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 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 an 8.5 basis points 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, 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. These challenges, in turn, can trigger 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 studies the quantitative labor market consequences of a temporary but 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 two years, which approximates the size and duration of the trade-cost shock during the COVID-19 pandemic.[1] We also examine how the effects of the shock depend on its size (i.e., $x = 6\%, 18\%$, or 24%), actual persistence (i.e., $\tau = 1, 3, 4, 5$, or 6), or persistence perceived by economic agents. We place special emphasis on how the shock impacts labor markets within the United States, due to the richness of our framework in modeling U.S. regions and mobility patterns, but turn to cross-country results towards the end of the paper.

We make use of the quantitative trade model developed by Rodriguez-Clare, Ulate, and Vasquez (2024, henceforth RUV) but pair it with novel data and a focus on analyzing the short-run 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

[1] One of the reasons we stop the shock after two years in our baseline is to avoid comparing our model-generated data to real-world data affected by the war in Ukraine that started in February of 2022. However, we perform robustness exercises with respect to the duration of the shock.

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.[2]

We capture DNWR as in Schmitt-Grohe and Uribe (2016), indicating that the nominal wage in any period must be no less than a factor δ times the nominal wage in the previous period.[3] 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.[4] 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 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.[5]

We assemble a 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. We leverage 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)

[2]Our baseline model does not feature regional mobility within countries. However, in an unreported extension, we have verified that the consequences of allowing migration across U.S. regions are fairly small.

[3]See 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 framework uses this modeling device as a parsimonious way to capture such frictions in a rich dynamic quantitative trade model.

[4]Our baseline analysis also assumes fixed exchange rates between the U.S. dollar and other countries' currencies. However, we have also conducted an alternative analysis with flexible exchange rates, and the implications for the United States are very similar.

[5]Introducing other types of nominal anchors prevents us from using the efficient Alvarez-and-Lucas type algorithm developed in RUV to deal with DNWR, increasing computation time by orders of magnitude.

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 (as in 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. 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), the units of analysis certainly have differential exposures to the shock. This is due to the fact that region-sectors differ in many relevant aspects such as 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., $\gamma = 1\%$, 2%, 3%, or 5%). Finally, we obtain ν directly from RUV, and take σ from the trade literature.[6]

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 lower labor force participation. Once the shock dissipates, there is negative pressure on nominal wages as the economy adjusts to the lower trade costs, which can generate unemployment in the presence of DNWR. The impact of the trade-cost shock on the labor market varies by sector. There is a temporary employment increase in manufac-

[6]We take into consideration the fact that the trade elasticity varies depending on the frequency, use a value that is appropriate for the relevant frequency, and perform robustness exercises with respect to other values.

turing, a relatively tradable sector where the United States is a net importer. By contrast, services and agriculture experience temporary employment reductions. The manufacturing sector, where wages increase the most during the high trade cost period, experiences most of the 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 and Hawaii) tend to experience a more significant decline in labor force participation than those with larger manufacturing sectors (such as Ohio and Pennsylvania).

We validate our model's fit by regressing changes in GDP per capita and other labor market responses on model-predicted changes (in the spirit of Davis and Weinstein, 2001; Costinot and Donaldson, 2012; Adao et al., 2020). We find that changes in data outcomes align reasonably well with the model-predicted ones, especially for U.S. states, where our calibration is more detailed. There, the model explains 12% of non-employment variation despite many unmodeled economic and health shocks during the analysis period.

We also investigate how different assumptions affect our results. We consider alternative specifications where we assume different expectations of the shock's duration by economic agents (following Fan et al., 2023) or vary the trade elasticity, the persistence of the shock, the size of the shock, or the nominal growth rate of world GDP. Our conclusions are qualitatively robust across these specifications. Quantitatively, a key lesson is that more monetary accommodation can mitigate the impact of the shock on unemployment.

Turning to cross-country results, the consequences of the shock for labor force participation vary internationally and depend on size and trade openness. Countries like China and the United States, which are relatively large and less reliant on international trade, experience a smaller decrease in labor force participation. By contrast, small and open economies like Ireland 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 as a whole. 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 (like fiscal-stimulus measures or extended unemployment insurance). We seek to hone in on the specific effects of an international trade-cost shock. However, the model has a broad range of applications, as its framework helps elucidate how the employment effects of various shocks can propagate through the input-output network. For example, negative demand or productivity shocks can lead to similar outcomes to those of a trade-cost shock in labor markets, particularly under DNWR.[7]

Our paper contributes to the literature studying the causes and consequences of disruptions in global supply chains. While there are some papers examining 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.

[7]Specifically, technology and trade costs enter the structure of the model in a very similar way, implying that productivity shocks in other countries can lead to similar outcomes in the U.S. as those under trade-cost shocks. On the demand side, we find little correlation between demand shocks, such as fiscal-stimulus measures, and pre-shock industrial composition (a key determinant of relative impacts across U.S. states), indicating that incorporating fiscal aspects into the counterfactuals might not affect the relative effects much.

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 some elements that other papers in this literature have studied (explicit lockdown measures, inventories, capital investment, shipping networks, 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 have also examined migration shocks (Caliendo et al., 2021, 2022) or automation (Galle and Lorentzen, 2022).[8] 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. By contrast, our paper uses a quantitative framework similar to the one in RUV to study the labor market effects of recent global supply chain disruptions, modeled as an unexpected increase in international trade costs.[9]

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 calibration. Section 4 presents the results of our baseline analysis for U.S. states along with our empirical validation. 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.

[8]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).

[9]Our paper also adds to the rapidly growing trade literature that discusses or incorporates nominal elements (see RUV, Comin and Johnson, 2020; Costinot et al., 2022; Fadinger et al., 2022; Kim et al., 2024).

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 ($I = 87$: the 50 U.S. states, 36 other countries, and an aggregate rest of the world region) and S sectors ($S = 15$: home production, 12 manufacturing sectors, services, and agriculture). In the baseline model, we assume that there is no mobility across countries or states of the U.S. Allowing for migration across U.S. states makes little difference for our results.

Total consumption in a given region is a Cobb-Douglas aggregate of consumption across all the market sectors with given time-invariant expenditure shares.[10] 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 region, with an elasticity of substitution σ_s.

We denote the region i, sector s, and time t triad as (i, s, t). Production uses labor and intermediate inputs. 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 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. $\phi_{i,s} + \sum_k \phi_{i,ks} = 1$.

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

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 due to supply 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:

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

We denote the number of agents participating in (i, s, t) by $\ell_{i,s,t}$. 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 $(i, s, t-1)$, i.e.:

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

Given this rigidity, employment does not necessarily have to equal labor supply; it could be strictly below it.[11] This is captured by the following weak inequality:

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

Importantly, unemployment can only occur 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:

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

[11] 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.

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 level of real consumption which does not depend on labor market conditions. By contrast, a given market sector $s > 0$ yields a level of real consumption $c_{i,s,t}$ which is endogenous.

Given the existence of downward nominal wage rigidity, agents must consider the possibility of unemployment when choosing their sector. To simplify the analysis, we assume a representative agent in each sector-region.[12] 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, 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

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

captures the idea that central banks are unwilling to allow inflation or unemployment to be too high while at the same time being amenable for quantification.[13] 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 for solving the model, it has limitations and might not reflect the optimal monetary policy of any given country. Thus, we refrain from discussing the implications of the trade-cost shock on 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 the agents in our baseline specification have "perfect foresight", which is relaxed in Section 5). As the shock hits, employment, prices, production, and trade respond accordingly.[14]

[13] 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).

[14] Appendix B derives and discusses an exposure measure that can be used to assess how vulnerable any given region is to a specific trade shock in the spirit of Adao et al. (2020).

3 Data, Calibration, and Shocks

3.1 Data Construction

We use trade and employment data for 50 U.S. states, 36 other countries, and an aggregate rest of the world. We consider home production and 14 market sectors: services, agriculture and 12 manufacturing subsectors. We mostly follow RUV but use 2019 as the base year. We summarize the data construction below, with details in Appendix C.

Labor, input, and consumption shares: Data from the BEA and the OECD's Inter-Country Input-Output Database (ICIO) are used to calculate value-added shares (the labor share in the model) and input-output coefficients for each region. Consumption shares are inferred from trade flows, labor shares, and input shares.

Bilateral trade flows: The model requires bilateral trade flows between regions for all sectors, constructed in four steps described below. Details are in Appendix C.2. First, we use sector-level bilateral trade data among countries directly from the ICIO database.

Second, we use the Commodity Flow Survey (CFS) to measure bilateral trade flows in manufacturing between U.S. states. As in Stumpner (2019), we use the 2007 mapping between commodities and industries to compute trade flows at the state-sector level. In contrast with Stumpner (2019), we exclude international shipments and those mapped to wholesale and retail. Additionally, since some CFS industry aggregates (adding across all states) might not coincide with the amounts that the United States trades with itself according to ICIO, we multiply the CFS flows by a "proportionality" constant that scales the CFS values up or down such that the sum of U.S. internal flows across all states adds up to the total U.S. internal trade from ICIO. Note that this proportionality constant (which is industry-specific but the same for all states) keeps the relative importance of each state in each industry the same as in the raw CFS. Nevertheless, this adjustment is necessary not to distort the relative importance of U.S. internal trade versus its trade with other countries.

In the third step, we use the Import and Export Merchandise Trade Statistics from the U.S. Census to calculate 2019 sector-level trade flows in manufacturing and agriculture between U.S. states and other countries. In the final step, we use data from BEA and ICIO to construct service trade flows based on a gravity model. We apply a similar method to agricultural trade using Agricultural Census data.

Labor supply and labor mobility: Employment data by sector comes from WIOD, ILO, and BLS. Labor force participation is the share of individuals aged 25-65 employed or unemployed. U.S. intersectoral mobility data comes from the CPS, with frictionless mobility assumed for other countries. Interstate mobility data in the U.S. comes from the ACS.

Nominal GDP and lockdown days: We use nominal GDP data from the BEA (U.S. states) and the World Bank (countries), along with 2020 lockdown days from the Oxford COVID-19 Government Response Tracker (OxCGRT). We use this data to construct outcomes and controls in our model-validation exercise in Section 4.1.

3.2 Parameter Calibration

We now describe the parameters used in the baseline specification. Notice that γ (the nominal growth rate of world GDP in U.S. dollars) and δ (the DNWR 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 1% and 5%) in Section 5. The implications go in the expected direction. The higher the γ, the less binding the DNWR is, and the less unemployment is generated in the model. For a high γ of 5% or higher, the model has essentially the same behavior as the model without DNWR. The outcomes of the model unrelated to unemployment are only slightly affected by the choice of γ.

The inverse elasticity of moving across sectors (ν) 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. Finally, we assume that $\sigma_s = \sigma \ \forall s$, which implies that the trade elasticity $(1 - \sigma_s)$ is the same in all sectors. The trade elasticity is a parameter that depends on the frequency of the underlying shock with respect to which the elasticity is being measured, as documented, among others, by Boehm et al. (2023). In our baseline, we use $\sigma = 2.44$ (the midpoint of the estimates in Boehm et al., 2023), but we discuss robustness to alternative values of σ in Section 5.

