Trade with Nominal Rigidities: Understanding the Unemployment and Welfare Effects of the China Shock*

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We present a dynamic quantitative trade and migration model that incorporates downward nominal wage rigidities and show how this framework can generate changes in unemployment and labor participation that match those uncovered by the empirical literature studying the "China shock." We find that the China shock leads to average welfare increases in most U.S. states, including many that experience unemployment during the transition. However, nominal rigidities reduce the overall U.S. gains by around two thirds. In addition, there are 18 states that experience welfare losses in the presence of downward nominal wage rigidity that would have experienced gains without it.

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1 Introduction

A concern about international trade often raised by the public and the popular press is that it may destroy jobs and lead to unemployment. Trade economists have increasingly taken this concern seriously, but the focus has been on the long-run.[1] Thus, we still lack a framework to understand the possibly adverse short-run employment effects of trade shocks. The need for such a framework becomes particularly salient in light of the findings by Autor, Dorn, and Hanson (2013, henceforth ADH) and others indicating that U.S. local labor markets more exposed to the "China shock" experienced significant increases in unemployment and decreases in labor force participation relative to less exposed regions. If trade shocks can lead to temporary increases in unemployment, how does this change the way we evaluate their welfare effects?

In this paper, we propose a dynamic quantitative trade and migration model in which shocks can trigger increases in unemployment and decreases in labor force participation during a transition period, while allowing for the computation of the implied aggregate and distributional welfare effects. The key feature of the model is downward nominal wage rigidity (DNWR) as in Schmitt-Grohe and Uribe (2016), constraining the nominal wage in any period to be no less than a factor δ times the nominal wage in the previous period. We embed this feature into a dynamic model in the spirit of Caliendo, Dvorkin, and Parro (2019, henceforth CDP), which we extend to allow for a difference between the elasticity governing workers' mobility across sectors ($1/\nu$ in our model) and the elasticity governing mobility across local labor markets ($1/\kappa$ in our model).

We calibrate the key model parameters δ, ν, and κ to results from ADH on how labor force participation, unemployment, and population across U.S. labor markets are affected by the China shock. Using dynamic exact hat algebra, we simulate the effects of the China shock from the year 2000 onwards. The results indicate that although the China shock improves the terms of trade for almost all states (i.e., only two states would experience a welfare loss in the absence of DNWR), employment actually falls in most states during

[1] Davidson et al. (1999), Helpman et al. (2010), Kim and Vogel (2021), and Galle et al. (2023) are papers that focus on the long-run impacts of unemployment. An important exception looking at short-run employment effects is Dix-Carneiro et al. (2023), which we discuss below.

the transition, both through an increase in unemployment and a decline in labor force participation. These employment effects have significant welfare implications, as they lead to a two-thirds reduction in the U.S. welfare gains from the China shock.

The intuition behind our results is as follows. With flexible wages, the increase in China's relative productivity would require a downward adjustment in the U.S. relative wage. DNWR prevents this adjustment from taking place through a large decline in the U.S. nominal wage, and a nominal anchor (described below) prevents it from occurring through a large increase in the Chinese dollar wage. The result is temporary unemployment in the U.S. In turn, with home production available to workers, this triggers further declines in labor participation, as more workers prefer to engage in home production rather than face the possibility of unemployment.

In Section 2, we argue that DNWR is a plausible mechanism to explain the unemployment effects of the China shock. First, there is substantial empirical evidence that DNWR is present in the data (Grigsby et al., 2021; Hazell and Taska, 2023). Second, we show that DNWR is not inconsistent with the dynamic pattern of the unemployment response to the China shock. Third, we use measures of DNWR to show that U.S. regions with more stringent pre-shock measures of DNWR experienced significantly higher unemployment effects from the China Shock.

Section 3 presents our model. There are multiple sectors linked by an input-output structure, sector-level trade satisfies the gravity equation, and a home-production sector leads to an upward-sloping labor supply curve. Trade takes place between regions, and workers can move across regions belonging to the same country. Each period, workers draw idiosyncratic shocks to the utility of working in each sector-region. Based on these draws, the costs of moving, and expected future utility (including the risk of unemployment), workers choose which sector-region to participate in. Wages are subject to DNWR in all manufacturing sectors, but are otherwise determined by labor supply and demand.

Given the presence of DNWR, we need to close the model with a nominal anchor that prevents nominal wages from rising enough to make the DNWR always non-binding.[2] We assume that world nominal GDP in dollars grows at a constant and

[2]Our baseline analysis also assumes that third countries have flexible exchange rates vis-á-vis the dollar,

exogenous rate.[3] While this nominal anchor is a simplification, it allows us to solve our otherwise-unwieldy dynamic trade and migration model.[4] Qualitatively, we would obtain similar results if we assumed instead that China uses a combination of monetary and exchange rate policies to prevent both an appreciation of its currency and large inflationary pressures – thereby preventing the Chinese wage in dollars from increasing – while the U.S. does not fully offset this with its own policies (even though it had the tools required to do so if it had been its priority).

Section 4 describes our data construction. We combine multiple data sources, proportionality assumptions, and implications from a gravity model to construct sector-level trade flows across all region pairs in our sample. We also construct migration flows between all sector-states in the U.S. The resulting dataset contains 87 regions (50 U.S. states, 36 additional countries, and the rest of the world), and 15 sectors (home production, 12 manufacturing sectors, services, and agriculture).

Section 5 describes our calibration procedure for parameters ν, κ, and δ as well as for the China shock, which we operationalize as productivity changes in China that vary across sectors and years. For any set of parameter values and productivity changes, we use dynamic hat algebra to compute implied annual changes in trade flows as well as changes in labor-force participation, unemployment, and population over the 2000-2007 period. We then iterate over the parameter values and productivity changes until the sector-level annual changes in U.S. imports from China match those predicted in the data and the ADH-style regression coefficients in the model match those obtained by ADH in the data. In our baseline specification, we introduce DNWR only in the manufacturing sectors. The calibration leads to a value of $\delta \approx 0.99$, implying that – with constant world nominal GDP – wages can fall around 1% annually without the DNWR becoming binding. This value is in line with the one in Schmitt-Grohe and Uribe (2016).

