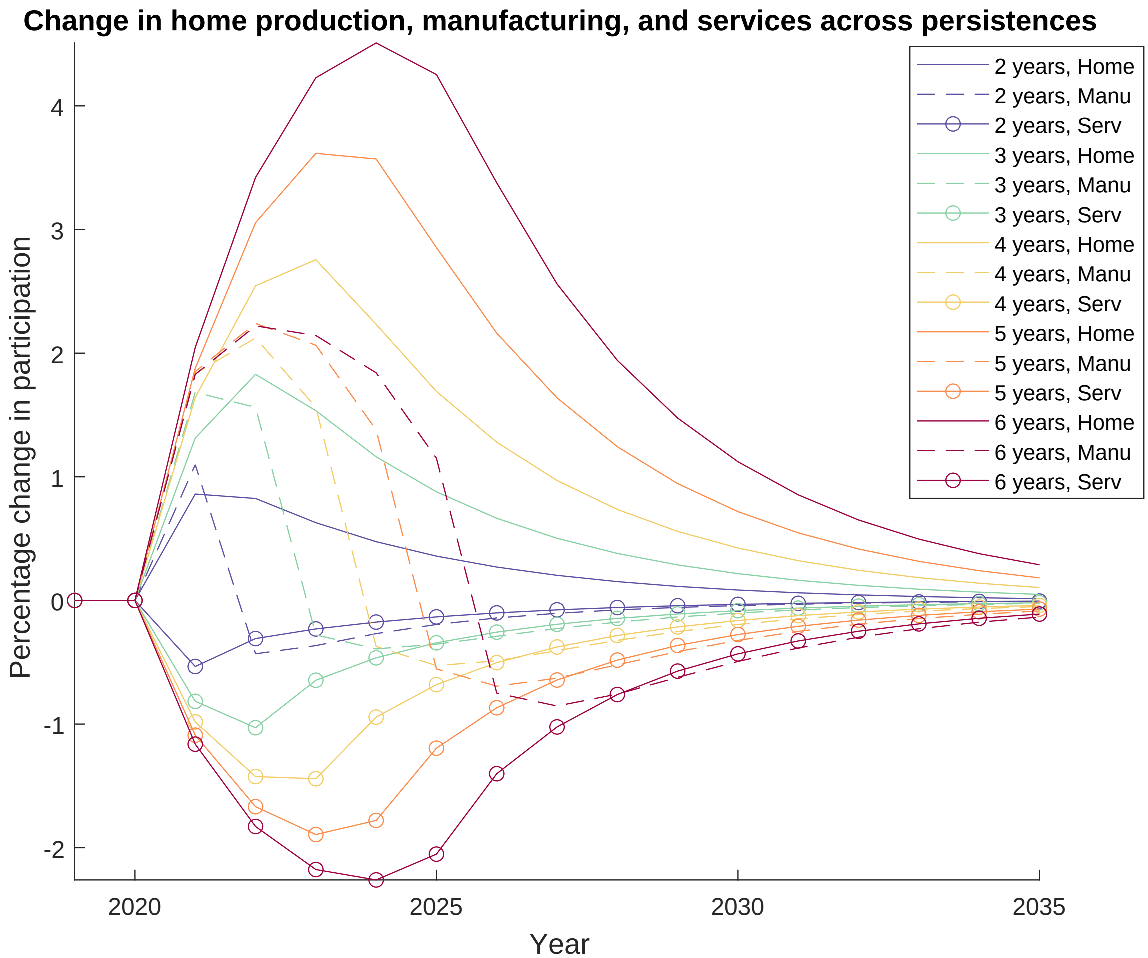

Figure 5: Paths of aggregate U.S. participation for home production, manufacturing, and services across different values for the persistence of the shock. Blue depicts a 2-year persistence, green 3, yellow 4, orange 5, and red 6. A solid line depicts home production, a dashed line depicts manufacturing, and a line with circle markers depicts services.

the effects discussed earlier and generates more unemployment for a given value of γ (the growth rate of world nominal GDP in dollars). In turn, more unemployment discourages participation in the manufacturing sector.

Next, we consider the effects of assuming different values for the annual growth rate of world nominal GDP in dollars (γ). Figure 7 depicts the cumulative change in participation in the broad sectors of home production, manufacturing, and services for different values of γ. A higher γ makes the DNWR less likely to bind and decreases the unemployment generated by the shock. In addition, it leads to a smaller participation increase in home production, a larger increase in manufacturing, and a smaller fall in services. The manu-

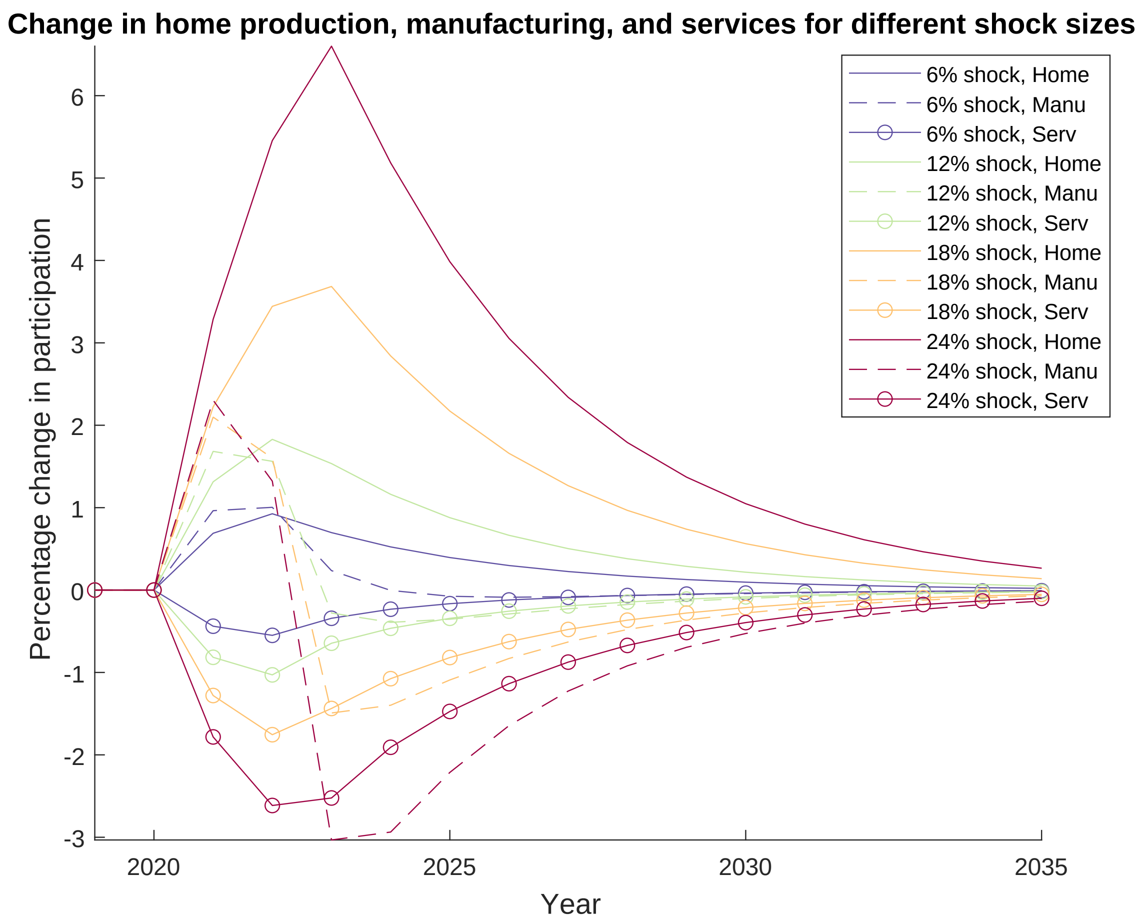

Figure 6: Paths of aggregate U.S. participation for home production, manufacturing, and services across different sizes of the shock. Blue depicts a 6% shock, green 12%, orange 18%, and red 24%. A solid line depicts home production, a dashed line depicts manufacturing, and a line with circle markers depicts services.

facturing sector is particularly sensitive to the value of γ (as it is to the size of the shock) because it is the sector where most of the unemployment occurs when the shock dissipates. If agents realize that a lot of unemployment will be generated, they will hesitate to go into manufacturing in the first place.