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 two years. In alternative exercises described in Section 5, we explore how the effects of the shock depend on its size (e.g., 24% instead of 12%) and perceived or actual persistence.[15]

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 appendix Figure D.1. This index increased by approximately 12% from its pre-pandemic level of 330 in December 2019 to around 370 in December 2021 (a window of two years corresponding to our baseline shock duration).

The choice of a two-year duration for the shock is based on suggestive evidence that global supply chain disruptions had largely subsided by 2022. Another reason we stop the shock after two years in our baseline is to avoid comparing our model-generated data to real-world data affected by the war in Ukraine that started in February of 2022. Thus, we assume that high trade costs are in effect for 2020 and 2021 but then dissipate by 2022.

[15]While we model a shock to all region-sectors (as opposed to estimating which region-sectors were subject to a more severe shock due to shipping networks as in Ganapati et al., 2021), different region-sectors are differentially exposed to the shock due to their differential trade exposure as discussed in appendix B.

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. The 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 two years (2020-2021). We discuss the effects on aggregate U.S. labor force participation, employment, and unemployment, as well as on labor supply to the broad sectors of manufacturing, services, and agriculture. Furthermore, we assess how these effects vary across U.S. states. Importantly, we also compare real-world changes in GDP per capita and other labor market responses across U.S. states against their model-generated counterparts and find a reasonable fit.

Figure 1 displays the effects of the shock on model-implied employment-related outcomes for the United States as a whole. The green dashed line shows the cumulative percentage change in labor supply since 2019, the red line with circular markers shows the level of unemployment (in percent), and the blue crossed line depicts the cumulative percentage change in employment since 2019.[16]

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 -0.35% occurring in 2021. 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 rise even faster, resulting in a decrease in real wages (see appendix figure D.2), which is what causes some individuals to exit the labor force.

[16] The blue line is essentially the combination of the green and red lines (labor supply and unemployment).

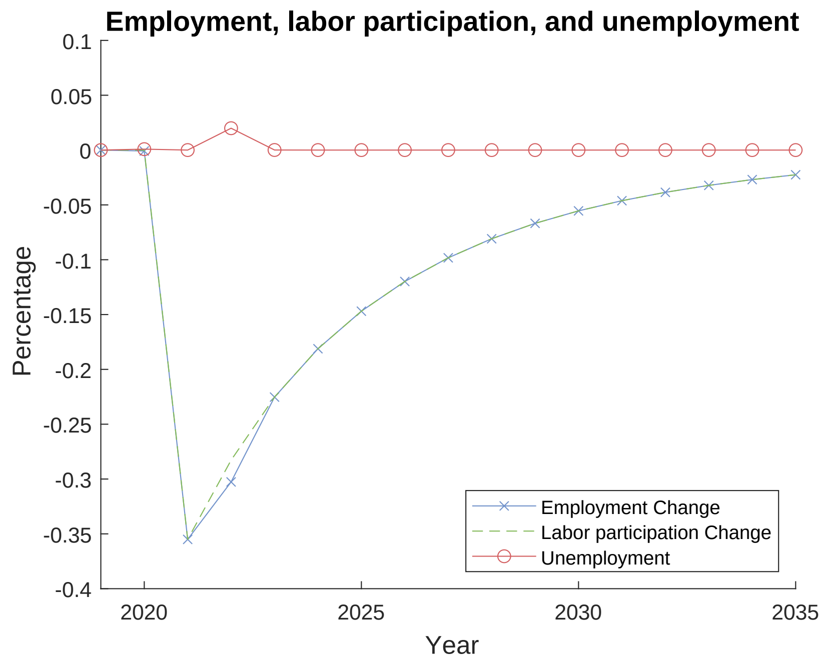

Figure 1: Paths of relevant variables for the U.S. on aggregate. The cumulative percentage change in employment since 2019 is in blue, the cumulative percentage change in labor supply since 2019 is in green, and the level of unemployment (in percent) is in red. The years in the x-axis go from 2019 until 2035.

The recovery of labor supply once the shock disappears is slow, by 2027 labor supply is still 0.1% lower than pre-shock. In the model, the costs of switching between market sectors and the costs of entering/exiting the labor force are implicitly calibrated based on pre-pandemic mobility patterns. These patterns suggest substantial costs associated with relocating across sectors, which explains the gradual labor-force recovery.

A small amount of unemployment of around 2 basis points is generated in 2022 when the shock dissipates. 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.[17] Consequently, those locations hit the DNWR and experience some temporary

[17] 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.

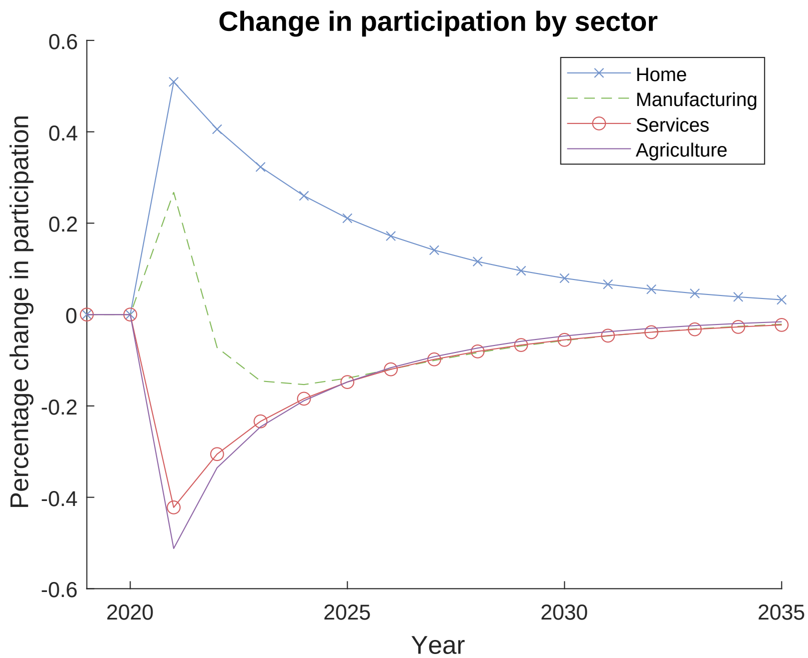

Figure 2: Paths of aggregate participation for different broad U.S. sectors. The percentage change in home production from the baseline year of 2019 is in blue, the percentage change in labor supply to the manufacturing sector since 2019 is in green, the same concept for the service sector is in red, and for the agricultural sector is in purple.

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 our model does not incorporate the lockdowns or health disruptions induced by the COVID-19 pandemic. We abstract from these features in an attempt to focus on 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. In addition, the amount of unemployment generated depends on the degree of monetary accommodation, as discussed in Section 5.

Figure 2 displays the cumulative percentage change since 2019 of activity (i.e., the number of people engaged) in four broad sectors for the United States 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 increase 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 other sectors. Several forces affect employment in each market sector. First, there is a general decrease in demand due to the aggregate fall in employment (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 goods, 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 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.3 depicts the evolution of relative sectoral prices (nominal sectoral prices divided by the aggregate price index). Manufacturing experiences the highest increase in relative price (around 3.5%). Agriculture's relative price increases slightly (up to 1%), while the relative price of services decreases (around -1%).

Turning to regional results, Figure 3 presents a map of the cumulative percentage change in labor force participation between 2019 and 2021 for U.S. states. Some 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

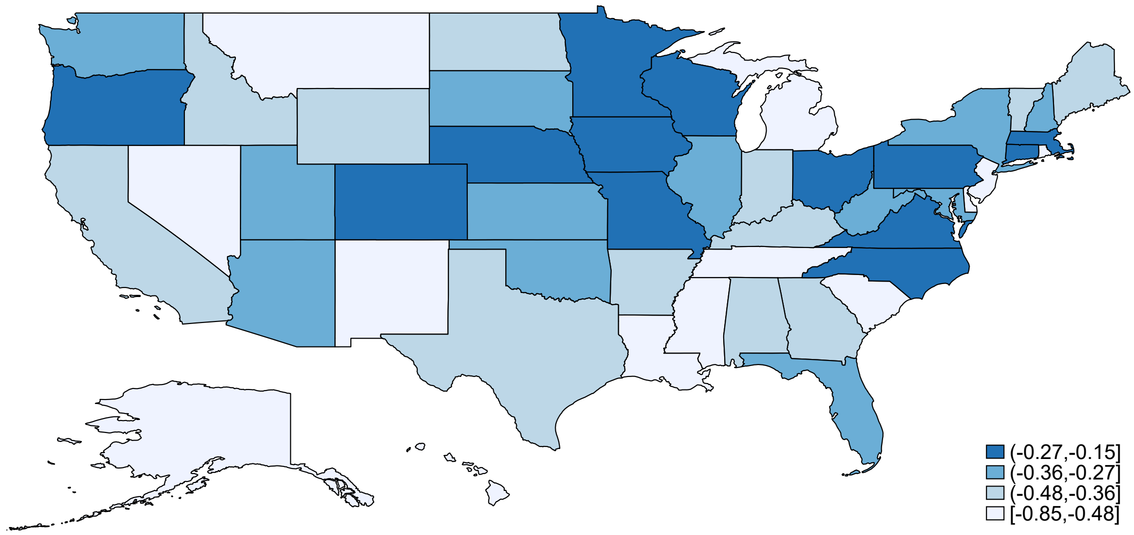

Figure 3: Map for the cumulative percentage change in participation between 2019 and 2021 across U.S. states. Darker shades of blue represent smaller falls in participation.

period, and exposure to trade with other countries and U.S. states, among others.

Our analysis so far has focused on the labor-market effects of trade-cost shocks. However, exposure to these shocks may correlate with other factors, such as demand, supply, or fiscal-stimulus shocks, particularly during COVID-19. Our model does not account for fiscal stimulus, as incorporating endogenous government actions into our dynamic trade framework is beyond this paper's scope. When considering how our results might interact with fiscal-stimulus measures, a key issue is how additional government spending during COVID-19 correlates with a region's manufacturing employment share (one of the main determinants of the sectoral patterns we document). For example, if the states most affected by trade shocks (as shown in Figure 3) received more fiscal support, this might have mitigated the regional disparities we document. However, we find only a weak and insignificant correlation (-0.11) between manufacturing employment shares before the shock and the change in social expenditure per capita between 2019 and 2021 across U.S. states, suggesting our relative results would not be dramatically different if fiscal stimulus were to be incorporated into our framework.[18]

[18] Additionally, we show in the robustness to our model-validation results presented in the next subsection (appendix Table D.1) that this is robust to controlling for fiscal spending during the 2019-2021 period.

4.1 Validation of the Baseline Results for U.S. States

So far, we have exclusively presented and discussed model-generated results. We are now interested in testing how the model predictions compare to real-world data. Specifically, following Davis and Weinstein (2001), Costinot and Donaldson (2012), and Adao et al. (2020), we test the fit of the model by running the following regression:

$$\hat{Y}_i = \alpha^Y + \rho^Y \hat{Y}_i^M + \gamma X_i + v_i^Y, \tag{1}$$

where $\hat{Y}_i$ represents the change in one of our per-capita outcomes of interest (i.e., sectoral employment changes, non-employment, and GDP) observed in the data, $\hat{Y}_i^M$ represents the equivalent model-implied outcome, X_i is a vector of characteristics that capture shocks unrelated to trade costs that impacted real-world outcomes during the pandemic (which our model seeks to abstract from), and v_i^Y corresponds to the error term. Under the hypothesis that the model is correctly specified, the pass-through coefficient from predicted to actual changes, ρ^Y, should equal one.