Section 6 presents the results of the baseline quantitative analysis. In the short run, unemployment increases in the regions most exposed to the China shock, but this un-

but the alternative of fixed exchange rates for developed countries makes little difference for our results.

[3] We further set this rate to zero, which is without loss of generality in the context of our model.

[4] Assuming other types of nominal anchors prevents our model from being solved with an efficient Alvarez-and-Lucas (Alvarez and Lucas, 2007) type algorithm that we develop to deal with the DNWR, thereby increasing the time required to solve the model by several orders of magnitude.

employment dissipates over time as the nominal wage adjusts downward. In the long run, since the real wage governs labor supply and there is no unemployment, employment eventually increases after the economy fully adjusts to the positive terms of trade shock. We compute welfare as the present discounted value of utility flow, with a discount rate of 0.95. We find that welfare increases in 30 U.S. states, including many that experience unemployment during the transition. For the U.S. as a whole, although the China shock remains beneficial, DNWR reduces the aggregate welfare gains by roughly two-thirds (from 31 to 12 basis points). There are 18 states that experience welfare losses in the presence of downward nominal wage rigidity that would have experienced gains without it. The spatial heterogeneity in the employment and income effects of the China shock implied by our model is similar to that implied by the empirical results in ADH. This stands in contrast to previous quantitative trade models, such as CDP and Galle et al. (2023), which deliver too little dispersion, as shown in Adao et al. (2023).

Section 7 studies how varying some of the key assumptions in the baseline specification affects our results. We discuss alternative scenarios where we allow the China shock to last until 2011 in the spirit of Autor et al. (2021) and use alternative migration assumptions across U.S. states. We highlight that while the baseline specification is broadly consistent with the dynamic pattern of the cross-sectional response to the China shock, the specification where the shock lasts until 2011 improves the fit along this dimension by increasing the persistence of the cross-sectional unemployment and non-participation effects. Interestingly, assuming that the China shock lasted until 2011 implies that the welfare gains of the shock through the lens of the model roughly disappear.

Section 8 discusses two additional topics. First, we argue that, assuming that labor supply is a function of the real wage, ADH's exposure measure to the China shock becomes a relevant statistic in the model only due to DNWR. Second, we explore the model-implied tradeoff between unemployment and inflation. For a neighborhood around our baseline, decreasing cumulative unemployment generated by the shock by one p.p. over ten years requires accepting roughly two more p.p. of cumulative inflation.

Our paper follows in the footsteps of a large literature that analyzes the impacts of trade shocks on different regions or countries. Quantitative papers such as CDP, Galle et al. (2023), and Adao et al. (2023) focus on the effects of the China shock on regions of the U.S. Our model incorporates nominal rigidities as a mechanism to deliver involuntary unemployment, which is an uncommon feature in this literature despite its prominence in the empirical papers studying the China shock.

Another literature explores the effect of trade on unemployment using search and matching models (e.g. Davidson and Matusz, 2004; Helpman et al., 2010; Kim and Vogel, 2021; Galle et al., 2023; Dix-Carneiro et al., 2023; Carrere et al., 2020; Gurkova et al., 2023). In static models with search and matching, trade shocks can affect aggregate unemployment by reallocating labor across sectors with different frictional unemployment rates, as in Helpman et al. (2010), or by changing the profitability of posting vacancies, as in Kim and Vogel (2021). Galle et al. (2023) focus on the second of these mechanisms, and show that U.S. regions more exposed to the China shock experience increases in unemployment. This is due to the decreased profitability of posting vacancies in those areas facing intensified import competition. However, for the U.S. as a whole, unemployment declines because the China shock is, on aggregate, a positive terms-of-trade shock, thereby enhancing the profitability of posting vacancies.

Dix-Carneiro et al. (2023) allow for both of these mechanisms in a dynamic multi-sector model to study the role of trade imbalances on the labor market during the transition after the China shock. In their analysis, the China shock entails both a gradual increase in productivity (to match China's increase in total exports) and a change in households' intertemporal preferences (to match China's increase in net exports). According to the model simulation, the effect of the China shock on aggregate U.S. unemployment is negligible, and there are no region-level results connecting to the ADH evidence.

Also related to our paper is Eaton et al. (2013), which studies the extent to which unmodeled cross-country relative wage rigidities can explain the increases in unemployment and decreases in GDP observed in countries undergoing sudden stops. Relative to this paper, our contribution is to extend the analysis to terms-of-trade shocks in a multi-sector model with migration and to quantify the effect of the China shock on unemployment and nonemployment across U.S. states from the year 2000 onward.

2 A Case for DNWR

2.1 Support for DNWR in the Recent Literature

While the idea that DNWR may be central in explaining various macroeconomic phenomena has a venerable tradition in macroeconomics (e.g., Keynes, 1936), it laid somewhat dormant for decades as other forms of rigidity such as Calvo frictions, quadratic adjustment costs, or menu costs became popular. However, there has recently been a resurgence in the popularity of DNWR in the macro and labor literatures.

The first reason for the resurgence of DNWR in the literature is the strong empirical support found for it in the micro data. Grigsby et al. (2021) find evidence of DNWR for a sample of workers who remain employed with the same firm. Moreover, although wages could, in principle, be more flexible for new hires than continuing workers, Hazell and Taska (2023) find evidence that the wage for new hires is rigid downward, but flexible upward, in particular rising during expansions but not falling during contractions.

Jo (2022) analyzes five distinct wage-setting schemes: flexible, Calvo, long-term contracts, symmetric menu costs, and DNWR, and shows that only DNWR is consistent with U.S. data from the CPS. Fallick et al. (2020) find a significant amount of DNWR in the U.S., and no evidence that the substantial degree of labor market distress during the Great Recession reduced it. To be clear, the presence of DNWR does not mean that nominal wages never fall, it simply means that the fraction of nominal wages that experience a decrease is small and varies little with the state of the business cycle.