The amount of unemployment generated across values of γ differs substantially. While for $\gamma = 4\%$ unemployment reaches 0.32% at its peak, this maximum can reach 1.3% if $\gamma = 3\%$, and almost 3% if $\gamma = 2\%$. In this sense, the model is highly non-linear due to the one-sided nature of the DNWR. More monetary policy accommodation (i.e., a higher γ) when the shock disappears can help alleviate the unemployment consequences of the

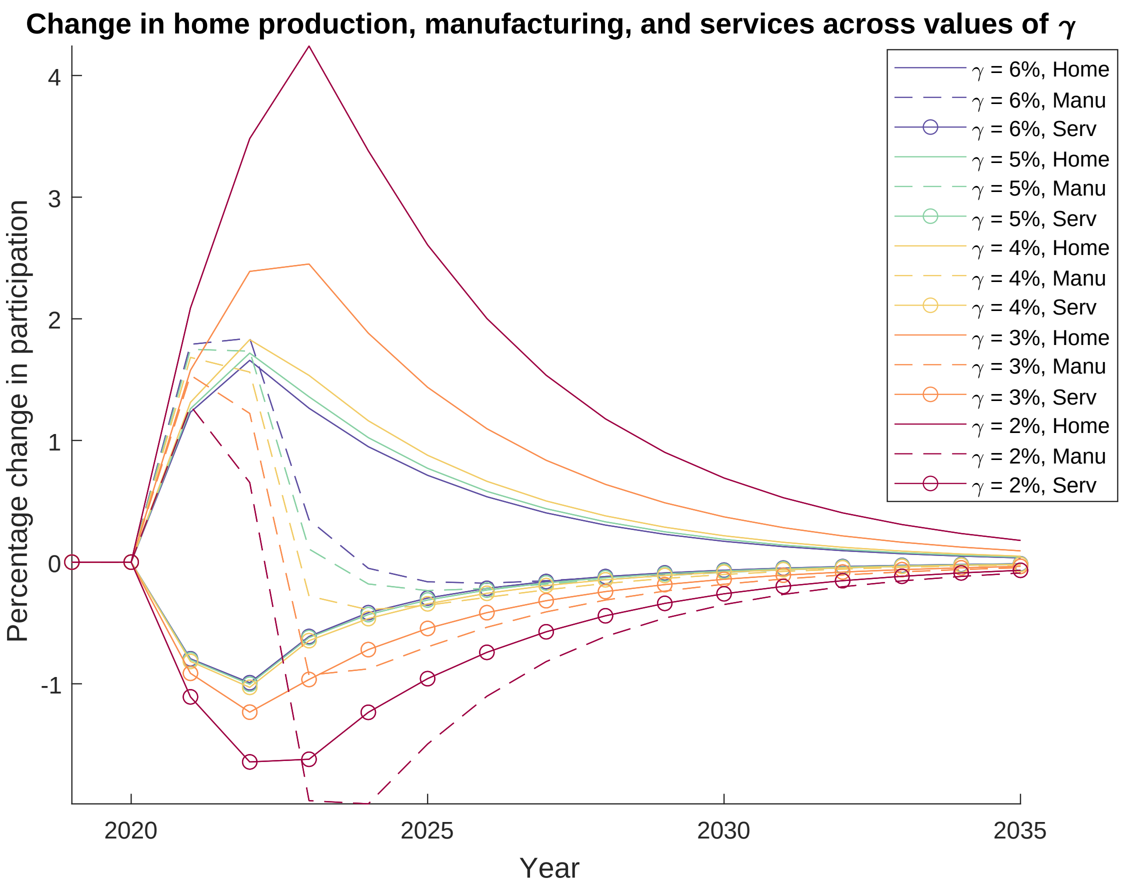

Figure 7: Paths of participation for home production, manufacturing, and services across different values for the growth of world nominal GDP in dollars (γ). Blue depicts 6% growth, green 5%, yellow 4%, orange 3%, and red 2%. A solid line depicts home production, a dashed one depicts manufacturing, and a line with circle markers depicts services.

shock.

Allowing for migration within U.S. states has a small impact on the results discussed so far. Note that when migration across U.S. states is allowed, there is a new elasticity $1/\kappa$ of moving across states that comes into play. RUV calibrate κ to 12 in order to match the evidence found by Autor et al. (2013) on how population across states responds to the China shock. Given that the population response is small, the elasticity of moving across states is calibrated to be low. Additionally, since U.S. states do not have extreme variation in their exposure to the shock we study, the need for reallocation is not too large.

Finally, changes in the inverse elasticity of moving across sectors (ν) do not have a major impact on the results. Naturally, the higher the ν, the lower the elasticity with which agents move across sectors, and hence the smaller the reallocation that occurs due to the trade-cost shock. However, for reasonable values of ν between 0.35 and 0.75 (recall that the baseline value is 0.55), the results discussed above do not change substantially.[17]

6 International Results

In this section, we turn our attention to how the impacts of the trade shock vary across countries. The shock itself is uniform in how it affects the iceberg trade costs of sending products across countries. Nevertheless, countries' exposures to the shock vary due to differences in their openness levels, size, and sectoral compositions. Figure 8 illustrates this idea by displaying the model-implied change in home production participation between 2019 and 2022 for all 38 countries in our sample. The figure shows that large countries such as the United States, China, Japan, Brazil, and India, which are less reliant on international trade due to the size of their domestic market, experience relatively smaller increases in home production participation due to the trade shock. In contrast, smaller and more open countries such as Ireland, Hungary, Estonia, Slovakia, and Cyprus, suffer a greater increase in home production participation (akin to a fall in the labor force).

Figure 9 gives a scatter plot between the exposure measure on the x-axis and the model-implied change in participation in home production between 2019 and 2022 on the y-axis. The plot reveals a tight relationship between the exposure measure and the change in participation. Although the exposure measure is a first-order approximation to the change in nominal GDP that operates through revenue exposure, it still provides a reasonably good fit to the change in participation between 2019 and 2022. A regression of participation change on the exposure measure plus a constant has an R-squared of 91%, and the exposure measure has a p-value substantially below 0.01%.

The reduction in welfare due to the increase in trade costs is almost perfectly correlated with the fall in labor force participation between 2019 and 2022, because it is driven exactly the same factors. Appendix figure D.4 displays the welfare change across countries.[18] The

[17]These results are not included for conciseness but they are available upon request.

[18]The welfare change is measured as the equivalent variation in consumption required by agents in the model in the base year to be indifferent between the counterfactual economy where the trade costs increase and

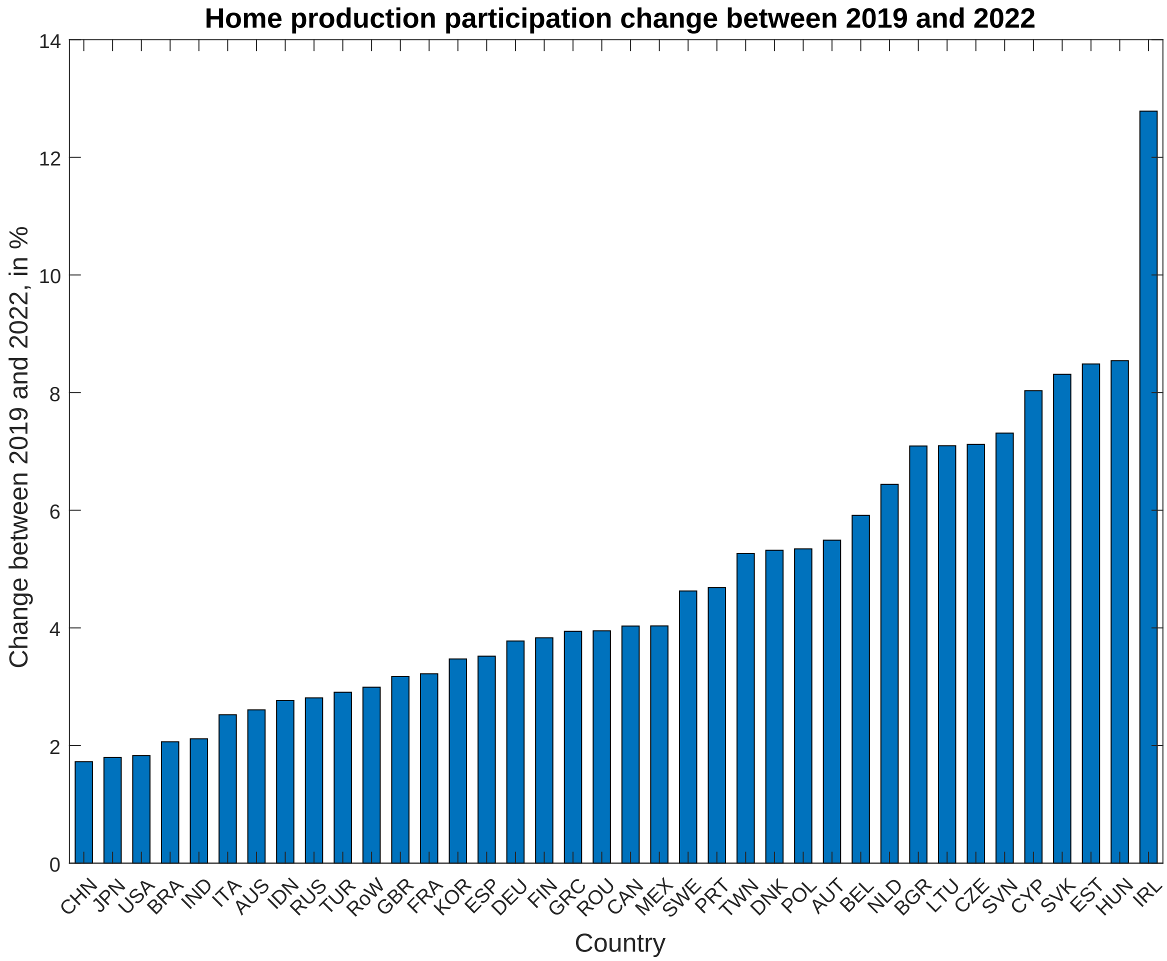

Figure 8: Percentage change in home production participation between 2019 and 2022 across countries, in percent. For country abbreviation codes see appendix C.1.

welfare loss for the United States is approximately 14 basis points. The minimum welfare loss of 13 basis points occurs in China, while the maximum one of 97 basis points occurs in Ireland. The unweighted average welfare loss across the 38 countries in the sample (including the "rest of the world" region) is 37 basis points, while the weighted one is 19 basis points. The fact that the unweighted welfare loss is almost twice as high as the weighted one provides another illustration that countries with smaller populations do much worse in response to the shock that countries with larger populations.