We implement specification (1) using data for the changes between 2019 and 2021 in state-level per-capita manufacturing, agricultural, and services employment, total non-employment, and GDP.[19] In all cases, we control for total lockdown days during 2020, initial manufacturing-employment share, and initial female-employment share.

The results of regression (1) are presented in Panel A of Table 1 (we postpone the discussion of Panel B, displaying the results once non-U.S. countries are included, to Section 6). For each regression, the table presents the estimate of the coefficient ρ^Y and its standard error, the p-value for the null hypothesis of $\rho^Y = 1$, and the partial R^2 (measuring the proportion of the variance in the data that is explained by the model, after partialling out all controls). Notice first that the coefficient estimated across outcomes is qualitatively

[19] We computed the changes until 2021 to exclude the effects of the war in Ukraine, which happened in early 2022 and brought about oil price increases and a signifcant increase in uncertainty, and because in our model's baseline specification the shock also lasts for two years.

Table 1: Model vs. Data

Panel A: Only U.S. states

	(1) GDP_PC	(2) Manuf	(3) Agric	(4) Services	(5) Non-emp
Model	1.16**	0.71	1.11	1.53*	1.93**
	(0.58)	(0.70)	(2.16)	(0.82)	(0.91)
P-val Coeff = 1	0.78	0.69	0.96	0.53	0.32
Partial R^2	0.073	0.011	0.0052	0.082	0.12
# Observations	50	50	50	50	50

Panel B: All regions (U.S. states plus other countries)

	(1) GDP_PC	(2) Manuf	(3) Agric	(4) Services	(5) Non-emp
Model	0.24	1.24***	0.69	0.00	0.29**
	(0.29)	(0.41)	(0.78)	(0.10)	(0.13)
P-val Coeff = 1	0.0097	0.55	0.70	1.8e-15	0.00000091
Partial R^2	0.011	0.20	0.035	0.000031	0.089
# Observations	87	87	87	87	87

Notes: This table presents regression results for the regression in equation (1) for several outcomes. The table shows the coefficient ρ^Y and its standard error (in parenthesis), the p-value for the null hypothesis of $\rho^Y = 1$, and the partial R^2 that captures the share of the variation in the data explained by the model. Panel A restricts the sample to U.S. states and Panel B includes all states and countries. In Column (1), the dependent variable is the percentage change between 2019 and 2021 in GDP per capita. In columns (2)-(5), the dependent variable is the change in per capita manufacturing employment, agricultural employment, services employment, and non-employment. Regression specifications are weighted by 2019 population. Standard errors are robust to heteroskedasticity. Asterisks denote statistical significance: *=10%, **=5%, ***=1%.

close to one. In fact, we cannot reject the null that each individual coefficient is equal to one (albeit the standard errors are relatively large given the low number of observations). By contrast, we can reject that several of the coefficients are equal to zero (as represented by the stars next to each coefficient). Overall, we observe that the change in labor market outcomes and nominal GDP per capita across U.S. states in the data behaves relatively similarly to the one predicted by the model, indicating that the model has a reasonable fit.[20] The fraction of the overall variation in the real-world outcomes that can be explained by

[20] Appendix table D.1 shows the robustness of our results to alternative regression specifications adding controls incrementally (including a control variable for fiscal-stimulus measures). Overall, we find similar point estimates as the ones in Table 1.

the model (as measured by the partial R^2) varies from 12% in the case of non-employment to very little in the case of changes in agricultural employment.

5 Alternative Specifications

This section explores how our results change if we make different assumptions regarding the value of the trade elasticity or the expectations that households initially had about the duration of the shock. We also touch briefly on the consequences of changing the actual persistence or size of the shock or the nominal growth rate of world GDP in dollars.

As discussed briefly in Subsection 3.2, the trade elasticity $(1 - \sigma)$ is a parameter that depends on the frequency of the underlying shock with respect to which the elasticity is being measured. In our baseline, we use a value of $\sigma = 2.44$, the midpoint of the estimates in Boehm et al. (2023). We now discuss the consequences of assuming $\sigma = 1.76$ (the estimate of Boehm et al. (2023) for the very short run), $\sigma = 3.12$ (the estimate of Boehm et al. (2023) for the long run), or $\sigma = 6$ (a more traditional estimate used in the trade literature).

Figure 4 displays the percentage changes in participation since 2019 in home production (top left), manufacturing (top right), and services (bottom left), as well as the unemployment generated by the shock in percentage (bottom right) for the United States as a whole across different values of the trade elasticity. The solid blue line depicts $\sigma = 1.76$, the dashed green line our baseline value of $\sigma = 2.44$, the orange line with circular markers $\sigma = 3.12$, and the burgundy line with crosses $\sigma = 6$.

The value of σ has a relatively small impact on the path of home production or service participation. By contrast, it has a big impact on the path of manufacturing participation and unemployment. The higher is σ, the easier it is to substitute foreign goods for domestic goods. Manufacturing is the most tradeable sector (and one where the United States is a big net importer), where foreign-to-domestic substitution can occur the most easily. As a result, participation in manufacturing increases much more (while trade costs are high) the

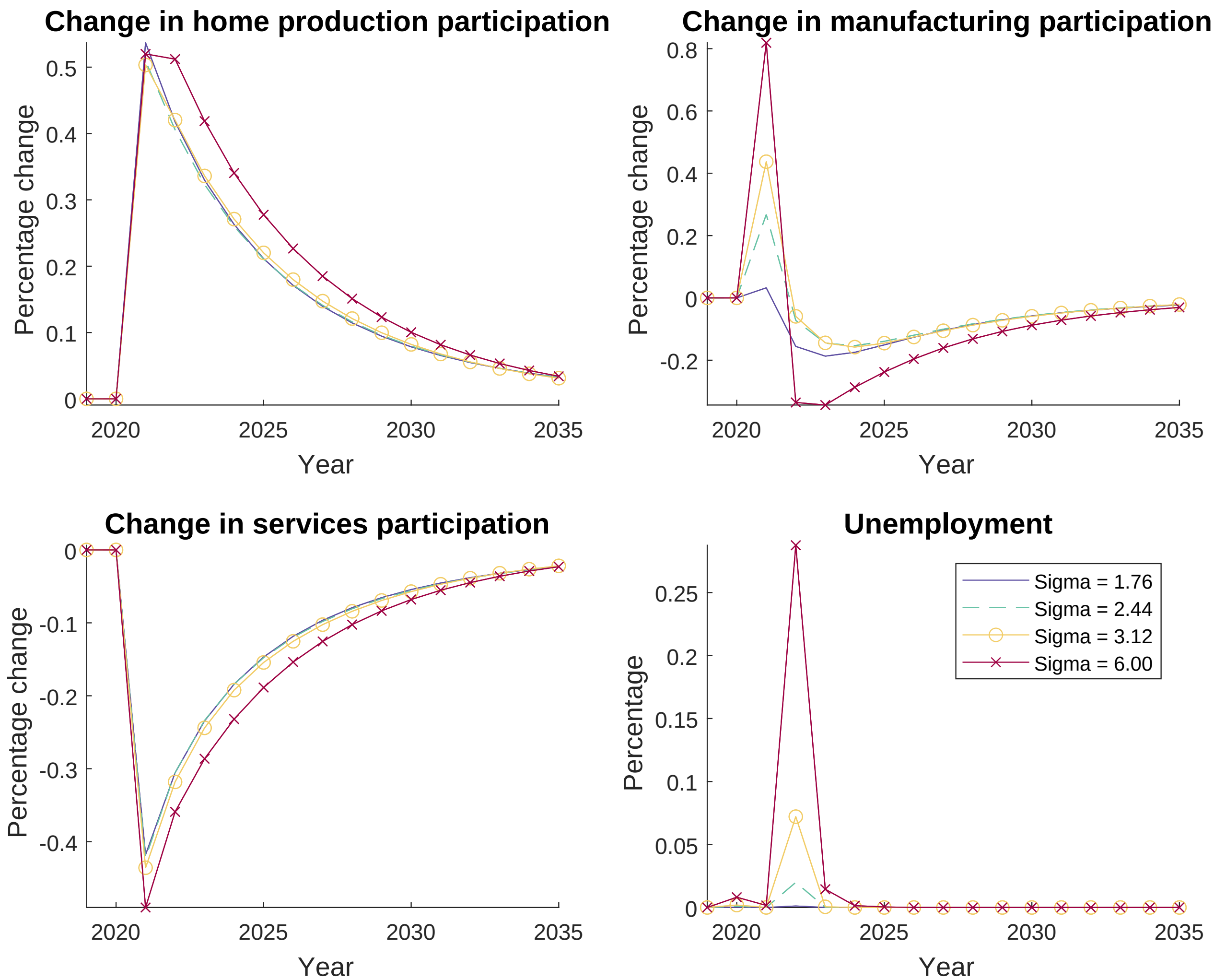

Figure 4: Paths of percentage changes in participation since 2019 in home production (top left), manufacturing (top right), and services (bottom left), as well as unemployment generated by the shock in percentage (bottom right) for the United States as a whole across different values for the trade elasticity. The solid blue line depicts a sigma of 1.76, the dashed green line a sigma of 2.44, the orange line with circular markers a sigma of 3.12, and the burgundy line with crosses a sigma of 6.

higher the sigma. Since manufacturing is also the sector where most of the unemployment occurs when the shock disappears, unemployment also increases substantially with σ.

We now turn to discussing the impact of the expectations that agents initially had about the duration of the trade-cost shock. So far, we have solved the model under perfect foresight, assuming that the shock lasts for two years and that all agents know this with certainty. Here, we discuss the implications of assuming that agents initially had different expectations of shock duration but, after two years, realize that the shock ends up lasting only two years (so the actual duration of the shock is constant across scenarios). We do this using techniques advanced by Fan et al. (2023).[21]

Figure 5 displays the same four outcomes as Figure 4, but now across different values for the initial expected duration of the shock. The solid blue line depicts a shock that is initially expected to last just one year and then lasts one more year for a total duration of two years. The dashed turquoise line depicts our baseline shock, which is expected to last two years and ends up lasting exactly that. The green-crossed, apricot-circled, orange-starred, and red-dash-dotted lines depict shocks that were initially expected to last 3, 4, 5, and 6 years respectively, but in 2022 are revealed to have lasted just two years.

When the shock is initially expected to last for just one year (solid blue line), agents stay put in their sectors, as it is pointless to decide a move that will only be effective next year if the shock will have already disappeared by then. The dashed turquoise line is our previously-discussed baseline case where the shock lasts for two years and agents have perfect foresight about this. Agents flow out from the labor force from 2020 to 2021, but not from 2021 to 2022, as they realize the shock will have disappeared by then. In all the other lines, agents initially expect the shock to last more than two years, so they flow out of the labor force between 2020 and 2021 and also between 2021 and 2022 (as in 2021 they have not learned the shock has disappeared). Once 2022 starts, the agents realize that the shock did not last as much as they initially expected, and they start reverting to the pre-shock allocation. We believe that two years is a reasonable approximation for the initial expected duration of the shock, but Figure 5 elucidates how our conclusions would change if agents were uncertain about shock duration.