The second reason behind the renewed prominence of DNWR in the literature is that it can help explain important issues in macro and labor. Shimer (2005) showed that a calibration of the standard search-and-matching model without wage rigidity leads to unemployment fluctuations that are much smaller than the ones in U.S. data, whereas in a version that incorporates wage rigidity these fluctuations match the data. Dupraz et al. (2019) show that symmetric wage rigidity models are unable to account for the skewness and asymmetry observed in the unemployment rate, while DNWR is able to do so.

In the international context, Fadinger et al. (2024) find that intensified export competition from Germany led to significant manufacturing employment losses but insignificant nominal wage responses in other Euro-Area countries. Moreover, German export competition had no significant employment effects on European countries with flexible exchange rates vis-a-vis the euro, suggesting that DNWR in the presence of a fixed exchange rate is the main explanation for these results. Costinot et al. (2022) study the collapse of the Finnish-Soviet trade agreement and find that it generated employment declines that were greater in the short run than in the long run and wage changes that were larger in the long run. They argue that this evidence is consistent with a model that incorporates DNWR but not with a frictionless search-and-matching model.

For the aforementioned reasons, it is fair to say that DNWR is an empirically well supported and mainstream tool of modern economics. Our paper brings this tool to the trade literature to explain important facts about the China Shock. In the following subsections, we provide additional evidence that DNWR is not incompatible with the persistent effects that the China shock had on aggregate employment, and that regions with more stringent DNWR experienced a higher increase in unemployment from the shock.

2.2 DNWR and Persistence in the Employment Effects of the Shock

Recent evidence (e.g., Dix-Carneiro and Kovak, 2017; Autor et al., 2021) has found that regions more exposed to import competition experienced persistent decreases in employment. Since DNWR can only lead to temporary increases in unemployment, this evidence could raise doubts about DNWR as the mechanism driving these persistent effects. However, persistent *employment* declines do not necessarily imply persistent *unemployment* effects, as they could be due to long-run declines in labor force participation.[5]

To study the persistence of the employment and unemployment effects of the China Shock, we take the analysis in Autor et al. (2021) as a baseline and implement four changes (described below) so that the regression results are comparable with those in ADH (which

[5]While Autor et al. (2021) show long-run effects of the China Shock, they focus on employment, compensation, transfers, and population effects, and do not explore separate effects in unemployment and non-participation. Similarly, the main analysis in Dix-Carneiro and Kovak (2017) relies on employer-employee data for Brazil and hence precludes any study of unemployment. The authors supplement their analysis with other data sources that include unemployment but focus on the distinction between formal and informal employment as opposed to unemployment and non-participation.

use different data and regression specification).[6] The resulting exercise mimics ADH for the ending year 2007 and extends it up to 2020.

First, we estimate the dynamic effect of the China Shock following a regression specification in the spirit of Autor et al. (2021), but that would allow us to stack the changes in the outcomes for the 1990 - 2000 period as in ADH. Our main regression specification is:

$$\Delta Y_{i,t+h} = \alpha_t + \beta_{1h} \Delta IP^{cu}_{i,\tau} + X'_{i,t}\beta_2 + \varepsilon_{i,t+h}, \tag{1}$$

where $\Delta Y_{i,t+h}$ is a vector of ten-year equivalent changes in outcome Y for CZ i between 1990 and 2000 stacked with the changes in the same outcome between years 2000 and $2000 + h$, for $h = 1, ..., 20$. The term $IP^{cu}_{i,\tau}$ is the growth in Chinese import competition in the τ intervals 1990-2000 and 2000-2007, respectively.

Second, we use the American Community Survey (ACS) for employment data instead of the Regional Economic Information System (REIS) data.[7] Third, we use the exact import exposure definition in ADH. Autor et al. (2021) use the growth in imports from China between 2000 and 2012 divided by domestic absorption (U.S. industry shipments plus net imports), whereas ADH use the growth in imports per worker between 1990 and 2000 stacked with the one between 2000 and 2007. Fourth, we use the same controls $X'_{i,t}$ as in ADH, which we take from ADH's replication files.

We estimate one regression per year using equation (1) for $h = 6, ..., 20$, implementing the same two-stage least squares strategy as in ADH (i.e., we instrument $\Delta IP^{cu}_{i,\tau}$ with $\Delta IP^{cu}_{oi,\tau}$, which only differs from $\Delta IP^{cu}_{i,\tau}$ by using imports from China in other high-income markets). Figure 1 reports the resulting estimates for each β_{1h} when the outcomes are the following ratios: total employment to population (panel a), not-in-the-labor-force (NILF) to population (panel b), and unemployment to population (panel c). Note that the coefficients for 2007 coincide with those in ADH.[8]

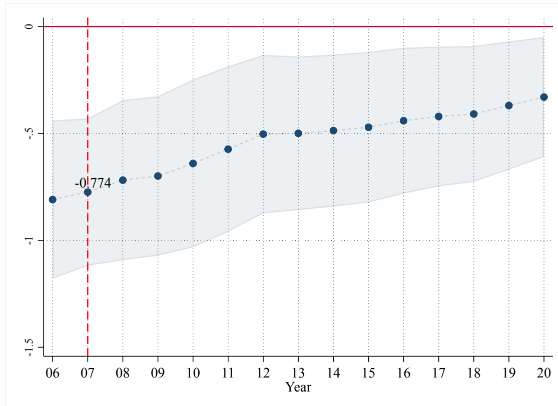
[6] These changes do not meaningfully affect the qualitative takeaways from this section. We stick with them to remain consistent with the point estimates from ADH (associated with the $2000-2007$ change), which are well known in the literature and which we use as our main calibration targets.

[7] ACS allows one to compute consistent measures of unemployment and non-participation. However, it does not include full geographic information for $2001-2005$. Therefore, we start the analysis with the $2000-2006$ change. We follow ADH in pooling a moving average of three ACS years.