Turning to results in specific sectors, figure 10 illustrates the change in model-implied manufacturing employment across countries between 2019 and 2022.[19] In addition to the

the baseline economy where they do not. The formula is given in RUV, it is a present value sum where we use an annual discount factor of $\beta = 0.95$.

[19]Similarly, appendix figures D.5 and D.6 show changes in service and agricultural employment across coun-

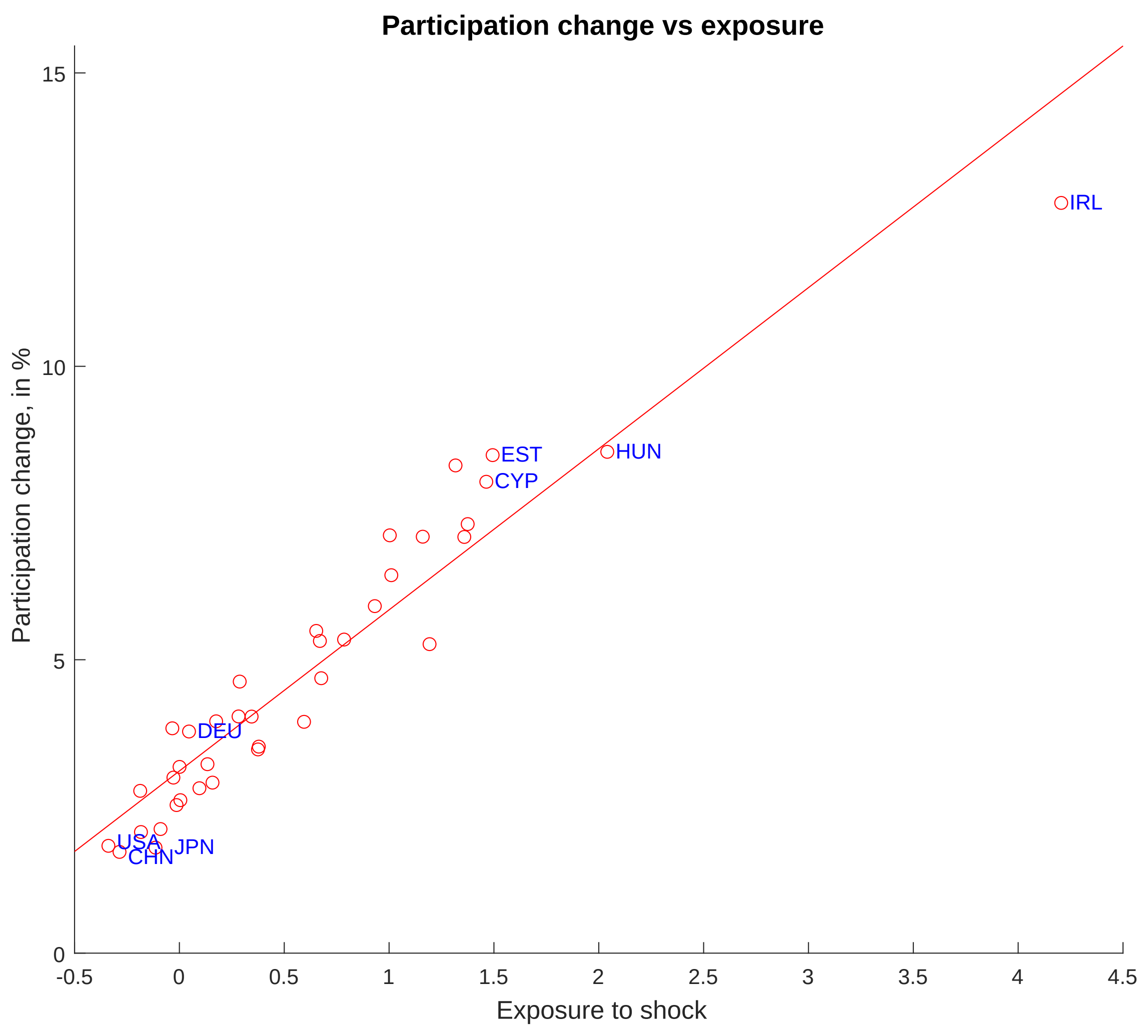

Figure 9: Scatter plot of the percentage change in home production participation between 2019 and 2022 against the exposure measure across countries. For country abbreviation codes see appendix C.1, for the definition of exposure see the text.

aforementioned factors that influence the overall change in labor participation, the change in manufacturing employment also depends on the initial deficit in manufacturing. Countries that are net manufacturing importers, such as the United States, Great Britain, Russia, or Cyprus, need to substitute foreign imports with domestic production, driving up the change in manufacturing employment.

tries between 2019 and 2022.

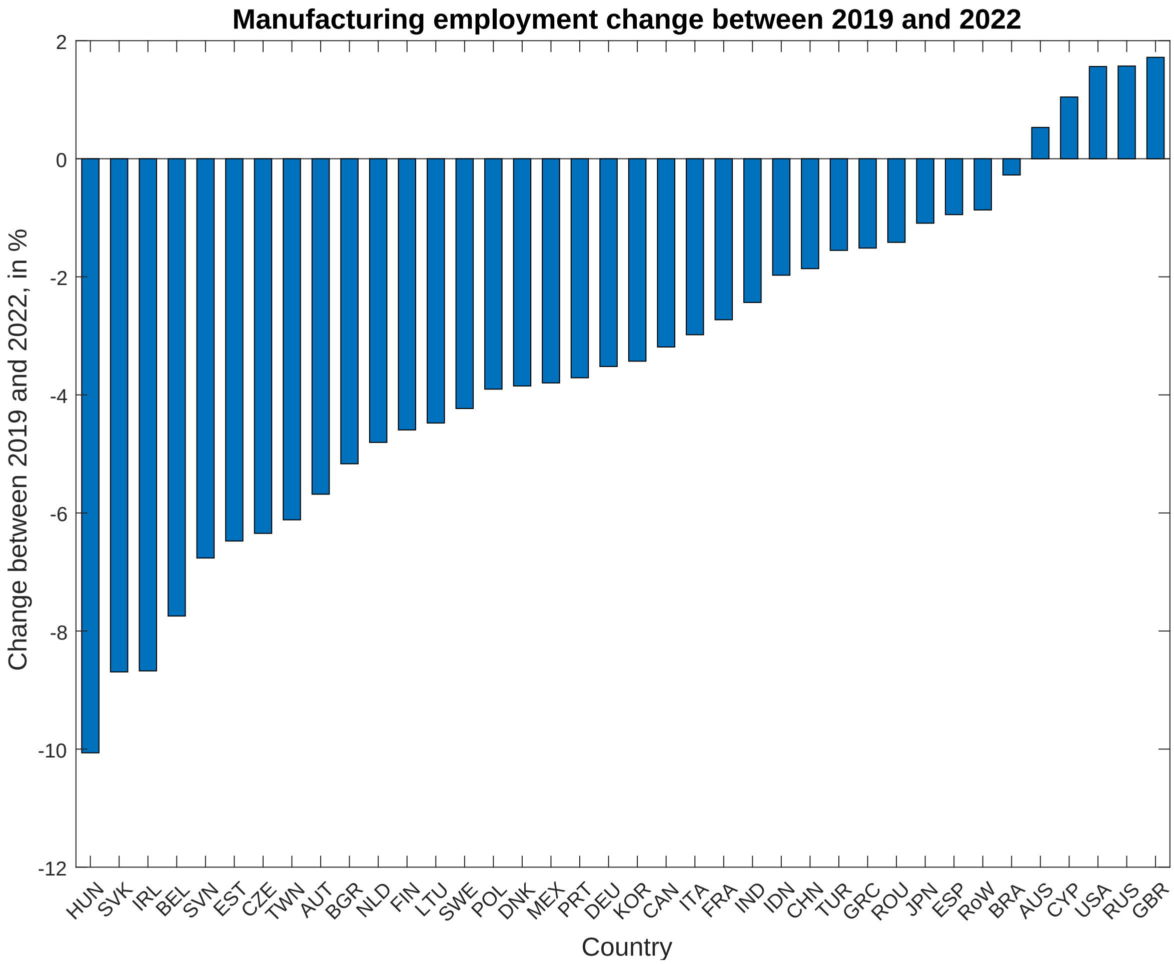

Figure 10: Percentage change in manufacturing employment between 2019 and 2022 across countries, in percent. For country abbreviation codes see appendix C.1.

7 Conclusion

In this paper, we use a dynamic quantitative trade model with an input-output structure and downward nominal wage rigidity to study the effects of temporary increases in trade costs. While the exercise is not meant to fully explain the labor market effects of the COVID-19 pandemic, the baseline quantification aims to isolate the effect of a trade cost increase of comparable magnitude and duration to the one experienced during the pandemic period. Using the structure of the model, we construct an exposure measure to test the model's fit with the data and isolate the effect coming from the change in trade costs.