Next, we focus on the implications of changing the actual persistence of the shock (reverting to our baseline assumption of perfect foresight). Different amounts of persistence are captured by having the shock revert after 1, 3, 4, 5, or 6 years instead of 2 years. Appendix Figure D.5 gives the results in the same format as Figures 4 and 5. A higher per-

[21]Specifically, the closest example is Figure 2 of Fan et al. (2023). Their techniques incorporating second-order approximations are not suitable for our paper due to the presence of the kinked DNWR in our model.

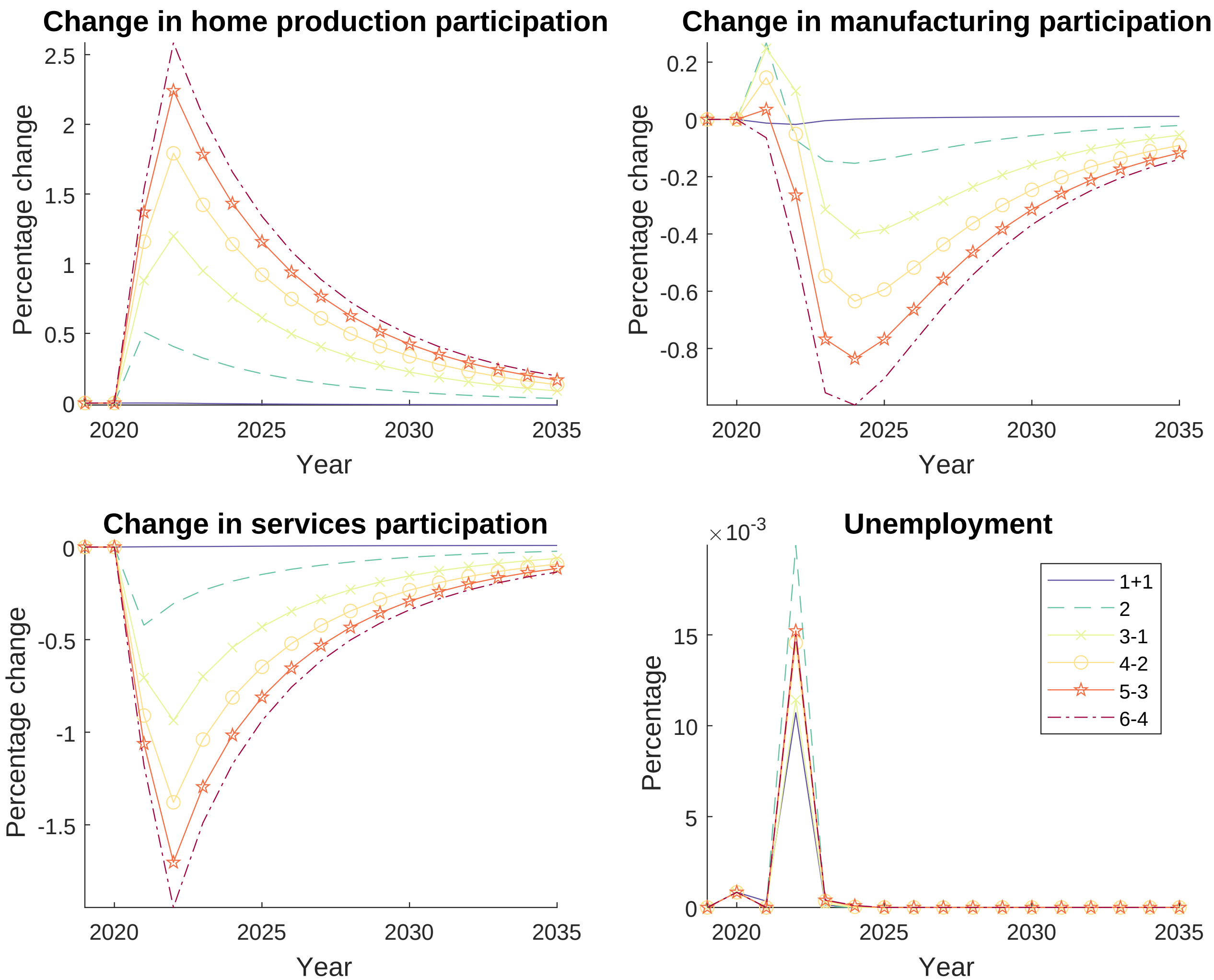

Figure 5: Paths of percentage changes in participation since 2019 in home production (top left), manufacturing (top right), and services (bottom left), as well as unemployment generated by the shock in percentage (bottom right) for the United States as a whole across different values for the initial expected duration of the shock (the actual realized duration of the shock always ends up being two years) in the spirit of Fan et al. (2023). The solid blue line depicts a shock that is initially expected to last just one year and then lasts one more year for a total duration of two years. The dashed turquoise line depicts our baseline shock, which is expected to last two years and ends up lasting that. The green-crossed, apricot-circled, orange-starred, and red-dash-dotted lines depict shocks that were initially expected to last 3, 4, 5, and 6 years respectively, but in 2022 are revealed to have lasted just two years.

sistence leads to a greater increase in home production and a more substantial decrease in services. Manufacturing, however, has a more complicated reaction to changes in persistence. This is because, 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 duration of the shock also affects the tradeoff of paying the moving cost to take advantage of a transitory shock. Notice that, while there are some similarities between Figure 5, comparing across the initial expected duration of the shock, and appendix Figure D.5, comparing across the actual duration of the shock, there are also important differences.

We can also explore the impact of varying the size of the shock. Appendix Figure D.6 depicts the results across four different values of the shock: 6%, 12%, 18%, and 24%. A larger shock tends to amplify 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). Appendix Figure D.7 displays the results. 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 manufacturing sector is particularly sensitive to γ (as it is to the shock's size) 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 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 only reaches 2 basis points at its peak, this maximum can reach 0.7% if $\gamma = 2\%$, and 1.5% if $\gamma = 1\%$ (as could be expected to be the case, for example, under a global liquidity trap). 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 shock.

6 International Results

So far, we have focused on the U.S. implications of the shock, even though our model includes 37 additional regions.[22] 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 openness levels, sizes, and sectoral compositions. Figure 6 illustrates this idea by displaying the model-implied change in home production participation between 2019 and 2021 for all 38 countries in our sample. The figure shows that large countries such as the United States, China, and Japan, 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. By contrast, smaller and more open countries such as Ireland, Cyprus, and Slovakia experience a greater increase in home production participation (akin to a fall in the labor force).

The reduction in welfare due to the increase in trade costs (displayed in appendix Figure D.8) is tightly correlated with the fall in labor-force participation between 2019 and 2021.[23] The welfare loss for the United States is approximately 9 basis points. The minimum welfare loss among non-U.S. countries is around 10 basis points and occurs in China, while the maximum of 84 basis points occurs in Ireland. The average welfare loss across the 38 countries is 26 basis points.

Turning to sectoral results, appendix Figure D.9 illustrates the model-implied change in manufacturing employment across countries between 2019 and 2021.[24] In addition to

[22]We mostly focused on the U.S. implications of the shock because our framework models the U.S. thoroughly, considering its division across 50 states and incorporating a rich mobility structure disciplined by data. By contrast, our modeling of other countries is necessarily more limited; countries do not feature internal regions, and we assume they have frictionless mobility for convenience. We take the U.S. implications of the model much more seriously while still thinking that the implications for other countries are worth a brief discussion.

[23]The welfare change is measured as the equivalent variation in consumption required by agents in the base year to be indifferent between the economy where trade costs increase and the economy where they do not. The formula, given in RUV, is a present value sum where we use an annual discount factor of $\beta = 0.95$.

[24]Similarly, appendix figures D.10 and D.11 show changes in service and agricultural employment across

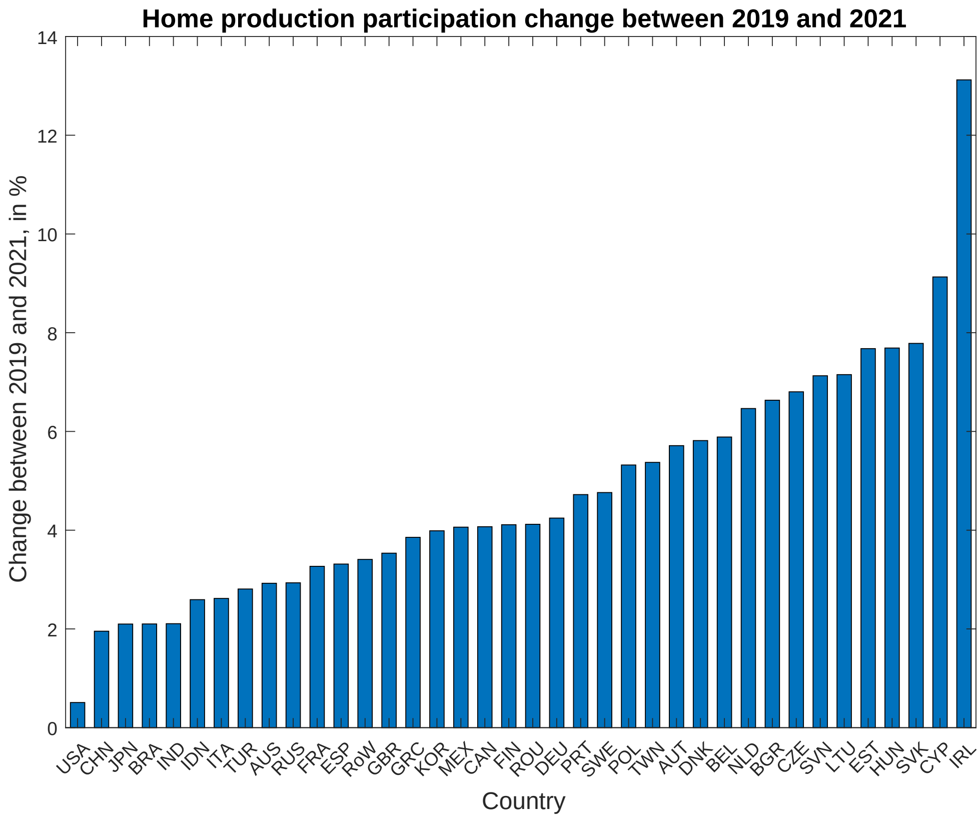

Figure 6: Percentage change in home production participation between 2019 and 2021 across countries, in percent. See appendix C.1 for country abbreviation codes.

the aforementioned factors that influence the 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 or Great Britain, substitute imports with domestic production, driving up manufacturing employment.

We also assess the model's predictions against real-world data using the test from specification (1). Reassuringly, Panel B of Table 1 shows a positive correlation between the model's predictions and observed data. However, in some cases, we can reject the hypothesis that the coefficient ρ^Y equals one, unlike for U.S. states where the model fits better. The better model performance for the U.S. is unsurprising, as the model is calibrated to capture sectoral mobility and geography within the U.S. However, the model still exhibits a decent fit for countries despite a much simpler calibration.

countries between 2019 and 2021.