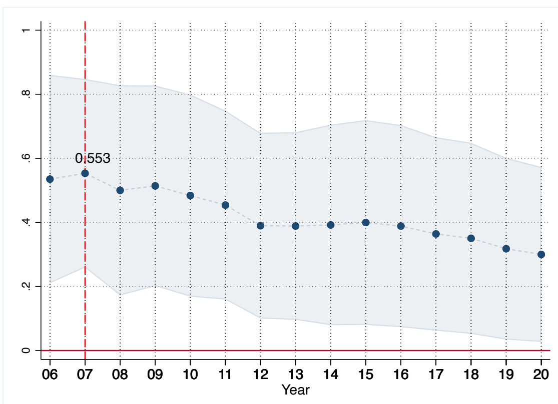
[8] Specifically, the coefficients for 2007 from panels (b) and (c) match those from Table 5, panel B, columns

Figure 1: Effects of the China Shock on employment and non-employment

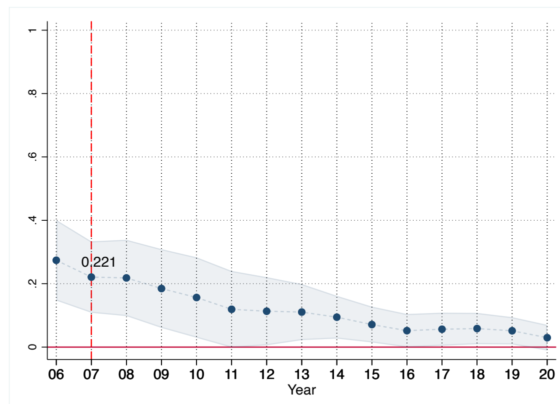
(a) Tot. employment/Pop.



(b) NILF/Pop.



(c) Unemployment/Pop.



Note: The panels report two-stage least squares coefficient estimates for β_{1h} in equation (1) and 95 percent confidence intervals for these estimates. Each coefficient comes from a separate IV regression following equation (1). Each regression stacks the change in the specified outcome between $1990 - 2000$ and between 2000 and the year indicated on the horizontal axis. The coefficients for 2007 (highlighted with the red dashed vertical line) match those from Table 5 in ADH.

Panel (a) of Figure 1 suggests that the China shock has long-term employment effects. Even by 2020, CZs that were more exposed to the increase in import competition from China experienced negative and significant effects on total employment divided by population. This finding is consistent with other recent evidence on the long-run impacts of disruptive trade shocks (Dix-Carneiro and Kovak, 2017; Autor et al., 2021).[9]

3 and 4 in ADH, respectively. The equivalent coefficient for panel (a) is not directly presented in ADH but it matches the sum of the effects for manufacturing and non-manufacturing employment (divided by working-age population) found by ADH.

[9]Using employer-employee data for Brazil, Dix-Carneiro and Kovak (2017) find a stark decreasing pattern on *formal* employment. Their regional analysis using decennial Census data also shows that trade-displaced formal-sector workers switch to informal employment and that the longer-term effect on non-employment is small and non-significant.

We uncover the separation of the employment effects into NILF and unemployment effects in panels (b) and (c). Panel (b) shows that by 2020, the effect on NILF is still around half the effect found by ADH for 2007, and continues to be statistically significant. By contrast, panel (c) shows that the unemployment effects diminish more rapidly. In particular, the unemployment effect became statistically non-significant in 2011, and while the effect became statistically significant again in some other years post 2011, it remained economically small.[10] By 2020, the unemployment effect was around one-tenth of what ADH found in 2007, which suggests that the unemployment effects are transitory and that most of the persistent employment effects of the shock are driven by effects on NILF.

2.3 Cross-sectional Evidence for DNWR

We borrow measures of DNWR from the empirical macro literature (e.g., Jo, 2022; Jo and Zubairy, 2023) and show that regions (CZs or States) with more stringent pre-shock measures of DNWR experienced significantly higher unemployment effects from the China Shock. To do so, we enrich the regression specification in equation (1) to add a differential effect depending on the degree of DNWR:

$$\Delta U_{i,t+h} = \gamma_t + \beta_{1,h}\Delta IP^{cu}_{i,\tau} + \beta_{2,h}Rig_{s(i),\tau} + \beta_{3,h}Rig_{s(i),\tau} \times \Delta IP^{cu}_{i,\tau} + X'_{i,t}\beta_4 + \varepsilon_{i,t+h}, \qquad (2)$$

where $\Delta U_{i,t+h}$ now refers to the change in unemployment-to-population ratio in a region (CZ or state). The variable $Rig_{s(i),\tau}$ represents a state-level proxy for the DNWR present in the state s to which CZ i belongs. We again instrument $\Delta IP^{cu}_{i,\tau}$ with $\Delta IP^{cu}_{oi,\tau}$ and we instrument $Rig_{s(i),\tau} \times \Delta IP^{cu}_{i,\tau}$ with $Rig_{s(i),\tau} \times \Delta IP^{cu}_{oi,\tau}$.

We use two main proxies for DNWR following Jo and Zubairy (2023). The first one is based on the share of workers with negative year-over-year hourly wage changes among all workers. The second one is based on the share of individuals with negative wage changes to total individuals with nonzero wage changes. Both measures are constructed based on individual-level year-over-year wage changes from CPS data. We pool obser-