Our analysis reveals three main results for the United States. First, there is a temporary but persistent decline in labor force participation: while the high trade cost is active, participating in the home production sector (which has a constant real utility flow) temporarily becomes more attractive. Second, there is a temporary increase in manufacturing employment, a highly tradable sector for which the United States is a net importer. By contrast, there are temporary reductions in service and agricultural employment. Third, unemployment is generated when the shock *disappears* because this is the moment when the downward nominal wage rigidity binds. The bulk of the unemployment is generated in manufacturing, where wages increase during the period of high trade costs and must decrease when the shock dissipates. In general, labor force participation tends to fall more in states with a larger service sector (such as Alaska, Nevada, and Hawaii) and less in states with larger manufacturing sectors (such as Ohio, Pennsylvania, and Wisconsin). In regards to the model's fit, we regress the change in nominal GDP across states predicted by the model and the data on our exposure measure and find remarkably similar point estimates.

Our country-level analysis finds that large or closed countries experience smaller declines in labor participation following the shock, while small or open economies experience larger ones. Although this result may seem intuitive, our model provides quantitative estimates of the changes in participation in home production derived from a state-of-the-art trade model, as well as changes in employment in specific sectors such as manufacturing, services, and agriculture.

The framework we propose offers policymakers a valuable tool for estimating the potential impacts of changes in trade costs across countries or sectors lasting different amounts of time. Given the increased risk of supply chain disruptions, our model can be useful in devising effective policy responses.

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Appendix

A Model Equations

The model economy is composed of multiple regions (indexed by i or j). There are M regions inside the U.S. (the 50 U.S. states), plus $I - M$ regions (countries) outside of the U.S. (for a total of I regions). We assume that there is no labor mobility across different countries, but can allow for mobility across different states of the U.S. There are $S + 1$ sectors in the economy (indexed by s or k), with sector zero denoting the home production sector and the remaining S sectors being productive market sectors. In each region j and period t, a representative consumer participating in the market economy devotes all income to expenditure $P_{j,t}C_{j,t}$, where $C_{j,t}$ and $P_{j,t}$ are aggregate consumption and the price index respectively. Aggregate consumption is a Cobb-Douglas aggregate of consumption across the S different market sectors with expenditure shares $\alpha_{j,s}$. As in a multi-sector Armington trade model, consumption in each market sector is a CES aggregate of consumption of the good of each of the I regions, with an elasticity of substitution $\sigma_s > 1$ in sector s.

Each region produces the good in sector s with a Cobb-Douglas production function, using labor with share $\phi_{j,s}$ and intermediate inputs with shares $\phi_{j,ks}$, where $\phi_{j,s} + \sum_k \phi_{j,ks} = 1$. TFP in region j, sector s, and time t is $A_{j,s,t}$. There is perfect competition and iceberg trade costs $\tau_{ij,s,t} \geq 1$ for exports from i to j in sector s. Intermediates from different origins are aggregated in the same way as consumption goods. Letting $W_{i,s,t}$ denote the wage in region i, sector s, at time t, the price in region j of good s produced by region i at time t is then

$$p_{ij,s,t} = \tau_{ij,s,t} A_{i,s,t}^{-1} W_{i,s,t}^{\phi_{i,s}} \prod_k P_{i,k,t}^{\phi_{i,ks}}, \tag{A1}$$

where $P_{i,k,t}$ is the price index of sector k in region i at time t. Given our Armington assumption, these price indices satisfy

$$P_{j,s,t}^{1-\sigma_s} = \sum_{i=1}^{I} p_{ij,s,t}^{1-\sigma_s}, \tag{A2}$$

with corresponding trade shares

$$\lambda_{ij,s,t} \equiv \frac{p_{ij,s,t}^{1-\sigma_s}}{\sum_{r=1}^{I} p_{rj,s,t}^{1-\sigma_s}}. \tag{A3}$$

Let $R_{i,s,t}$ and $L_{i,s,t}$ denote total revenues and employment in sector s of country i, respectively. Noting that the demand of industry k of country j of intermediates from sector s is $\phi_{j,sk} R_{j,k,t}$ and allowing for exogenous deficits, the market clearing condition for sector s in country i can be written as

$$R_{i,s,t} = \sum_{j=1}^{I} \lambda_{ij,s,t} \left(\alpha_{j,s} \left(\sum_{k=1}^{S} W_{j,k,t} L_{j,k,t} + D_{j,t} \right) + \sum_{k=1}^{S} \phi_{j,sk} R_{j,k,t} \right), \tag{A4}$$

where $D_{j,t}$ are transfers received by region j, with $\sum_j D_{j,t} = 0$. In turn, employment must be compatible with labor demand,

$$W_{i,s,t} L_{i,s,t} = \phi_{i,s} R_{i,s,t}. \tag{A5}$$

Agents can either engage in home production or look for work in the labor market. If they participate in the labor market, they can be employed in any of the S market sectors. We let $c_{i,0,t}$ denote consumption associated with home production in region i, and $c_{i,s,t}$ denote consumption associated with seeking employment in sector s and region i at time t. We assume that $c_{i,0,t}$ is exogenous and does not vary over time, while – as explained further below – $c_{i,s,t}$ is endogenous and depends on real wages and unemployment. Additionally, we denote the number of agents that participate in region i, sector s, at time t, by $\ell_{i,s,t}$.

Agents are forward looking and they face a dynamic problem where they discount the future at rate β. Relocation decisions are subject to sectoral and spatial mobility costs. Specifically, there are costs $\varphi_{ji,sk}$ of moving from region j, sector s to region i, sector k. These costs are time invariant, additive, and measured in terms of utility. Additionally, agents have additive idiosyncratic shocks for each choice of region and sector, denoted by $\epsilon_{i,s,t}$.

An agent that starts in region j and sector s observes the economic conditions in all labor markets and the idiosyncratic shocks, then earns real income $c_{j,s,t}$ and has the option to relocate. The lifetime utility of an agent who is in region j, sector s, at time t, is then:

$$\mathrm{v}_{j,s,t} = \ln(c_{j,s,t}) + \max_{\{i,k\}_{i=1,k=0}^{I,S}} \{\beta \mathbb{E}(\mathrm{v}_{i,k,t+1}) - \varphi_{ji,sk} + \epsilon_{i,k,t}\}.$$

We assume that the joint density of the vector ϵ at time t is a nested Gumbel:

$$F(\epsilon) = \exp\left(-\sum_{i=1}^{I}\left(\sum_{k=0}^{S}\exp\left(-\epsilon_{i,k,t}/\nu\right)\right)^{\nu/\kappa}\right),$$

where $\kappa > \nu$. This allows us to have different elasticities of moving across regions and sectors. Let $V_{j,s,t} \equiv \mathbb{E}(\mathrm{v}_{j,s,t})$ be the expected lifetime utility of a representative agent in labor market j, s. Then, using γ to denote the Euler-Mascheroni constant, we have

$$V_{j,s,t} = \ln(c_{j,s,t}) + \ln\left(\sum_{i=1}^{I}\left(\sum_{k=0}^{S}\exp\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)^{1/\nu}\right)^{\nu/\kappa}\right)^{\kappa} + \gamma\kappa. \tag{A6}$$

Denote by $\mu_{ji,sk|i,t}$ the number of agents that relocate from market js to ik expressed as a share of the total number of agents that move from js to ik' for any sector k'. Additionally, let $\mu_{ji,s\#,t}$ denote the fraction of agents that relocate from market js to any market in i as a share of all the agents in js. As shown in RUV, these fractions are given by

$$\mu_{ji,sk|i,t} = \frac{\exp\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)^{1/\nu}}{\sum_{h=0}^{S}\exp\left(\beta V_{i,h,t+1} - \varphi_{ji,sh}\right)^{1/\nu}} \tag{A7}$$

$$\mu_{ji,s\#,t} = \frac{\left(\sum_{h=0}^{S}\exp\left(\beta V_{i,h,t+1} - \varphi_{ji,sh}\right)^{1/\nu}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\left(\sum_{h=0}^{S}\exp\left(\beta V_{m,h,t+1} - \varphi_{jm,sh}\right)^{1/\nu}\right)^{\nu/\kappa}}. \tag{A8}$$

The total number of agents that move from js to ik is given by $\mu_{ji,sk} = \mu_{ji,sk|i,t} \cdot \mu_{ji,s\#,t}$. Participation in the different labor markets evolves according to

$$\ell_{i,k,t+1} = \sum_{j=1}^{I}\sum_{s=0}^{S}\mu_{ji,sk|i,t}\mu_{ji,s\#,t}\ell_{j,s,t} \tag{A9}$$

The aggregate price index in region i at time t is given by:

$$P_{i,t} = \prod_{s=1}^{S} P_{i,s,t}^{\alpha_{i,s}}. \tag{A10}$$

We assume that the income generated in a sector-region is equally shared between all participants in that sector-region. Since agents get real wage $W_{i,s,t}/P_{i,t}$ with probability $L_{i,s,t}/\ell_{i,s,t}$ if they seek employment in sector s of region i at time t, we have

$$c_{i,k,t} = \frac{W_{i,k,t}}{P_{i,t}} \cdot \frac{L_{i,k,t}}{\ell_{i,k,t}}. \tag{A11}$$