7 Conclusion

In this paper, we use a dynamic trade model with an input-output structure and DNWR to assess the effects of temporary trade-cost increases. While not aimed at fully explaining COVID-19 labor-market impacts, the model seeks to quantify the effects of trade-cost increases similar in scale to those seen during the pandemic.

We find four key results for the U.S. First, there is a temporary but persistent decline in labor force participation as home production becomes more appealing. 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, states with larger service sectors see bigger participation drops. Finally, we validate our model's fit by regressing real-world changes in GDP per capita and other labor market responses on model-predicted changes and find a reasonable level of agreement.

At the country level, we find that larger or more closed economies see smaller participation declines while smaller or more 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.

One limitation of our approach is that it does not account for the effects of fiscal-stimulus measures. In principle, the analysis could be extended by introducing the government as an additional agent that levies taxes and redistributes revenue to households. However, this introduces added complexity, especially in a dynamic context, as it would require addressing the government budget constraint and potential distortions across regions due to varying taxes and subsidies, which could affect market efficiency. This is certainly an avenue worth exploring in future research.

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Appendix

A Model Equations

The model economy comprises 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 participating in region i, sector s, at time t, by $\ell_{i,s,t}$.

Agents are forward looking and 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:

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

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 $W^{LCU}_{i,k,t}$ denote nominal wages in local currency units, the DNWR takes the following form:

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

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 $W_{i,k,t} = W^{LCU}_{i,k,t} E_{i,t}$ 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 $W^{LCU}_{i,k,t} = W_{i,k,t} \ \forall \ i \leq M$. 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, so the exchange-rate behavior 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 regions outside of the U.S. have a fixed exchange rate with respect to the U.S. (so the DNWR takes the same form in other countries as it does in the United States).[25] This is captured by setting $\delta_{i,k} = \delta_k \ \forall \ i$. 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

[25] Changing to a specification where other countries have flexible exchange rates with respect to the United States has minuscule implications for U.S. outcomes.

have not introduced a nominal anchor that prevents nominal wages from rising so much in each period as to 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

One may be interested in assessing how different regions are exposed to trade cost shocks. To this end, one can 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). 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 et al., 2020, henceforth AAE), but it includes new elements due to the presence of intermediate inputs in our model.[26] The exposure formula for region i after a change in the vector of trade costs $\hat{\tau}$ is given by:

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

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

[26] AAE adds labor force participation to a classic trade model but does not incorporate intermediate inputs via an input-output structure.

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, $\hat{\tau}_{ij,s} = \ln(\tau_{ij,s,2021}) - \ln(\tau_{ij,s,2019})$ denotes the log difference in the iceberg trade costs between the base year and the high-trade-cost years, and $\widehat{mc}_{i,s} = \ln(mc_{i,s,2021}) - \ln(mc_{i,s,2019})$ denotes the log difference in the marginal cost between the base year and the high-trade-cost years.[27] The changes in marginal costs $\widehat{mc}$, can themselves be expressed as a function of the change in trade costs, 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 baseline 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

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

on a given region by considering 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.

In order to derive the exposure measure, 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 AAE). 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):

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

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 $\omega_{i,s}$ 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:

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

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:

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

Therefore, we conclude that:

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

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

C Data Construction

Our data construction follows steps that are related to those in Rodriguez-Clare, Ulate, and Vasquez (2024) (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. Here we provide a summary of the main features of the data construction and refer the reader to the Online Appendix in RUV for further details.

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 Stumpner (2019) and use CFS tables that cross-tabulate establishments by their assigned NAICS codes against SCTG commodities shipped by establishments within each NAICS code.

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 shares 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 the 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 ages 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 Exhibits

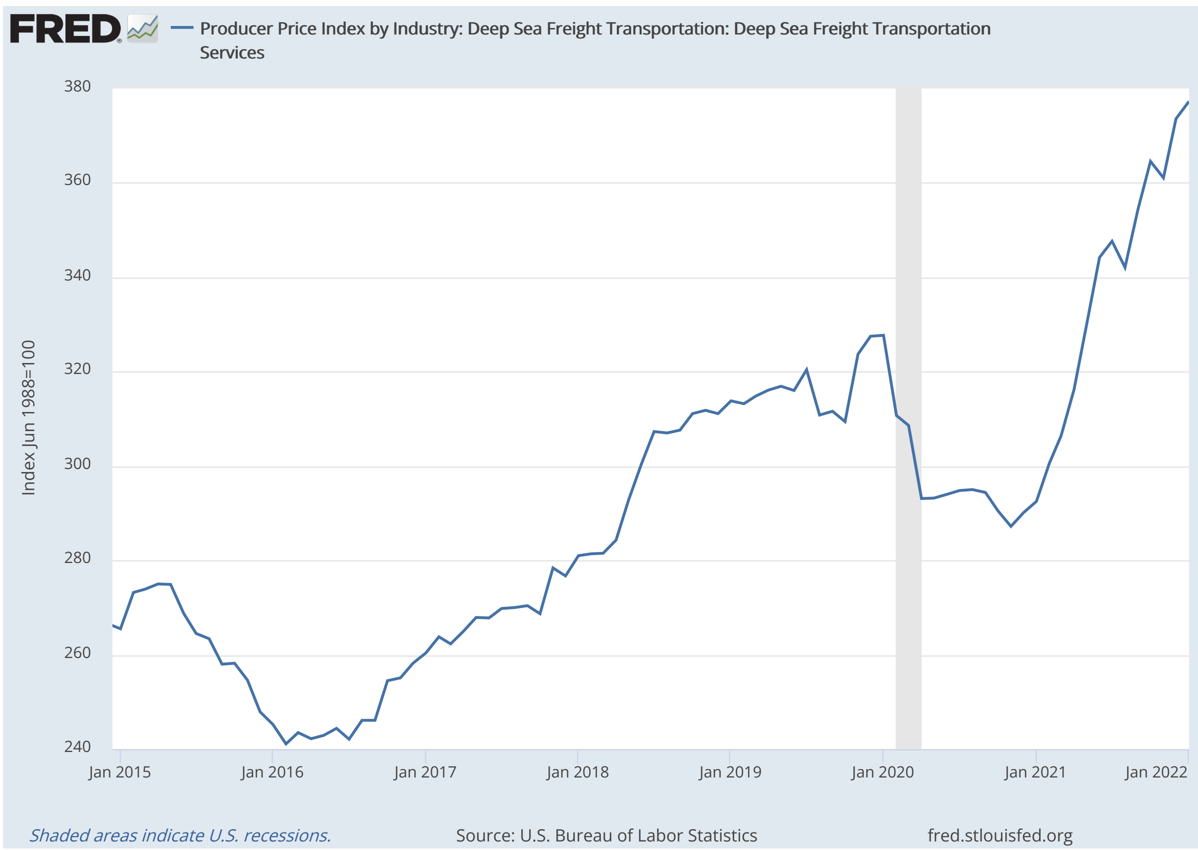

Figure D.1: PPI for deep sea freight transportation services between January 2015 and January 2022, taken directly from FRED.

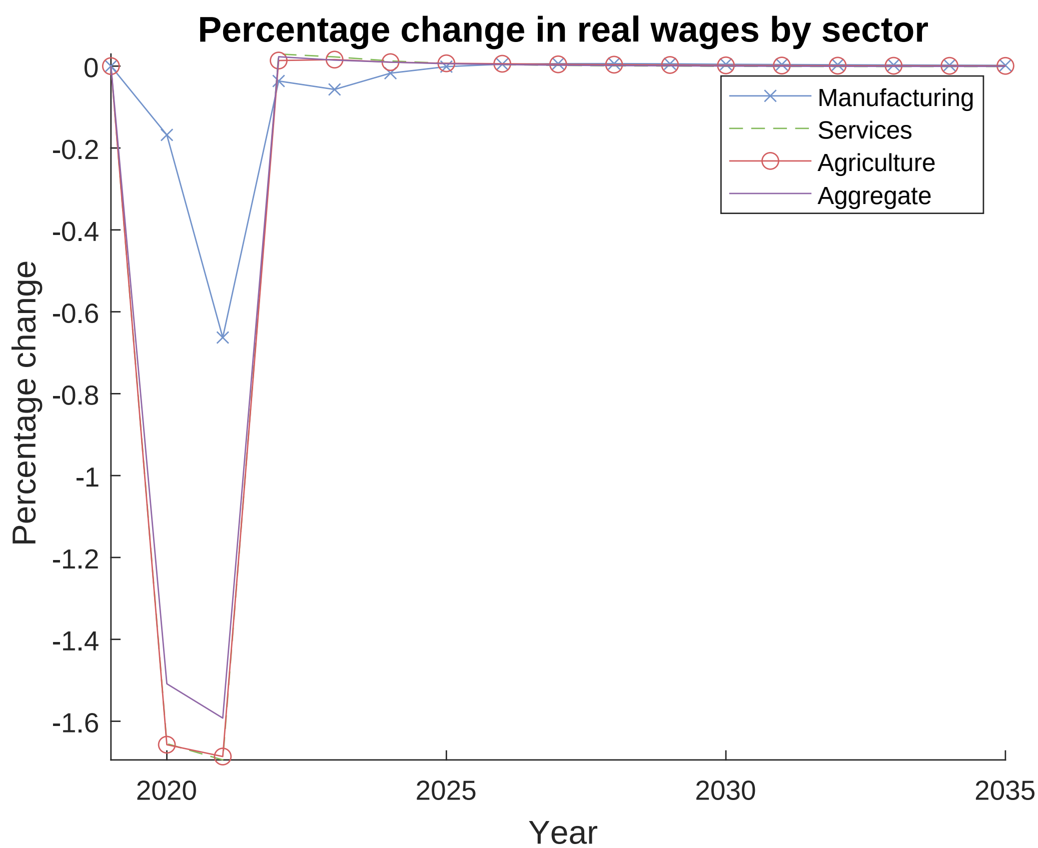

Figure D.2: Paths of cumulative percentage change since 2019 in real wages for manufacturing, services, agriculture, and on aggregate.