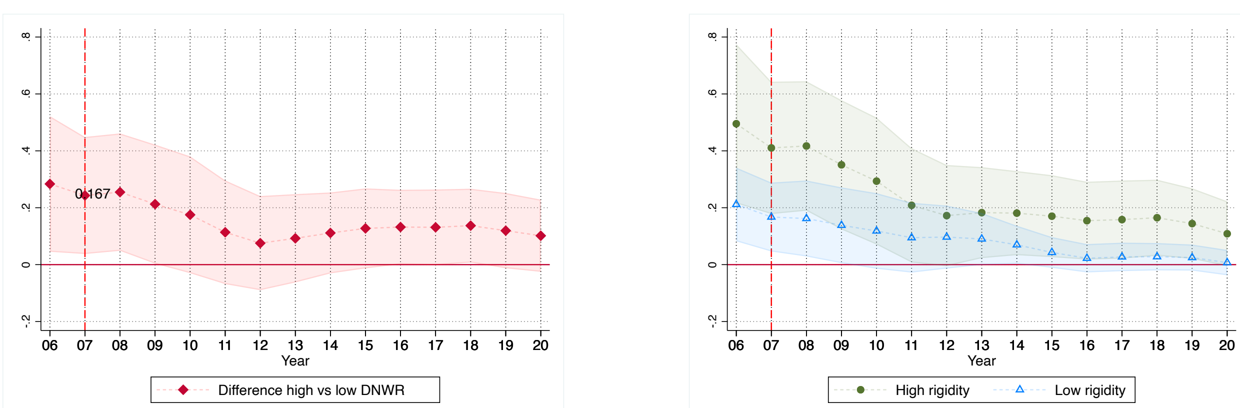
[10] Figure A.1 presents regression results using an alternative construction of the unemployment-to-population ratio, based on BLS county-level unemployment data and SEER working-age population data. The estimates remain both quantitatively and qualitatively consistent with those reported in Figure 1.

vations from 1987 to 1990 to define the rigidity shares for the 1990-2000 decade and observations from 1997 to 2000 to determine the rigidity shares post 2000.[11] We then define $Rig_{s(i),\tau}$ as a dummy, taking a value of one if a given state is below the mean share. Note that a value of one implies a lower share of negative wage changes, which in turn suggests more DNWR.

Panel (a) of Figure 2 displays the estimates of $\beta_{3,h}$ in equation (2). These estimates show the differential unemployment-to-population ratio increase for CZs with high vs. low DNWR. For 2007, the panel shows that CZs with high DNWR experienced an additional 0.17 percentage points increase in the unemployment-to-population ratio due to the China Shock, a magnitude that is large compared to the average effect (0.22) found in ADH. The differential effect is statistically significant at the beginning of the period and loses significance after some years. Panel (b) uses the estimates from the same regression to present the unemployment effects separated by category. While CZs in the high DNWR category experienced significantly larger unemployment effects at the beginning of the period, the unemployment effects in both categories fade out over time.[12]

Figure 2: China Shock and unemployment in CZs with high vs. low DNWR

(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2) when the measure of $Rig_{s(i),\tau}$ is a dummy taking value 1 in CZ i if the share of individuals with negative wage changes in state s is below the mean across all states.

[11] These shares are persistent over time. Only eight states switched between below/above median across the two decades.

[12] Appendix A shows that the findings in Figure 2 are robust to several alternative proxies of DNWR.

3 A Dynamic Spatial Trade and Migration Model with Downward Nominal Wage Rigidities

Building on Artuc et al. (2010) and CDP, we consider a dynamic multi-sector quantitative trade model with an input-output structure and forward looking agents that decide in which region and sector to work. Given our goals of matching the results in ADH, we introduce two key extensions to CDP: (i) DNWR as a mechanism that can generate unemployment; and (ii) a nested structure in the households' labor supply decision to allow for different elasticities of moving across regions and sectors. In this section, we present an abridged description of the model, relegating additional details to Appendix B.

3.1 Basic Assumptions

We assume that the world is composed of multiple economies or "regions" (indexed by i or j). There are M regions inside the U.S. (i.e., the 50 U.S. states), plus $I - M$ regions (countries) outside of the U.S. We assume that there is no labor mobility across different countries, but 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 $\phi_{j,s} + \sum_k \phi_{j,ks} = 1$. Total factor productivity 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

$$p_{ij,s,t} = \tau_{ij,s,t} A_{i,s,t}^{-1} W_{i,s,t}^{\phi_{i,s}} \prod_k P_{i,k,t}^{\phi_{i,ks}}, \tag{3}$$

where $P_{i,k,t}$ is the price index of sector k in region i at time t, satisfying:

$$P_{j,s,t}^{1-\sigma_s} = \sum_{i=1}^{I} p_{ij,s,t}^{1-\sigma_s}. \tag{4}$$

Let $R_{i,s,t}$ and $L_{i,s,t}$ denote total revenues and employment in sector s of region i, respectively. Noting that the demand of industry k of region j of intermediates from sector s is $\phi_{j,sk} R_{j,k,t}$ and allowing for exogenous deficits as in Dekle et al. (2007), the market clearing condition for sector s in region i can be written as

$$R_{i,s,t} = \sum_{j=1}^{I} \lambda_{ij,s,t} \left(\alpha_{j,s} \left(\sum_{k=1}^{S} W_{j,k,t} L_{j,k,t} + D_{j,t} \right) + \sum_{k=1}^{S} \phi_{j,sk} R_{j,k,t} \right), \tag{5}$$

where $D_{j,t}$ are transfers received by j, with $\sum_j D_{j,t} = 0$, and the trade shares satisfy

$$\lambda_{ij,s,t} = \frac{p_{ij,s,t}^{1-\sigma_s}}{\sum_{r=1}^{I} p_{rj,s,t}^{1-\sigma_s}}. \tag{6}$$

In turn, employment must be compatible with labor demand,

$$W_{i,s,t} L_{i,s,t} = \phi_{i,s} R_{i,s,t}. \tag{7}$$

3.2 Labor Supply

Agents are forward looking and face a dynamic problem with discount rate β. They face a cost $\varphi_{ji,sk}$ of moving from region j, sector s to region i, sector k.[13] 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 $\epsilon_{i,s,t}$. Agents can

[13] Zabek (2024) discusses the persistence of local ties and the implications for migration responses in depressed regions. However, measures of regional mobility that depend on the fraction of people born in a U.S. state would add additional state variables to our model in a way that becomes quickly intractable.

either engage in home production or look for work in any of the S market sectors. We denote the number of agents that participate in region i, sector s, at time t, by $\ell_{i,s,t}$.