We denote the number of agents that are actually employed in region i and sector k at time t with $L_{i,k,t}$. In a standard trade model, labor market clearing requires that the labor used in a sector and region be equal to labor supplied to that sector, i.e. $L_{i,k,t} = \ell_{i,k,t}$. We depart from this assumption and instead follow Schmitt-Grohe and Uribe (2016) by allowing for downward nominal wage rigidity, which might lead to an employment level that is strictly below labor supply,

$$L_{i,k,t} \leq \ell_{i,k,t}. \tag{A12}$$

All prices and wages up to now have been expressed in U.S. dollars. In contrast, a given region faces DNWR in terms of its local currency unit. Letting $W_{i,k,t}^{LCU}$ denote nominal wages in local currency units, the DNWR takes the following form:

$$W_{i,k,t}^{LCU} \geq \delta_k W_{i,k,t-1}^{LCU}, \qquad \delta_k \geq 0.$$

Letting $E_{i,t}$ denote the exchange rate between the local currency unit of region i and the local currency unit of region 1 (which is the U.S. dollar) in period t (in units of dollars per LCU of region i), then $W_{i,k,t} = W_{i,k,t}^{LCU} E_{i,t}$ and so the DNWR for wages in dollars entails

$$W_{i,k,t} \;\; \geq \;\; \frac{E_{i,t}}{E_{i,t-1}} \delta_k W_{i,k,t-1}.$$

Since all regions within the U.S. share the dollar as their LCU, then $E_{i,t} = 1$ and $W_{i,k,t}^{LCU} = W_{i,k,t}$ $\forall$ $i \leq M$. This means that the DNWR in states of the U.S. takes the familiar form $W_{i,k,t} \geq \delta_k W_{i,k,t-1}$. For the $I - M$ regions outside of the U.S., the LCU is not the dollar and so the behavior of the exchange rate impacts how the DNWR affects the real economy. The DNWR in dollars can then be captured using a country-specific parameter $\delta_{i,k}$, i.e.:

$$W_{i,k,t} \geq \delta_{i,k} W_{i,k,t-1}, \qquad \delta_{i,k} \geq 0. \tag{A13}$$

The baseline model assumes that all regions outside of the U.S. have a flexible exchange rate (so the DNWR never binds). This is captured by setting $\delta_{i,k} = \delta_k$ $\forall$ $i \leq M$ and $\delta_{i,k} = 0$ $\forall$ $i > M$. There is also a complementary slackness condition,

$$(\ell_{i,k,t} - L_{i,k,t})(W_{i,k,t} - \delta_{i,k} W_{i,k,t-1}) = 0. \tag{A14}$$

So far, we have introduced nominal elements to the model (i.e., the DNWR), but we have not introduced a nominal anchor that prevents nominal wages from rising so much in each period as too make the DNWR always non-binding. We now want to capture the general idea that central banks are unwilling to allow inflation to be too high because of its related costs. In traditional macro models, this is usually implemented via a Taylor rule, where the policy rate reacts to inflation. Instead, we use a nominal anchor that captures a similar idea in a way that naturally lends itself to quantitative implementation in our trade model. A similar nominal anchor is used in Guerrieri et al. (2021), albeit in the context of a static, closed economy model. In particular, we assume that world nominal GDP in dollars grows at a constant rate γ every year,

$$\sum_{i=1}^{I} \sum_{k=1}^{K} W_{i,k,t} L_{i,k,t} = (1+\gamma) \sum_{i=1}^{I} \sum_{k=1}^{K} W_{i,k,t-1} L_{i,k,t-1}. \tag{A15}$$

The main benefit of this nominal anchor assumption is that it allows us to solve our otherwise-unwieldy model using a fast contraction-mapping algorithm in the spirit of Alvarez and Lucas (2007) that we develop to deal with the complementary slackness condition brought by the DNWR.

Following CDP, we can think of the full equilibrium of our model in terms of a temporary equilibrium and a sequential equilibrium. In our environment with DNWR, given last period's nominal world GDP ($\sum_{i=1}^{I}\sum_{s=1}^{S} W_{i,s,t-1}L_{i,s,t-1}$), wages $\{W_{i,s,t-1}\}$, and the current period's labor supply $\{\ell_{i,s,t}\}$, a temporary equilibrium at time t is a set of nominal wages $\{W_{i,s,t}\}$ and employment levels $\{L_{i,s,t}\}$ such that equations (A1)-(A5) and (A12)-(A15) hold. In turn, given starting world nominal GDP ($\sum_{i=1}^{I}\sum_{s=1}^{S} W_{i,s,0}L_{i,s,0}$), labor supply $\{\ell_{i,s,0}\}$, and wages $\{W_{i,s,0}\}$, a sequential equilibrium is a sequence $\{c_{i,s,t}, V_{i,s,t}, \mu_{ji,sk|i,t}, \mu_{ji,s\#,t}, \ell_{i,s,t}, W_{i,s,t}, L_{i,s,t},\}_{t=1}^{\infty}$ such that: (i) at every period t $\{W_{i,s,t}, L_{i,s,t}\}$ constitute a temporary equilibrium given $\sum_{i=1}^{I}\sum_{s=1}^{S} W_{i,s,t-1}L_{i,s,t-1}$, $\{W_{i,s,t-1}\}$, and $\{\ell_{i,s,t}\}$, and (ii) $\{c_{i,s,t}, V_{i,s,t}, \mu_{ji,sk|i,t}, \mu_{ji,s\#,t}, \ell_{i,s,t}\}_{t=1}^{\infty}$ satisfy equations (A6)-(A11).

We are interested in obtaining the effects of the trade cost shock as it is introduced in an economy that did not previously expect this shock. In order to do this we will use the exact hat algebra methodology of Dekle et al. (2007), extended to dynamic settings by Caliendo et al. (2019). Specifically, we use $\hat{x}_t$ to denote the ratio between a relative time difference in the counterfactual economy ($\dot{x}'_t$) and a relative time difference in the baseline economy ($\dot{x}_t$), i.e. $\hat{x}_t = \dot{x}'_t / \dot{x}_t$ for any variable x. Then we compare a counterfactual economy where the knowledge of the trade shock is unexpectedly introduced in the year 2020 (and agents have perfect foresight about the path of the shock from then on), with a baseline economy where the trade shock does not occur.

B Exposure of a Region to a Trade Shock

Notice that, omitting the time subscript and introducing equation (A4) into it, equation (A5) can be written as:

$$W_{i,s}L_{i,s} = \phi_{i,s}\sum_{j=1}^{I}\lambda_{ij,s}X_{j,s},$$

where $X_{j,s}$ is the total expenditure of location j in sector s and the trade shares can now be expressed as

$$\lambda_{ij,s} = \frac{(mc_{i,s}\tau_{ij,s})^{1-\sigma_s}}{\sum_{r=1}^{I}(mc_{r,s}\tau_{rj,s})^{1-\sigma_s}},$$

with

$$mc_{i,s} = \frac{W_{i,s}^{\phi_{i,s}} \prod_{k=1}^{S} P_{i,k}^{\phi_{i,ks}}}{A_{i,s}}, \tag{B1}$$

and

$$P_{i,s} = \left(\sum_{j=1}^{I} (mc_{j,s}\tau_{ji,s})^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}. \tag{B2}$$

We are interested in constructing an exposure measure for region i to a change in the whole vector of iceberg trade costs $\boldsymbol{\tau}$ (as done, for example, in Adao et al., 2020). We define as our outcome of interest the total wage bill (WB) in region i:

$$WB_i = \sum_{s=1}^{S} W_{i,s} L_{i,s}.$$

Then, we can obtain the exposure measure from a first order approximation to the previous equation (keeping the $X_{j,s}$ fixed as is commonly done when deriving such exposure measures):

$$\begin{aligned} d\ln WB_i &= \sum_{s=1}^{S} (1-\sigma_s) \underbrace{\frac{W_{i,s}L_{i,s}}{\sum_k W_{i,k}L_{i,k}}}_{\omega_{i,s}} \left(\sum_{j=1}^{I} \underbrace{\frac{\lambda_{ij,s}X_{j,s}}{\sum_n \lambda_{in,s}X_{n,s}}}_{r_{ij,s}} \left[d\ln\tau_{ij,s} + d\ln mc_{i,s} \right.\right. \\ &\quad \left.\left. - \sum_{q=1}^{I} \lambda_{qj,s}(d\ln\tau_{qj,s} + d\ln mc_{q,s}) \right] \right), \end{aligned} \tag{B3}$$

where $\omega_{i,s}$ corresponds to the share of wage bill from sector s in the total wage bill of region i and $r_{ij,s}$ corresponds to the share of sales of region i-sector s in region j. The formula is similar to the one in AAE, the differences are that here the marginal cost is allowed to vary with the trade shock (which is relevant due to the presence of intermediate inputs) and that in AAE $\ell_{i,s}$ corresponds to the share of labor in sector s in region i whereas here it is a share of the wage bill.

Taking the partial derivative of (B1) with respect to trade costs, we get:

$$d\ln mc_{i,s} = \sum_k \phi_{i,ks} d\ln P_{i,k}, \tag{B4}$$

which we can write as:

$$\widehat{\boldsymbol{mc}} = \boldsymbol{\Phi}\hat{\boldsymbol{P}}, \tag{B5}$$

where $\widehat{\boldsymbol{mc}}$ is a $(I \cdot S) \times 1$ vector of marginal cost changes, $\hat{\boldsymbol{P}}$ is a $(I \cdot S) \times 1$ vector of price changes, and Φ is a $(I \cdot S) \times (I \cdot S)$ block diagonal matrix that contains as its i-th diagonal block the input-output matrix of region I.