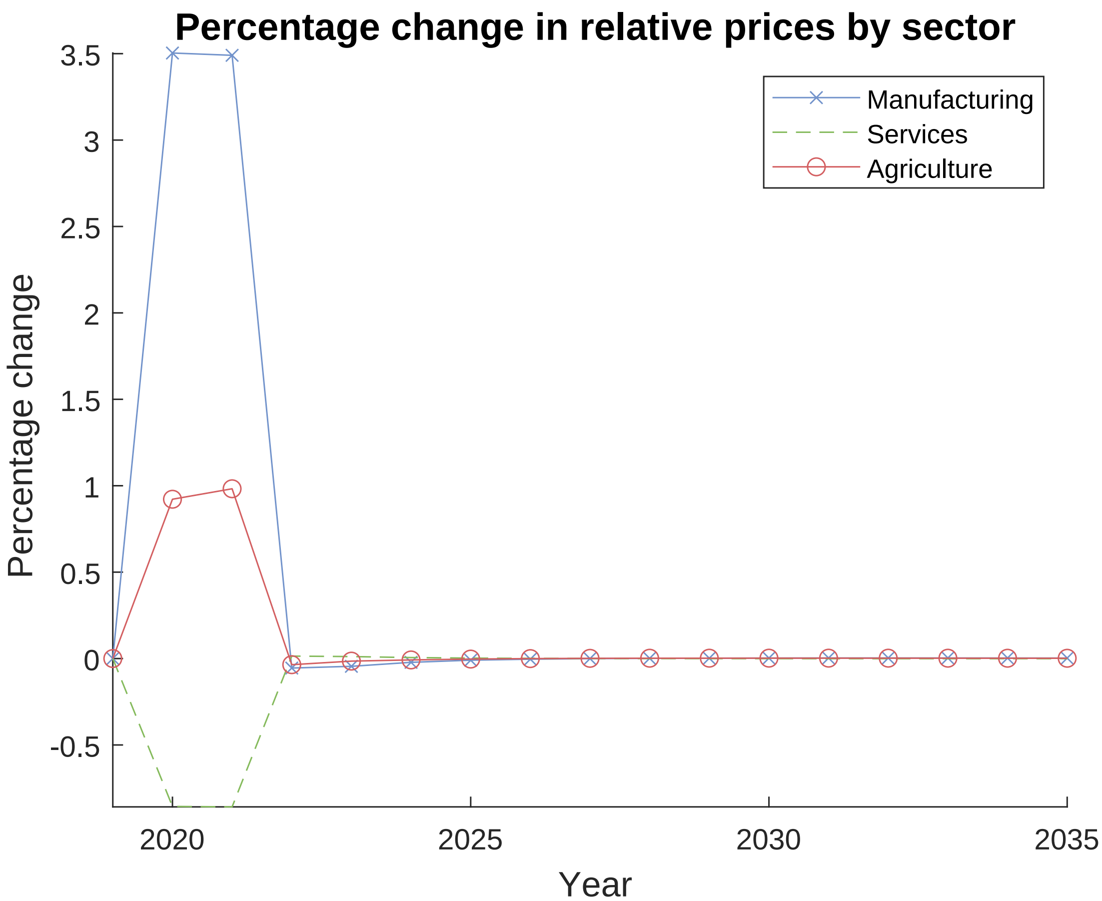

Figure D.3: Paths of cumulative percentage change since 2019 in the relative prices of manufacturing, services, and agriculture.

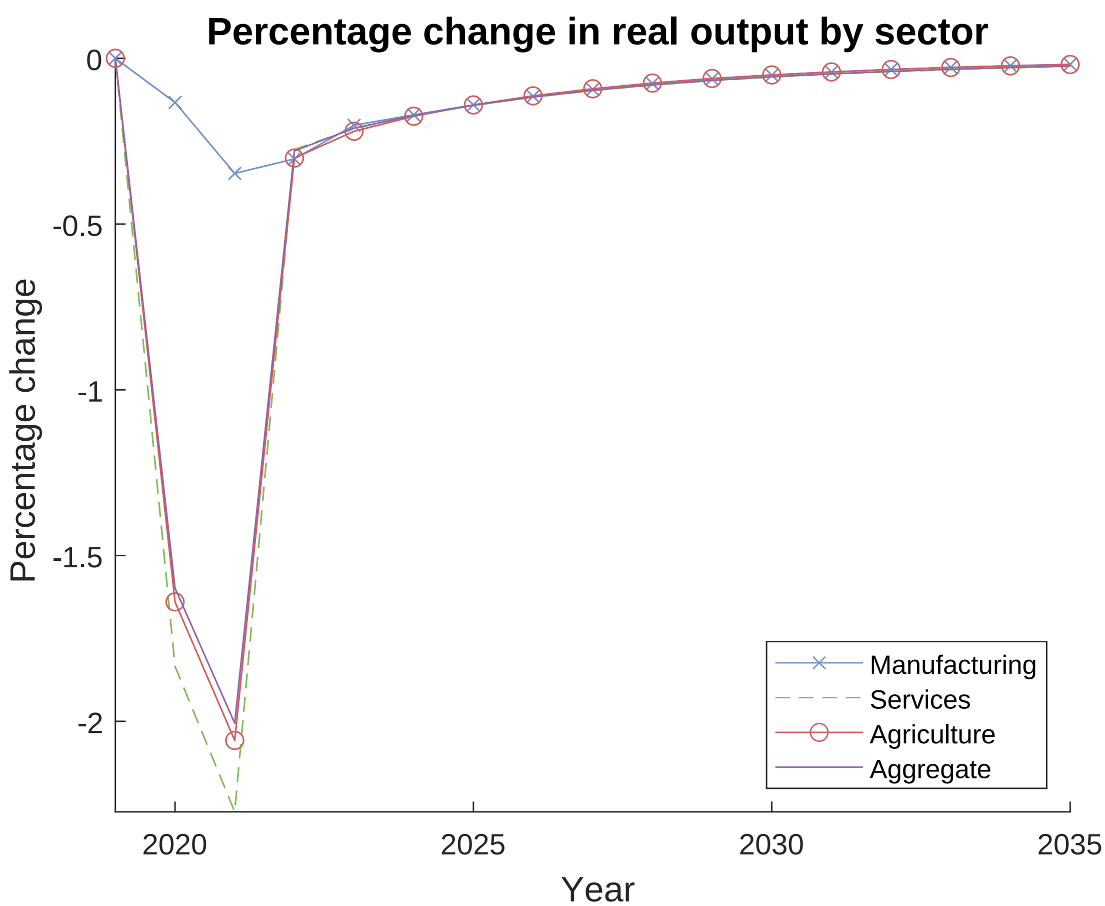

Figure D.4: Paths of cumulative percentage change since 2019 in real output for manufacturing, services, agriculture, and on aggregate.

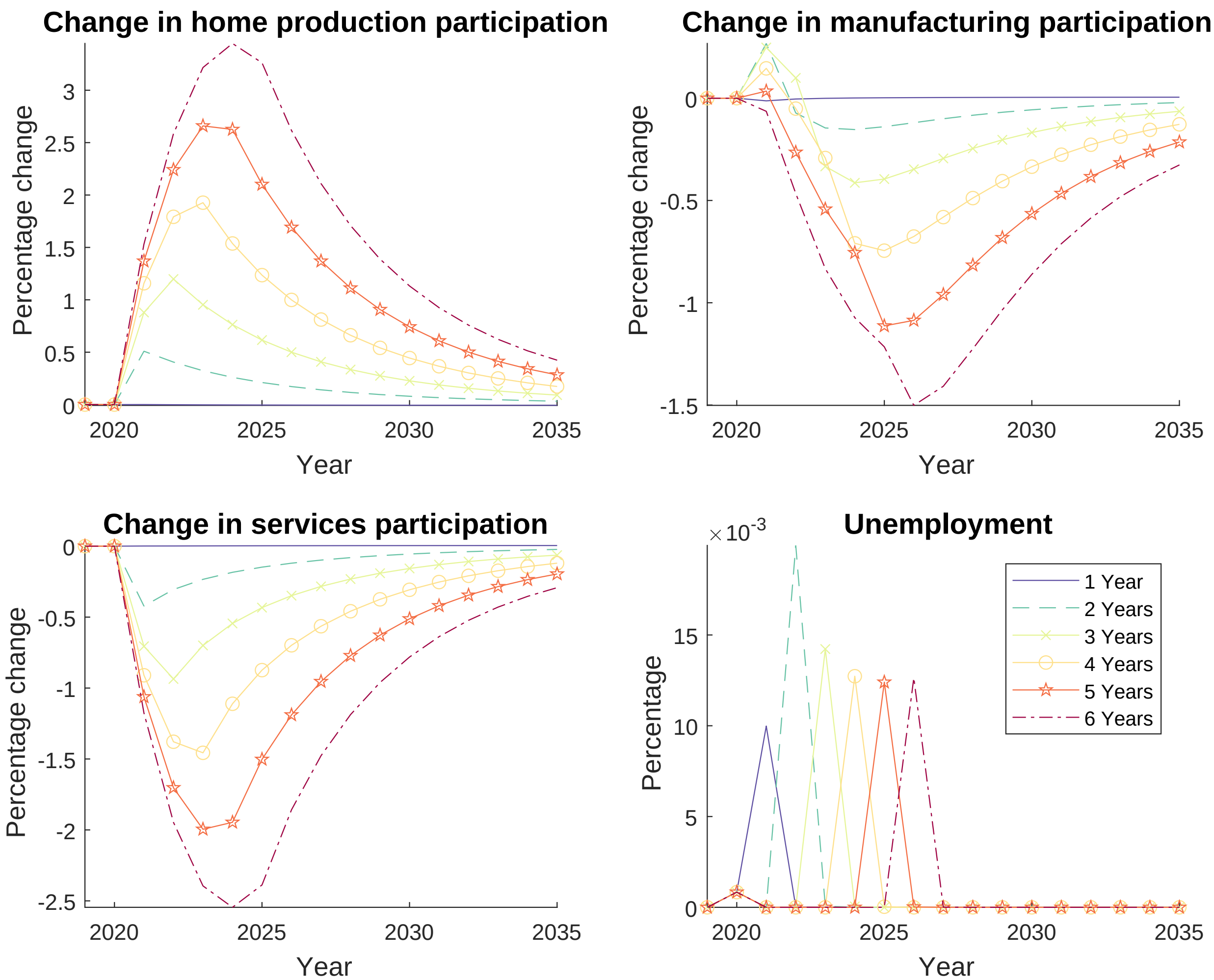

Figure D.5: Paths of percentage changes in participation since 2019 in home production (top left), manufacturing (top right), and services (bottom left), as well as unemployment generated by the shock in percentage (bottom right) for the United States as a whole across different values for the duration of the shock. The solid blue line depicts one year, the dashed turquoise line 2 years, the green starred line 3 years, the apricot circle line 4 years, the orange starred line 5 years, and the red dash dotted line 6 years.