An agent that starts in region j and sector s derives flow utility $U_{j,s,t}$ and decides whether to move knowing the economic conditions in all markets and the idiosyncratic shocks. Denoting with $\mathrm{v}_{j,s,t}$ the lifetime utility of an agent who is in (j,s,t) we have

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

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

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

with $\kappa > \nu$. This allows us to have different elasticities of moving across regions and sectors, which will be useful for the model to match the empirical evidence in ADH. 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. As shown in Appendix B.2, denoting the Euler-Mascheroni constant with γ, we have

$$V_{j,s,t} = U_{j,s,t} + \ln\left(\sum_{i=1}^{I}\left(\sum_{k=0}^{S}\exp\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)^{1/\nu}\right)^{\nu/\kappa}\right)^{\kappa} + \gamma\kappa. \tag{8}$$

Denote by $\mu_{ji,sk|i,t}$ the share of agents that relocate from market js to ik relative to the total number of agents that move from js to region i irrespective of the sector. Additionally, let $\mu_{ji,s\#,t}$ denote the fraction of agents that relocate from market js to any sector in i as a share of all the agents in js. In Appendix B.2, we show that

$$\mu_{ji,sk|i,t} = \frac{\exp\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)^{1/\nu}}{\sum_{h=0}^{S}\exp\left(\beta V_{i,h,t+1} - \varphi_{ji,sh}\right)^{1/\nu}}, \tag{9}$$

$$\mu_{ji,s\#,t} = \frac{\left(\sum_{h=0}^{S}\exp\left(\beta V_{i,h,t+1} - \varphi_{ji,sh}\right)^{1/\nu}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\left(\sum_{h=0}^{S}\exp\left(\beta V_{m,h,t+1} - \varphi_{jm,sh}\right)^{1/\nu}\right)^{\nu/\kappa}}. \tag{10}$$

The share of agents in js that move to ik is $\mu_{ji,sk,t} = \mu_{ji,sk|i,t} \cdot \mu_{ji,s\#,t}$, and participation in the different labor markets evolves according to

$$\ell_{i,k,t+1} \quad = \quad \sum_{j=1}^{I}\sum_{s=0}^{S}\mu_{ji,sk,t}\ell_{j,s,t}. \tag{11}$$

Without DNWR there would be no unemployment and hence the flow utility from participating in a sector-region would be the log of the associated real wage, $U_{i,s,t} = \ln(\omega_{i,s,t})$, where $\omega_{i,s,t} = W_{i,s,t}/P_{i,t}$ and $P_{i,t}$ is the aggregate price index in it,

$$P_{i,t} = \prod_{s=1}^{S} P_{i,s,t}^{\alpha_{i,s}}. \tag{12}$$

Equations (3)-(12) combined with $U_{i,s,t} = \ln(W_{i,s,t}/P_{i,t})$ and $L_{j,s,t} = \ell_{j,s,t}$ would characterize the equilibrium of a model that is similar to CDP.

With DNWR agents must take into account the possibility of unemployment when deciding where to participate. We assume that there is some level of insurance against unemployment among participants in each sector-region. Specifically, unemployed workers receive a transfer equal to a share $z \in (0,1]$ of the average income earned by all workers supplying labor in any given sector-region, funded by a tax on employed workers in that same sector-region. The probability of employment in (i,s) is $\pi_{i,s,t} \equiv L_{i,s,t}/\ell_{i,s,t}$, and we assume that workers supplying labor in (i,s) face a lottery with income $z\pi_{i,s,t}W_{i,s,t}$ with probability $1-\pi_{i,s,t}$ and income $(1-(1-\pi_{i,s,t})\,z)\,W_{i,s,t}$ with probability $\pi_{i,s,t}$.[14] Using $\omega_{i,s,t}$ to denote the average real wage among all workers supplying labor in (i,s), the expected (flow) utility associated with this lottery is

$$U_{i,s,t} = \ln\left(\Delta_{i,s,t}\omega_{i,s,t}\right), \tag{13}$$

where

$$\omega_{i,s,t} = \pi_{i,s,t} \cdot \frac{W_{i,s,t}}{P_{i,t}} \tag{14}$$

is expected income and $\Delta_{i,s,t} \leq 1$ is a factor capturing the risk associated with supplying labor in (i,s) in period t,

$$\Delta_{i,s,t} = z^{1-\pi_{i,s,t}} \left(\frac{1-z\,(1-\pi_{i,s,t})}{\pi_{i,s,t}}\right)^{\pi_{i,s,t}}. \tag{15}$$

[14]Expected income is then $(1-\pi_{i,s,t})z\pi_{i,s,t}W_{i,s,t} + \pi_{i,s,t}\,(1-(1-\pi_{i,s,t})z)\,W_{i,s,t} = \pi_{i,s,t}W_{i,s,t}$, so that the insurance scheme is fully funded within each sector-region.

For home production, we assume that $U_{i,0,t} = \ln(\omega_{i,0,t})$, with $\omega_{i,0,t}$ being the level of (non-market) consumption associated with home production in region i, which we assume to be exogenous and time invariant. Importantly, our setup does not allow unemployed workers to engage in home production. This implies that the threat of unemployment discourages participation, which is a useful feature that allows the model to match the ADH targets with a reasonable labor-supply elasticity.

3.3 Downward Nominal Wage Rigidity

In the standard trade model, labor market clearing requires that labor supply and demand equalize for each sector-region, 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 DNWR, which might lead to an employment level strictly below labor supply,

$$L_{i,k,t} \leq \ell_{i,k,t}. \tag{16}$$

All prices and wages up to now have been expressed in U.S. dollars, but regions face DNWR in terms of their local currency unit. Letting $W_{i,k,t}^{LCU}$ denote nominal wages in local currency units, the DNWR takes the following form:

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

Letting $E_{i,t}$ denote the exchange rate between i's local currency and region one's currency (which is the U.S. dollar) in period t, then the DNWR for wages in dollars entails

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

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

$$W_{i,k,t} \geq \delta_{i,k} W_{i,k,t-1}, \qquad \delta_{i,k} \geq 0. \tag{17}$$

In our baseline specification, we assume that all regions outside of the U.S. have a flexible exchange rate and so the DNWR never binds. We capture these assumptions by setting $\delta_{i,k} = \delta_k \; \forall \; i \leq M$ and $\delta_{i,k} = 0 \; \forall \; i > M$. Finally, equations (16) and (17) are satisfied with complementary slackness,

$$(\ell_{i,k,t} - L_{i,k,t})(W_{i,k,t} - \delta_{i,k} W_{i,k,t-1}) = 0. \tag{18}$$

3.4 Nominal Anchor

So far, we have introduced nominal elements to the model (i.e., the DNWR), but we have not introduced a nominal anchor that prevents nominal wages from rising so much in each period as to make the DNWR always non-binding. We 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. Instead, we use a nominal anchor that captures a similar idea in a way that lends itself to quantitative implementation in our rich trade model.