If we then take derivative with respect to trade costs in (B2), we get:

$$d \ln P_{i,k} = \sum_{j=1}^{I} \lambda_{ji,k}(d \ln \tau_{ji,k} + d \ln mc_{j,k}), \tag{B6}$$

which we can write as:

$$\hat{\boldsymbol{P}} = \Lambda_1 \hat{\boldsymbol{\tau}} + \Lambda_2 \widehat{\boldsymbol{mc}}, \tag{B7}$$

where Λ_1 is a $(I \cdot S) \times (I \cdot I \cdot S)$ matrix of trade shares, $\hat{\boldsymbol{\tau}}$ is a $(I \cdot I \cdot S) \times 1$ vector of trade cost changes, and Λ_2 is a $(I \cdot S) \times (I \cdot S)$ different (from Λ_1) matrix of trade shares. Introducing (B5) in this last equation, we get:

$$\begin{aligned} \hat{\boldsymbol{P}} &= \Lambda_1 \hat{\boldsymbol{\tau}} + \Lambda_2 \boldsymbol{\Phi} \hat{\boldsymbol{P}} \\ (I - \Lambda_2 \boldsymbol{\Phi})\hat{\boldsymbol{P}} &= \Lambda_1 \hat{\boldsymbol{\tau}} \\ \hat{\boldsymbol{P}} &= (I - \Lambda_2 \boldsymbol{\Phi})^{-1} \Lambda_1 \hat{\boldsymbol{\tau}}. \end{aligned} \tag{B8}$$

Therefore, we conclude that:

$$\widehat{\boldsymbol{mc}} = \boldsymbol{\Phi}(I - \Lambda_2 \boldsymbol{\Phi})^{-1} \Lambda_1 \hat{\boldsymbol{\tau}}. \tag{B9}$$

We can use this equation to write (B3) solely in terms of the trade cost shock.

C Data Construction

C.1 Data Description and Sources

List of sectors. We use a total of 14 market sectors. The list includes 12 manufacturing sectors, one catch-all services sector, and one agriculture sector (ICIO sectors D01T02, D03). We follow RUV in the selection of the 12 manufacturing sectors. These are: **1)** Food, beverage, and tobacco products (NAICS 311-312, ICIO sector D10T12); **2)** Textile, textile product mills, apparel, leather, and allied products (NAICS 313-316, ICIO sector D13T15); **3)** Wood products, paper, printing, and related support activities (NAICS 321-323, ICIO sectors D16, D17T18); **4)** Mining, petroleum and coal products (NAICS 211-213, 324, ICIO sectors D05T06, D07T08, D09, D19); **5)** Chemicals (NAICS 325, ICIO sectors D20, D21); **6)** Plastics and rubber products (NAICS 326, ICIO sector D22); **7)** Nonmetallic mineral products (NAICS 327, ICIO sector D23); **8)** Primary metal and fabricated metal products (NAICS 331-332, ICIO sectors D24, D25); **9)** Machinery (NAICS 333, ICIO sector D28); **10)** Computer and electronic products, and electrical equipment and appliance (NAICS 334-335, ICIO sectors D26, D27); **11)** Transportation equipment (NAICS 336, ICIO sectors D29, D30); **12)** Furniture and related products, and miscellaneous manufacturing (NAICS 337-339, ICIO sector D31T33). There is a **13)** Services sector which includes Construction (NAICS 23, ICIO sector D41T43); Wholesale and retail trade sectors (NAICS 42-45, ICIO sectors D45T47); Accommodation and Food Services (NAICS 721-722, ICIO sector D55T56); transport services (NAICS 481-488, ICIO sectors D49-D53); Information Services (NAICS 511-518, ICIO sectors D58T60, D61, D62T63); Finance and Insurance (NAICS 521-525, ICIO sector D64T66); Real Estate (NAICS 531-533, ICIO sector D68); Education (NAICS 61, ICIO sector D85); Health Care (NAICS 621-624, ICIO sector D86T88); and Other Services (NAICS 493, 541, 55, 561, 562, 711-713, 811-814, ICIO sectors D69T75, D77T82, D90T93, D94T96, D97T98).

List of countries: As in RUV, we use data for 50 U.S. states, 36 other countries and a constructed rest of the world. The list of countries is: Australia (AUS), Austria (AUT), Belgium (BEL), Bulgaria (BGR), Brazil (BRA), Canada (CAN), China (CHN), Cyprus (CYP), Czechia (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany

(DEU), Greece (GRC), Hungary (HUN), India (IND), Indonesia (IDN), Italy (ITA) Ireland (IRL), Japan (JPN), Lithuania (LTU), Mexico (MEX), the Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Russia (RUS), Spain (ESP), the Slovak Republic (SVK), Slovenia (SVN), South Korea (KOR), Sweden (SWE), Taiwan (TWN), Turkey (TUR), the United Kingdom (GBR), and the rest of the world (RoW).

C.2 Data on Bilateral Trade

For bilateral trade between countries we use the OECD's Inter-Country Input-Output (ICIO) Database. For data on bilateral trade in manufacturing between U.S states, we combine the Commodity Flow Survey (CFS) with the ICIO database. The CFS records shipments between U.S states for 43 commodities classified according to the Standard Classification of Transported Goods (SCTG). We follow CDP and use CFS tables that cross-tabulate establishments by their assigned NAICS codes against SCTG commodities shipped by establishments within each of the NAICS codes.

For data on bilateral trade in manufacturing and agriculture between U.S states and the rest of the countries, we follow RUV and obtain sector-level imports and exports between the 50 U.S. states and the list of other countries from the Import and Export Merchandise Trade Statistics database, which is compiled by the U.S. Census Bureau.

For data on services and agriculture expenditure and production, we use U.S. state-level services GDP from the Regional Economic Accounts of the Bureau of Economic Analysis (BEA), U.S. state-level services expenditure from the Personal Consumption Expenditures (PCE) database of BEA and total production and expenditure in services from ICIO (for other countries). We also use the Agricultural Census and the National Marine Fisheries Service Census to get state-level production data on crops, livestock, and seafood. For other countries we compute production and expenditure in agriculture from ICIO.

For data on sectoral and regional value added share in gross output, we use data from the Bureau of Economic Analysis (BEA) by subtracting taxes and subsidies from GDP data. In the cases when gross output was smaller than value added we constrain value added to be equal to gross output. For the list of other countries we obtain the share of value added in gross output using data on value added and gross output data from ICIO.

C.3 Data on Employment and Labor Flows

For the case of countries, we take data on employment by country and sector from the WIOD Socio Economic Accounts (WIOD-SEA) and International Labor Organization (ILO). For the case of U.S. states, we take sector-level employment (including unemployment and non-participation) from a combination of the Census and the American Community Survey (ACS). As in RUV, we only keep observations with age between 25 and 65, who are either employed, unemployed, or out of the labor force. We construct a matrix of migration flows between sectors and U.S. states by combining data from the ACS and the Current Population Survey (CPS). Finally, we abstract from international migration.

D Additional Figures

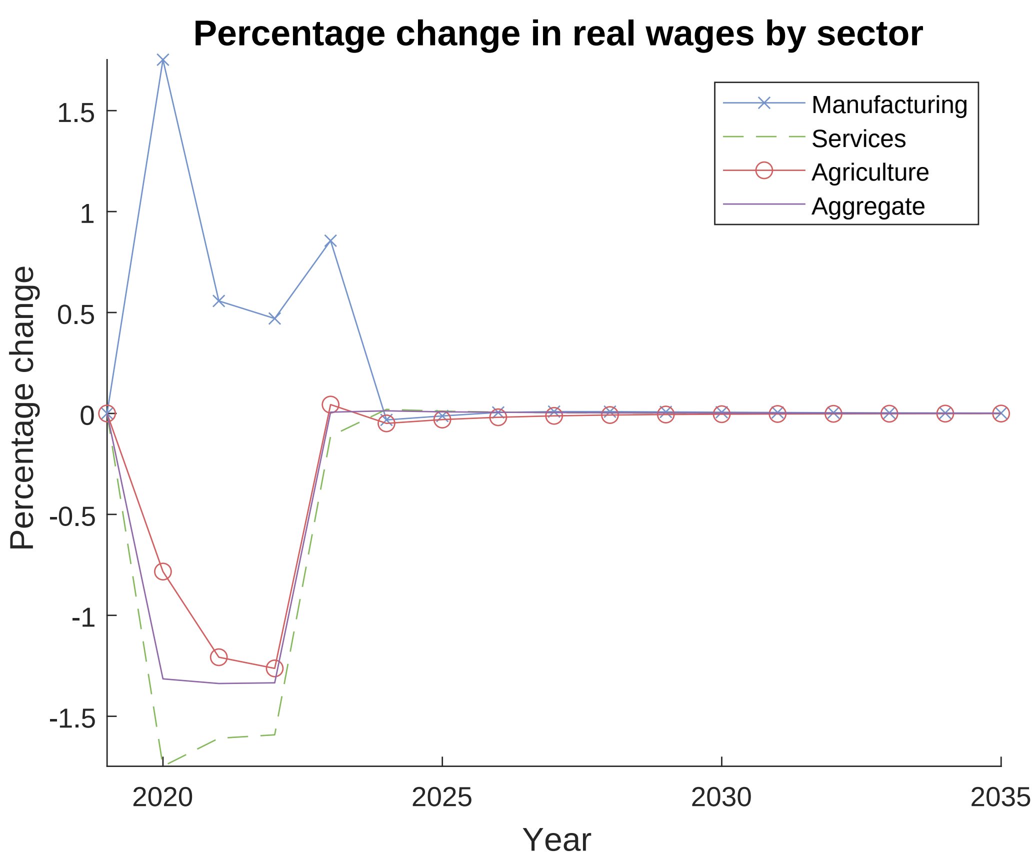

Figure D.1: Paths of cumulative percentage change since 2019 in real wages for manufacturing, services, agriculture, and on aggregate.