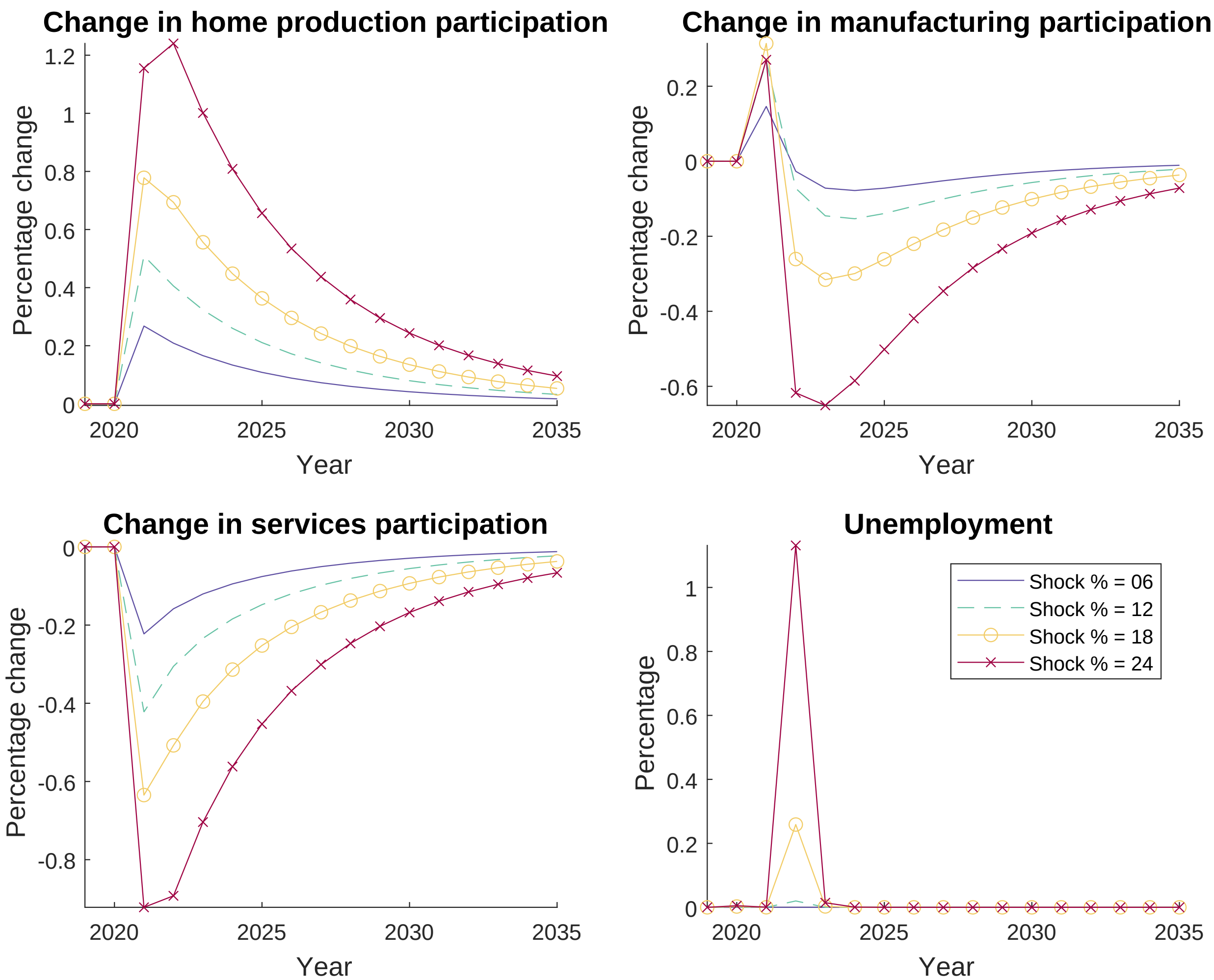

Figure D.6: Paths of percentage changes in participation since 2019 in home production (top left), manufacturing (top right), and services (bottom left), as well as unemployment generated by the shock in percentage (bottom right) for the United States as a whole across different values for the size of the shock. The solid blue line depicts a shock of 6%, the dashed green line 12%, the apricot line with circular markers 18%, and the burgundy line with crosses 24%.

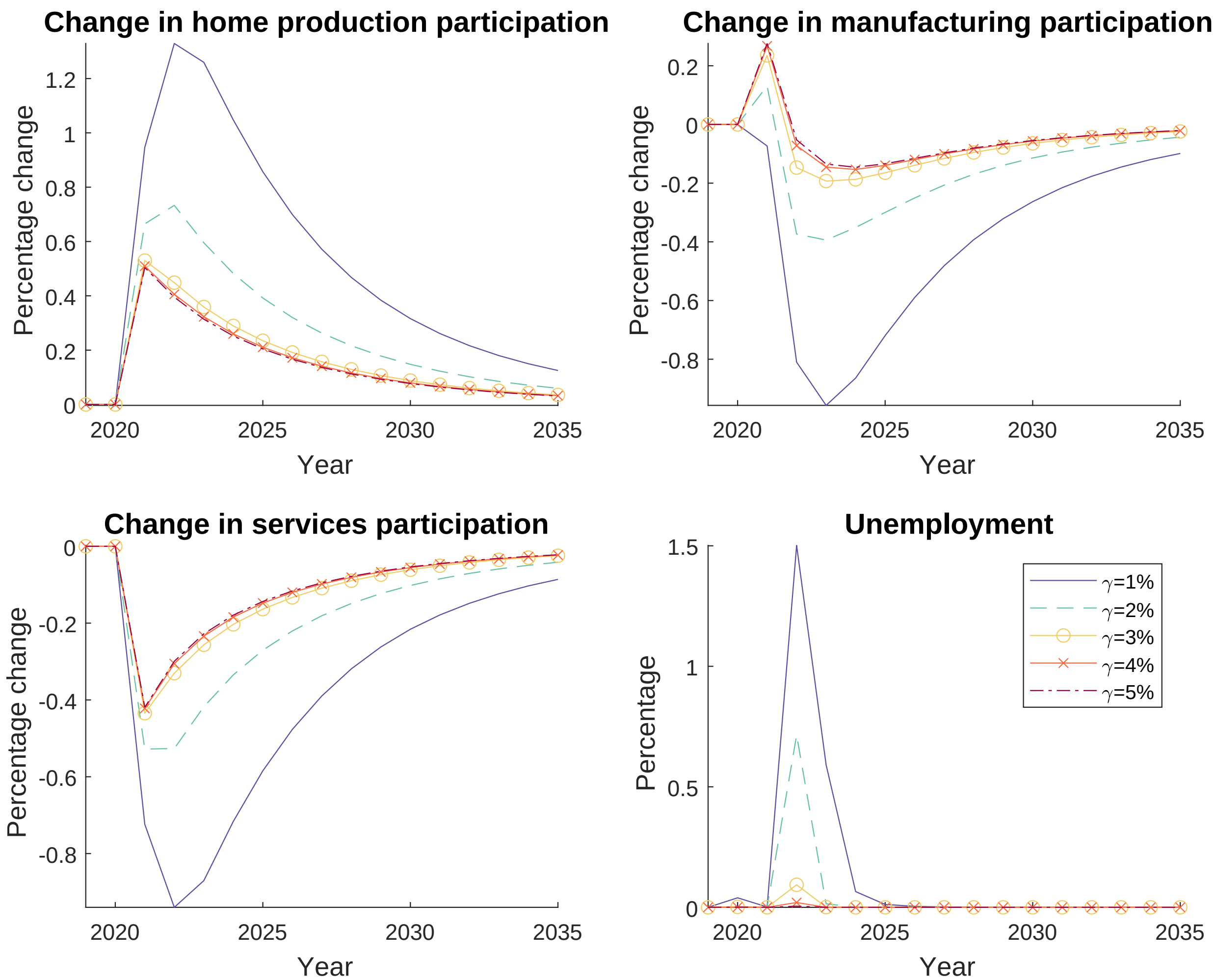

Figure D.7: Paths of percentage changes in participation since 2019 in home production (top left), manufacturing (top right), and services (bottom left), as well as unemployment generated by the shock in percentage (bottom right) for the United States as a whole across different values for growth of world nominal GDP in dollars. The solid blue line depicts a growth rate of 1%, the dashed green line 2%, the apricot line with circular markers 3%, the orange starred line 4%, and the burgundy dash dotted line 5%.

Table D.1: Model vs. Data for U.S. States: Robustness

	(1) GDP_PC	(2) Manuf	(3) Agric	(4) Services	(5) Non-emp
Panel A: No controls					
$\hat{\rho}^Y$	1.38***	0.88	2.81	1.67	1.83*
	(0.47)	(0.71)	(1.70)	(1.05)	(1.03)
P-val Coeff = 1	0.43	0.87	0.29	0.53	0.43
Partial R^2	0.12	0.015	0.023	0.071	0.093
Panel B: + Lockdowns control					
$\hat{\rho}^Y$	1.59***	0.70	2.31	1.84*	2.08**
	(0.57)	(0.72)	(1.91)	(0.98)	(0.95)
P-val Coeff = 1	0.30	0.67	0.50	0.40	0.26
Partial R^2	0.16	0.0085	0.016	0.089	0.12
Panel C: + Manuf. share control					
$\hat{\rho}^Y$	1.58**	0.72	2.56	1.39	1.80**
	(0.63)	(0.69)	(1.68)	(0.89)	(0.90)
P-val Coeff = 1	0.36	0.69	0.36	0.67	0.38
Partial R^2	0.12	0.010	0.021	0.053	0.094
Panel D: + Fem. share (Table 1)					
$\hat{\rho}^Y$	1.16**	0.71	1.11	1.53*	1.93**
	(0.58)	(0.70)	(2.16)	(0.82)	(0.91)
P-val Coeff = 1	0.78	0.69	0.96	0.53	0.32
Partial R^2	0.073	0.011	0.0052	0.082	0.12
Panel E: + Fiscal control					
$\hat{\rho}^Y$	1.59***	0.38	1.28	1.49*	1.73*
	(0.34)	(1.03)	(1.76)	(0.80)	(0.90)
P-val Coeff = 1	0.088	0.55	0.87	0.55	0.42
Partial R^2	0.28	0.0028	0.0075	0.073	0.093
# Observations	50	50	50	50	50

Notes: This table presents regression results for the regression in equation (1) for several outcomes and specifications. The information is presented analogously to Table 1. Panel A shows the regression without controls. Panel B adds the number of lockdown days in 2020 as control. Panel C adds to the previous panel the share of manufacturing employment. Panel D adds the female share in employment, thus, presenting our baseline in Table 1. Panel E adds a control variable for fiscal expansion (the change in debt to GDP between 2019 and 2022). Regression specifications are weighted by 2019 population. Standard errors are robust to heteroskedasticity. Asterisks denote statistical significance: *=10%, **=5%, ***=1%.