Specifically, we assume that world GDP in dollars grows at a γ constant gross rate,

$$\sum_{i=1}^{I} \sum_{s=1}^{S} W_{i,s,t} L_{i,s,t} = \gamma \sum_{i=1}^{I} \sum_{s=1}^{S} W_{i,s,t-1} L_{i,s,t-1}. \tag{19}$$

This nominal anchor has some desirable properties. First, 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 equations (16)-(18) implied by the DNWR. We describe this algorithm in Section B.7. Second, for certain combinations of γ and δ, it can be seen as capturing a given level of world aggregate demand in the context of a global savings glut. Intuitively, we would obtain similar results if we removed (19) and assumed instead that something prevents the Chinese wage in dollars from rising. This could occur if China wants to preserve its competitiveness and uses a combination of monetary and exchange rate policies to prevent the Chinese wage in dollars from increasing, while the U.S. does not offset this with its own policies (perhaps because of inattentiveness). We further discuss alternative nominal assumptions in Section 8.2.

Consider a shock that requires the relative wage of some sector k in region i to fall in order to maintain full employment in that sector-region. If δ_k is low enough, or the exchange rate can depreciate (e.g., $\delta_{i,k}$ is low), then nominal wages can adjust downwards as required to avoid unemployment. Relatedly, if γ is high enough then again there would be no unemployment, since no downward adjustment is needed in the nominal wage. However, there are combinations of $\delta_{i,k}$ and γ that can lead to unemployment after the shock, although there would then be a decline in unemployment as the DNWR and/or the anchor allow for adjustment year after year.

3.5 Equilibrium

Following CDP, we can think of the full equilibrium of our model in terms of temporary and sequential equilibria. In our environment with DNWR, given last period's world nominal GDP, 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 (3)-(7) and (16)-(19) hold. Without DNWR then $L_{i,s,t} = \ell_{i,s,t}$ for all i, s, and (relative) wages would be determined by equations (3)-(7), with equations (16)-(19) just serving to pin down nominal wages. DNWR implies that labor demand and supply may not be equalized, so we need all equations in (3)-(7) and (16)-(19).

In turn, given initial 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 $\{\omega_{i,s,t},\ \Delta_{i,s,t}\ V_{i,s,t},\ \mu_{ji,sk|i,t},\ \mu_{ji,s\#,t},\ \ell_{i,s,t},\ W_{i,s,t},\ L_{i,s,t}\}_{t=1}^{\infty}$ 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) $\{\omega_{i,s,t}, \Delta_{i,s,t}, V_{i,s,t}, \mu_{ji,sk|i,t}, \mu_{ji,s\#,t}, \ell_{i,s,t}\}_{t=1}^{\infty}$ satisfy equations (8)-(15).

3.6 Dynamic Hat Algebra

Our goal is to use a calibrated version of the model to compute the employment and welfare effects of a trade shock. We do this using data for U.S. states as well as other countries, but without needing to calibrate technology levels and iceberg trade costs along the transition and without requiring data on nominal wages per efficiency unit of labor. We follow the exact hat algebra methodology of Dekle et al. (2007) and its extension to dynamic settings proposed by CDP. Consequently, our counterfactual exercises only require data on revenues $R_{i,s,t}$, value added $Y_{i,s,t} \equiv W_{i,s,t} L_{i,s,t}$, trade deficits $D_{i,t}$, mobility matrices $\mu_{ji,sk|i,t}$ and $\mu_{ji,s\#,t}$, labor supply levels $\ell_{j,s,t}$, and trade shares $\lambda_{ij,s,t}$ in period zero ($t = t_0$), whatever shocks we are interested in, and the model's parameters, namely $\delta_{i,k}$, γ, κ, ν, $\{\sigma_s\}$, $\{\alpha_{j,s}\}$, $\{\phi_{i,s}\}$, and $\{\phi_{i,sk}\}$.

We use $\dot{x}_t$ to denote x_t / x_{t-1} for any variable x. Appendix B.3 describes how to express the equilibrium system in dots and leave it in terms of observables in period zero. We assume that the economy starts from a point where every region had full employment.[15] Appendix B.4 describes the algorithm we use to solve the system "in dots".

We are interested in obtaining the effects of the China shock as it is introduced in an economy that did not previously expect this shock. In order to do this, 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 China shock is unexpectedly introduced in the year 2001 (and agents have perfect foresight about the path of the shock from then on), with a baseline economy where no shocks occur. Appendices B.5 and B.6 describe how to express and solve the equilibrium system "in hats".

Our general equilibrium model also allows us to compute the welfare effects of the shock. Using the utility framework described in Section 3.2, we can express the welfare change in sector s of region j due to the China shock as

$$\mathcal{V}_{j,s} = \sum_{t=1}^{\infty} \beta^t \ln \left(\frac{\hat{\Delta}_{j,s,t} \hat{\omega}_{j,s,t}}{\left(\hat{\mu}_{jj,ss|j,t}\right)^{\nu} \left(\hat{\mu}_{jj,s\#,t}\right)^{\kappa}} \right).$$

This expression corresponds to the permanent equivalent variation in real income for

[15] Assuming that the U.S. had full employment in the year 2000 is not problematic, since that year was the peak of a business cycle, with a historically low unemployment rate of just 4%. The existence of 4% unemployment is consistent with our assumption of "full employment" because the concept of unemployment in our model is that of "cyclical" unemployment, i.e., the unemployment in excess of the natural rate.

workers originally employed in region j in sector s, so that $V'_{j,s,0} = V_{j,s,0} + \mathcal{V}_{j,s}/(1-\beta)$.[16] For intuition, consider a shock that decreases the expected risk-adjusted real wage in sector j,s, $\hat{\Delta}_{j,s,t}\hat{\omega}_{j,s,t} < 1$. Without mobility we would simply have

$$\mathcal{V}_{j,s} = \sum_{t=1}^{\infty} \beta^t \ln \left(\hat{\Delta}_{j,s,t}\hat{\omega}_{j,s,t} \right),$$

which is the present discounted value of the changes in the real wage. Mobility allows workers in the sector to transition to other sectors and regions, as captured by $\hat{\mu}_{jj,ss|j,t} < 1$ and $\hat{\mu}_{jj,s\#,t} < 1$. Finally, given those mobility measures, higher variability parameters ν and κ imply larger gains from moving out of the affected sector.