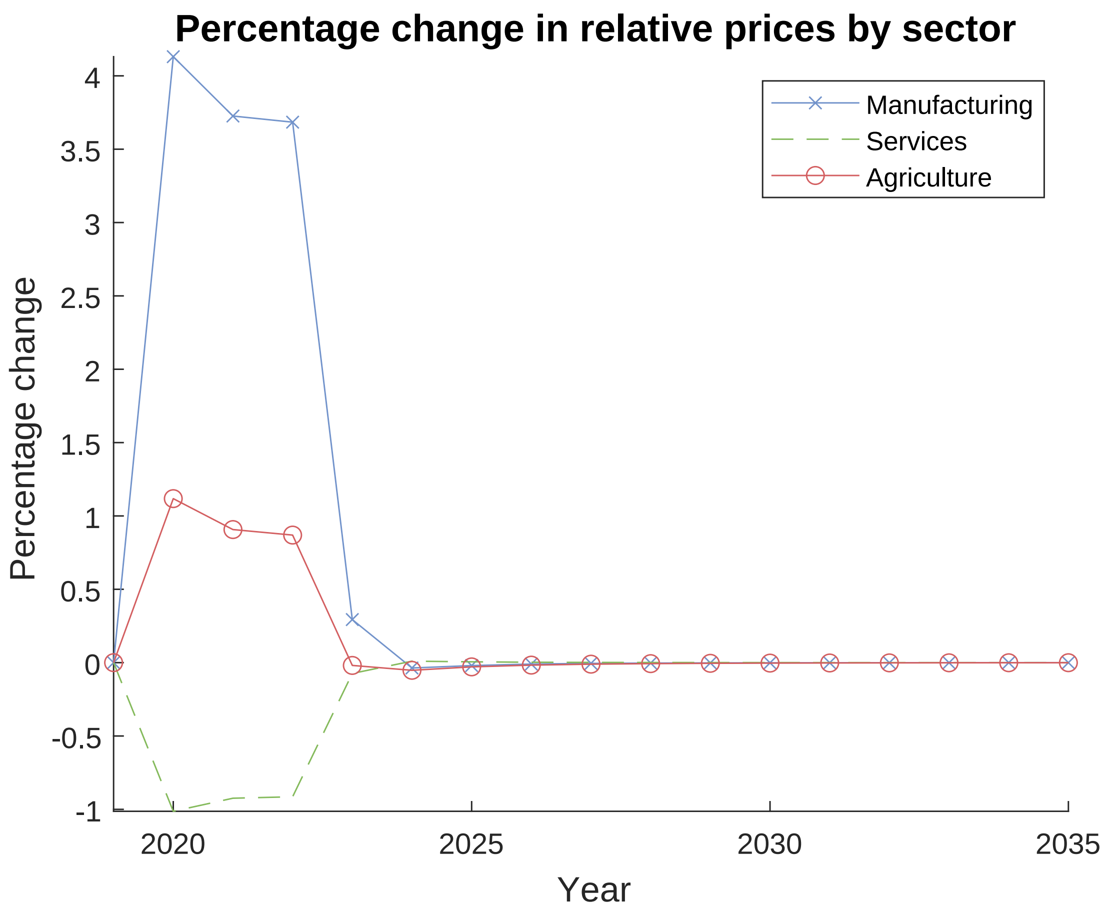

Figure D.2: Paths of cumulative percentage change since 2019 in the relative prices of manufacturing, services, and agriculture.

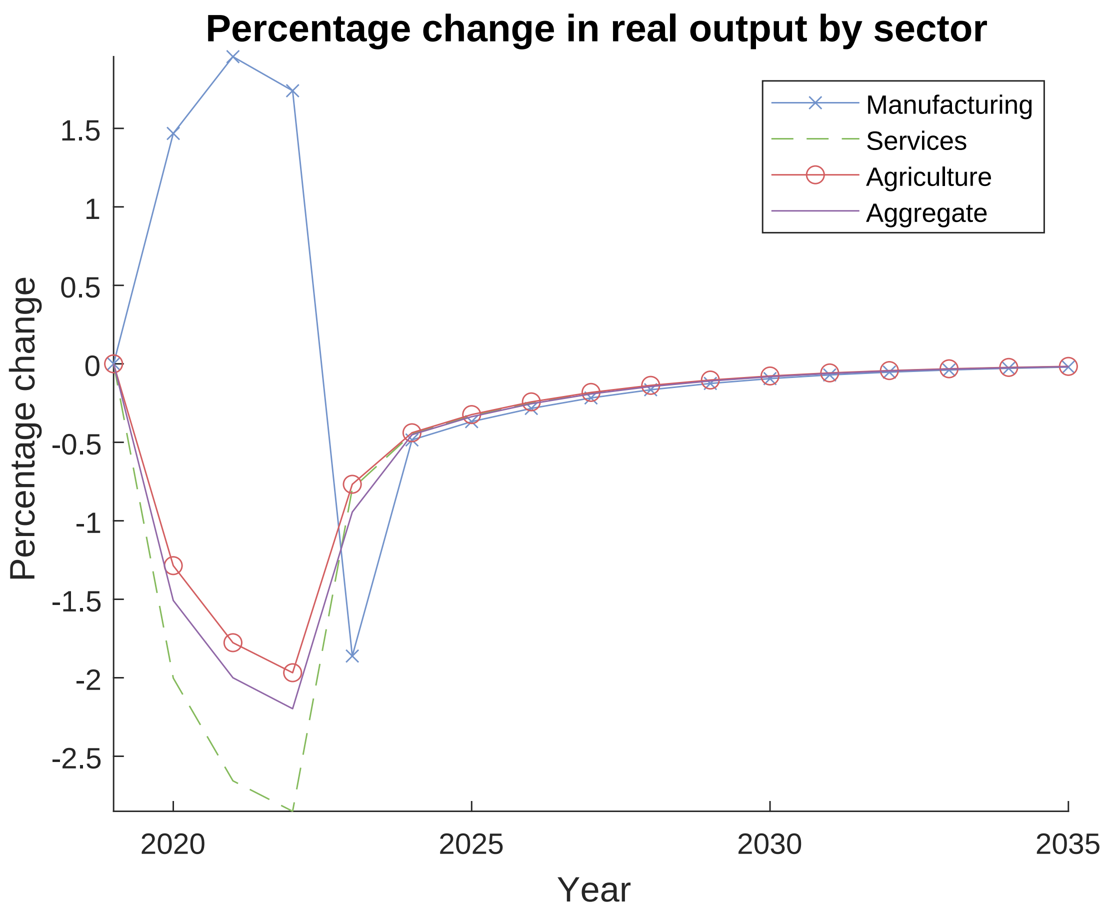

Figure D.3: Paths of cumulative percentage change since 2019 in real output for manufacturing, services, agriculture, and on aggregate.