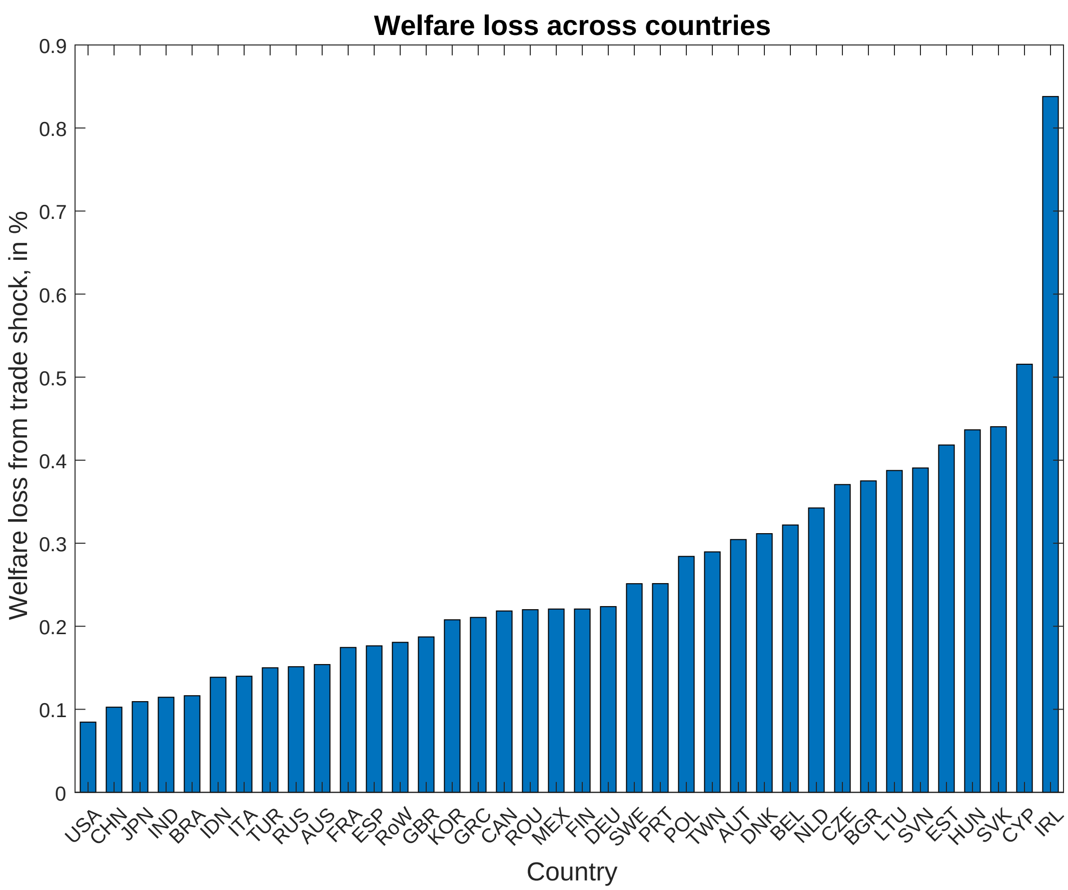

Figure D.8: Welfare loss from the trade shock across countries, in percent. For country abbreviation codes see appendix C.1.

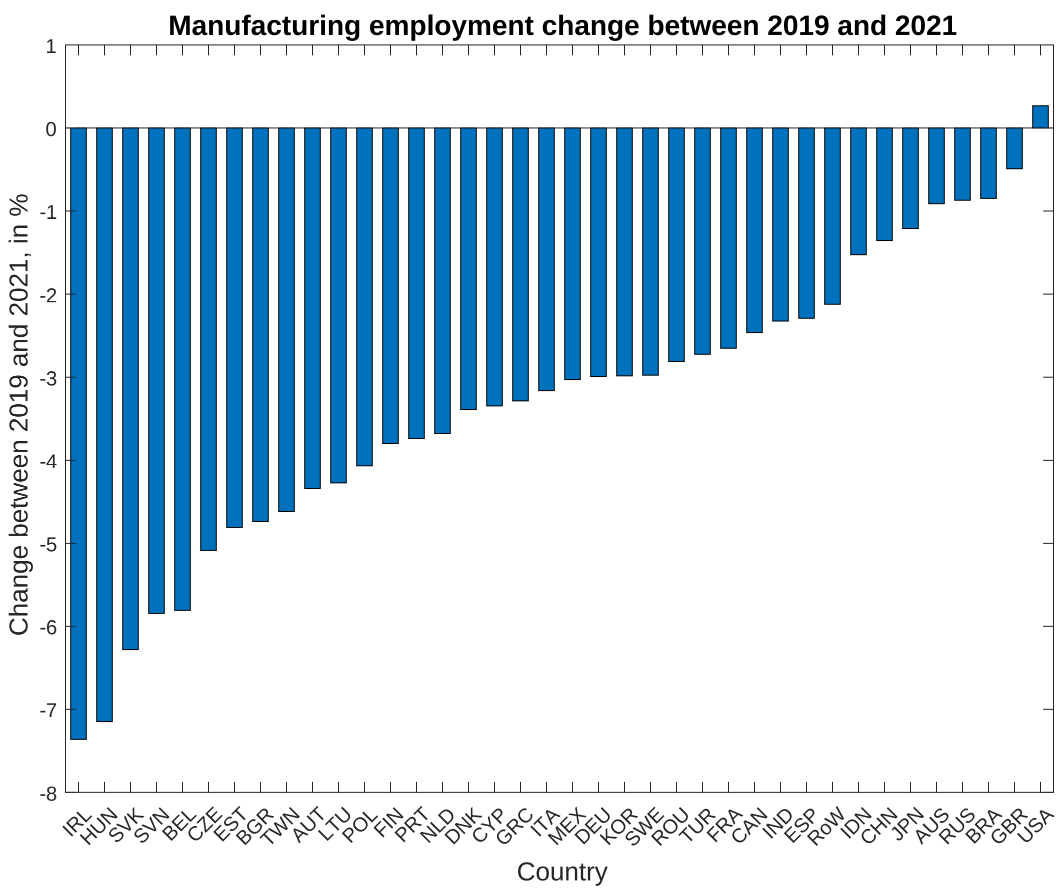

Figure D.9: Percentage change in manufacturing employment between 2019 and 2021 across countries, in percent. See appendix C.1 for country abbreviation codes.

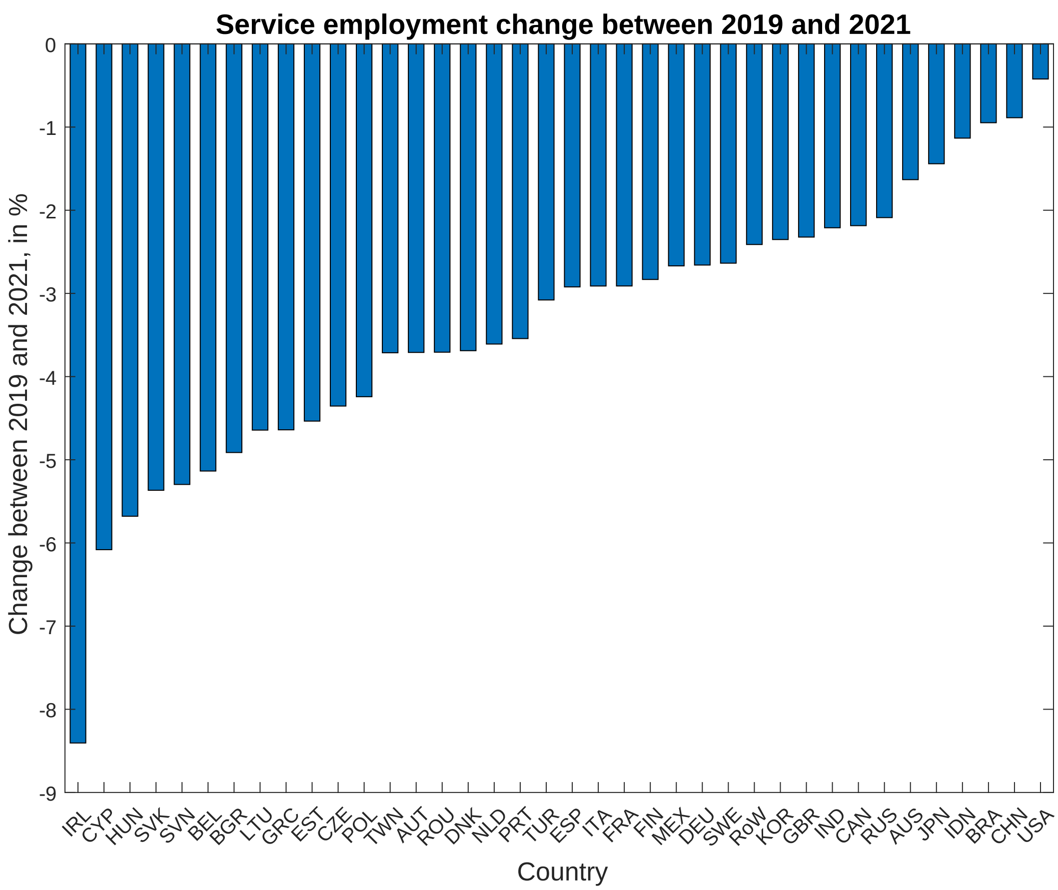

Figure D.10: Percentage change in service employment between 2019 and 2021 across countries, in percent. For country abbreviation codes see appendix C.1.

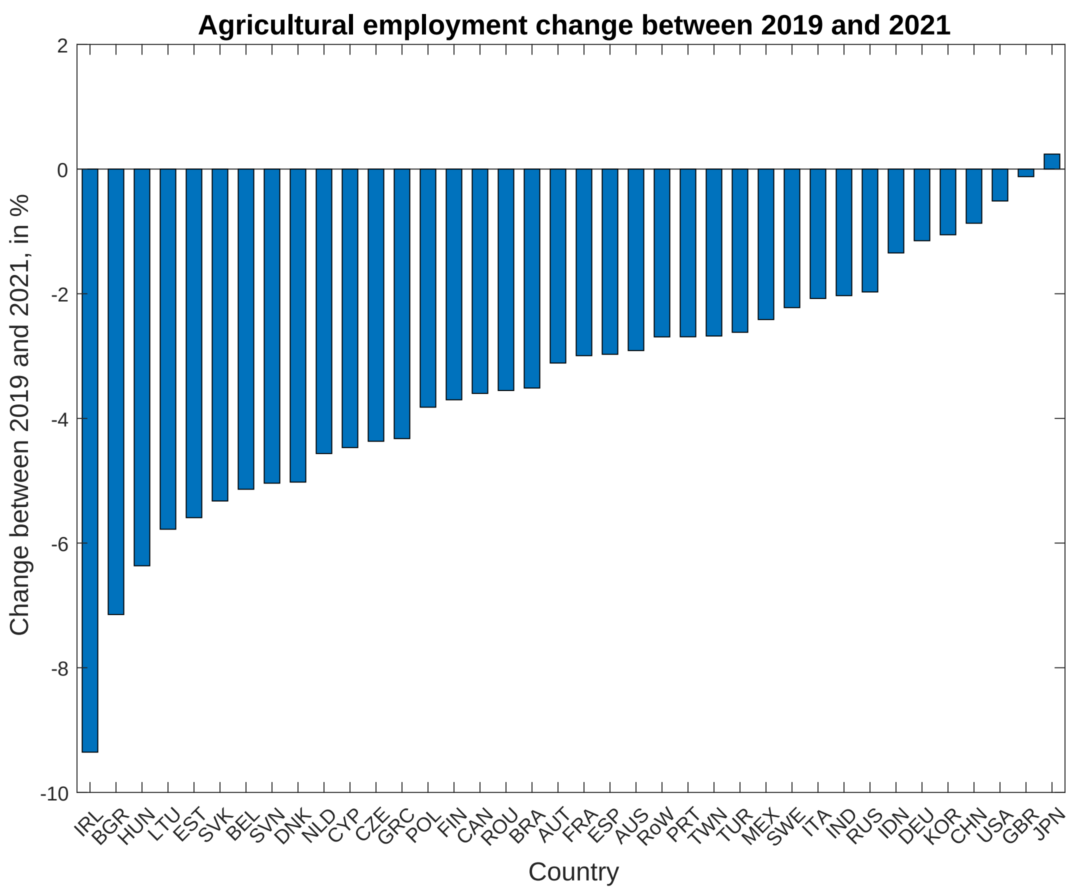

Figure D.11: Percentage change agricultural employment between 2019 and 2021 across countries, in percent. For country abbreviation codes see appendix C.1.