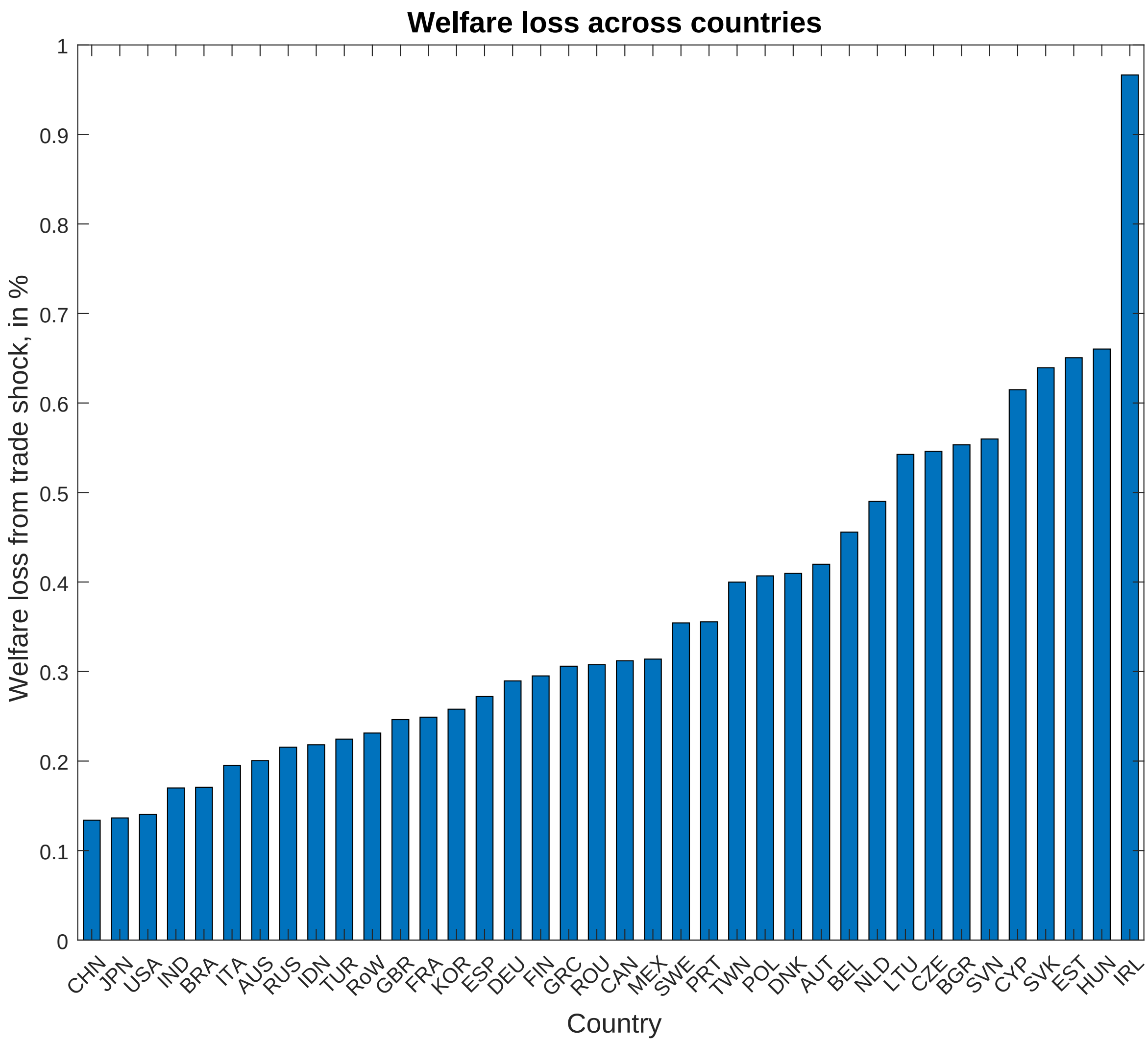

Figure D.4: Welfare loss from the trade shock across countries, in percent. For country abbreviation codes see appendix C.1.

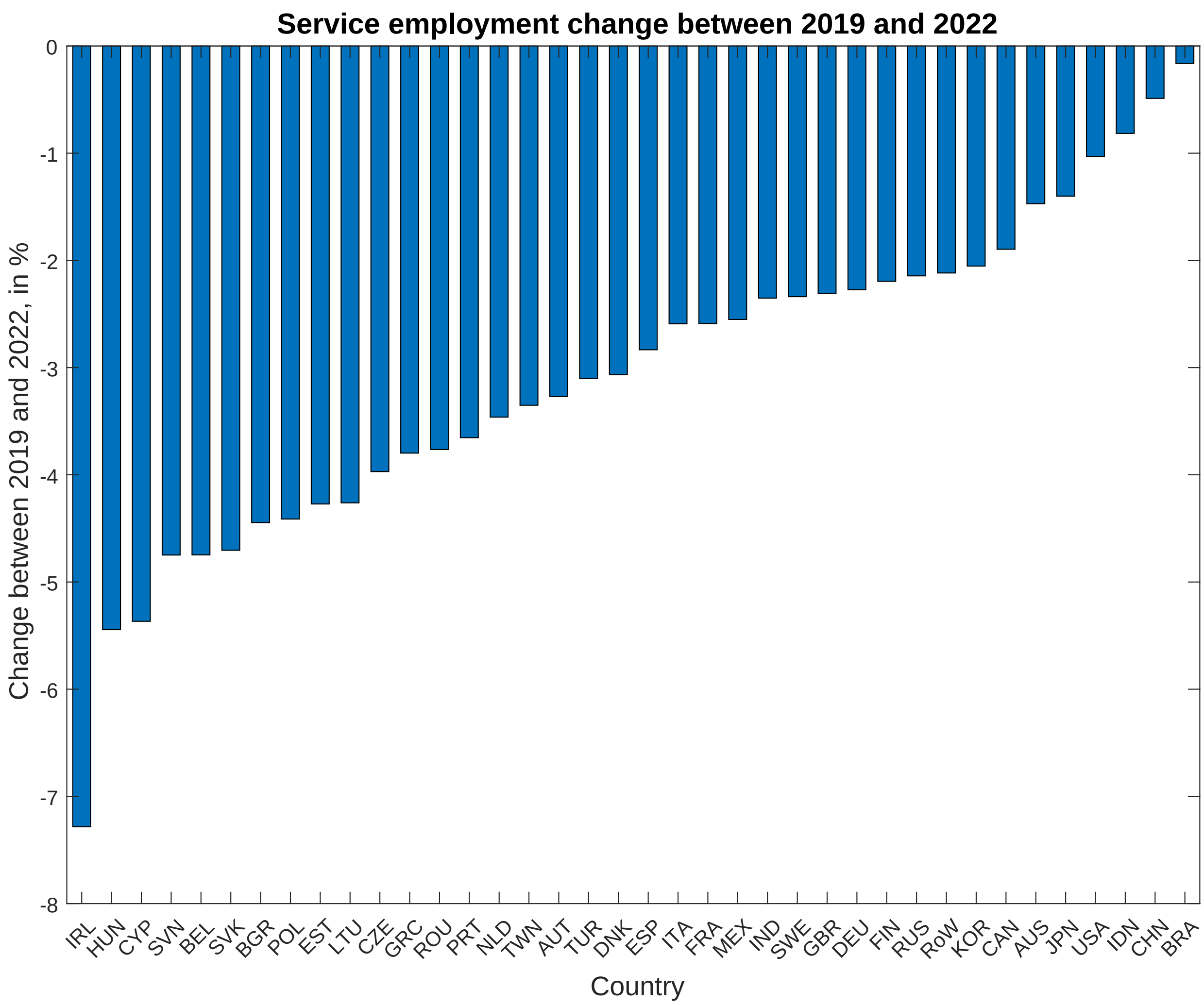

Figure D.5: Percentage change in service employment between 2019 and 2022 across countries, in percent. For country abbreviation codes see appendix C.1.

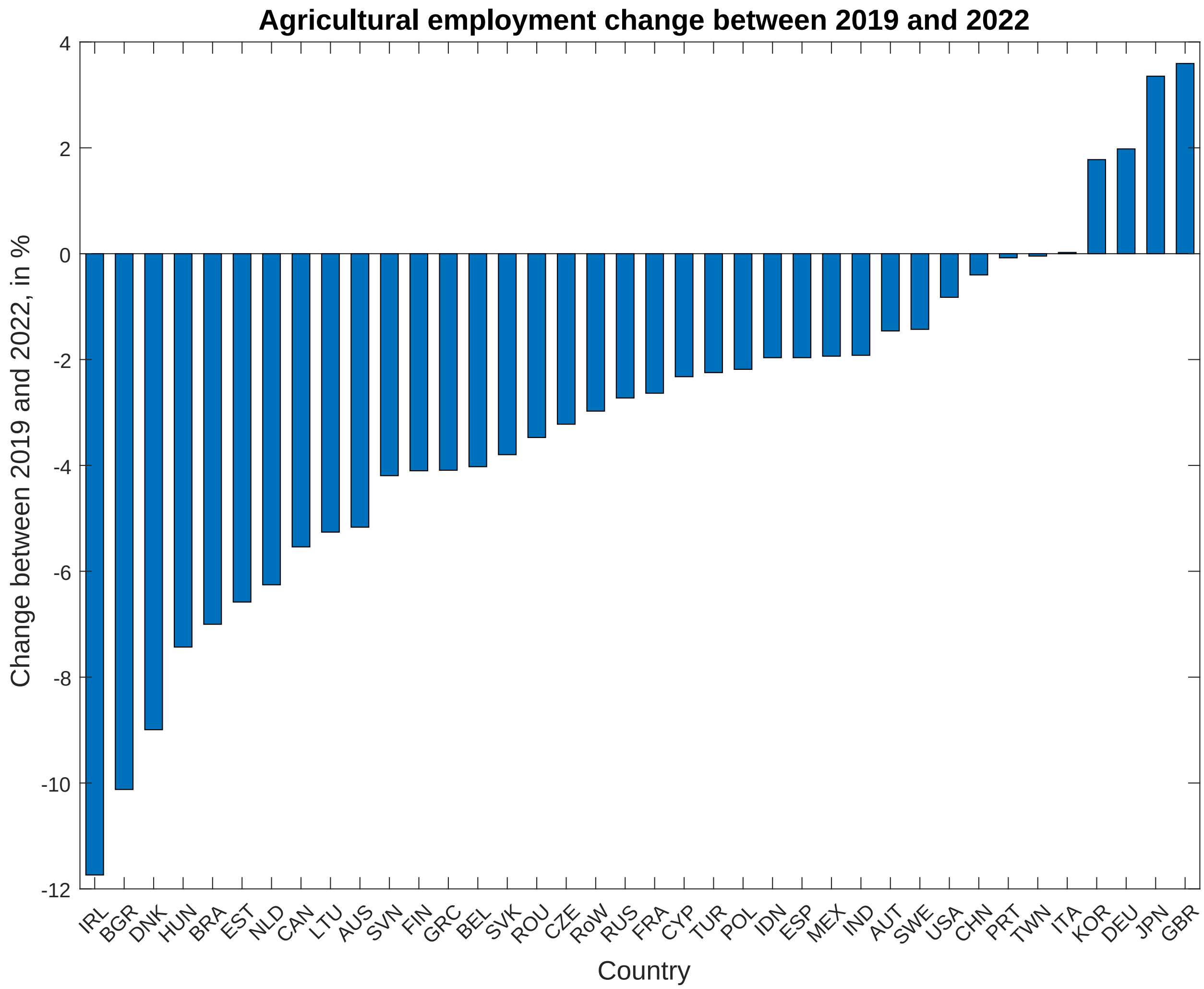

Figure D.6: Percentage change agricultural employment between 2019 and 2022 across countries, in percent. For country abbreviation codes see appendix C.1.