The welfare expression above is given at the sector-region level. However, in some parts of the paper we will refer to welfare measures at the regional level. Such regional welfare measures are computed as weighted averages of the corresponding sector-region welfare levels, with weights given by the initial population shares.

4 Data for the Quantitative Exercise

We provide a brief description of our data construction procedure here and relegate details to Appendix C. We use trade, production, and employment data for 50 U.S. states, 36 countries, and a rest of the world region, for a total of 87 regions. We consider 14 market sectors: 12 manufacturing sectors, one service sector, and one agricultural sector.

Labor, consumption, and input shares For each region j and each sector k, our model requires data to compute the share of labor in production $\phi_{j,k}$, the share of intermediates $\phi_{j,sk}$ $\forall s$, and the consumption shares $\alpha_{j,k}$. We use data from the Bureau of Economic Analysis (BEA) for U.S. states and from the World Input-Output Database (WIOD) to compute the share of value-added in gross output of region j, which in our model is equivalent to $\phi_{j,k}$. We also scale the relative importance of each U.S. state in the total value added of the U.S. so that the sum of value added across states matches the aggregate

[16] See Appendix B.8 for details. Trade imbalances supported by transfers imply that consumption may differ from real income. We follow Costinot and Rodriguez-Clare (2014) and measure welfare by real income rather than consumption to avoid attributing a direct gain to the foreign transfer.

value-added of the U.S. according to WIOD. We compute $\phi_{j,sk}$ as the share of purchases of sector k coming from sector s (the input-output coefficient) using WIOD data.

Bilateral trade flows We construct bilateral trade flows between all region pairs for each sector in four steps. First, we take sector-level bilateral trade flows between countries from WIOD. Second, we follow CDP to calculate the bilateral trade flows in manufacturing among U.S. states by combining WIOD and the Commodity Flow Survey (CFS). Third, we use the Import and Export Merchandise Trade Statistics to compute – for manufacturing and agriculture – the sector-level bilateral trade flows between each U.S. state and each other country in our sample. Fourth, we combine data for region-level production and expenditure in services from the Regional Economic Accounts of BEA, WIOD data, and data on bilateral distances to construct service trade flows among all regions following a gravity structure. We follow a similar approach for agriculture, using data from the Agricultural Census, the National Marine Fisheries Service Census, and WIOD.

Labor flows across sectors and regions For the U.S. states, we combine data from the Current Population Survey (CPS), the American Community Survey (ACS), the state-to-state migration data from the IRS SOI Tax Stats, and the BLS sector-state level employment data to construct the matrix of migration flows $\mu_{ji,sk,t}$ between 1999 and 2000. The final migration data (i) satisfies that the total movements between states across sectors add up to the total state-to-state movements in the IRS data and (ii) is consistent with the change in the stock of workers across sector-state pairs between 1999 and 2000 in the BLS and Census data. Finally, we assume that there is no migration between countries, and that, for countries outside of the U.S., there are no costs of moving across sectors within a region. Given this, one can infer the matrix of migration flows for non-U.S. countries from the labor distribution in 1999 and 2000, as detailed in Appendix C.3.

5 Calibration

In this section, we describe how we calibrate our main parameters (δ, ν, κ), as well as the China shock. We focus on the effect of the China shock as captured by a set of productivity shocks in China given by $\{\hat{A}_{China,s,t}\}$ that apply only to the 12 manufacturing sectors. Inspired by ADH, and following CDP and Galle et al. (2023), we calibrate these shocks to match the changes in U.S. imports from China predicted from the changes in imports from China to other high-income countries.[17]

We decompose the total productivity shock in sector s and time t into the product of a sector-level productivity increase that is constant from 2000 to an end year and a productivity increase over time that is constant across sectors, i.e. $\hat{A}_{China,s,t} = \hat{A}^1_{China,t}\hat{A}^2_{China,s}$. The end year will be 2007 in our baseline specification and 2011 in a specification with a longer-lasting China shock.[18] This means we have to estimate 19 parameters (or 23).

We choose $\{\hat{A}^1_{China,t}\}$ and $\{\hat{A}^2_{China,s}\}$ to match two targets. The first target is the vector of annual predicted changes in U.S. imports from China in all manufacturing sectors combined, obtained from the following regression:

$$\Delta X_{C,US,t} \quad = \quad a + b_1 \Delta X_{C,OC,t} + \varepsilon_t,$$

where $\Delta X_{C,US,t}$ is the change in U.S. imports from China between year $t-1$ and year t in all manufacturing sectors, $\Delta X_{C,OC,t}$ is the corresponding change in imports from China by the other high-income countries, and b_1 is the coefficient of interest. The predicted values from this regression are denoted $\{\widehat{\Delta X_{C,US,t}}\}$. The second target is the vector of predicted changes in U.S. imports from China between 2000 and the end year across sectors, obtained from the regression:

$$\Delta X^{end-2000}_{C,US,s} \quad = \quad b_2 \Delta X^{end-2000}_{C,OC,s} + \varepsilon_s,$$

where $\Delta X^{end-2000}_{C,US,s}$ is the change in U.S. imports from China between 2000 and our end year in sector s, $\Delta X^{end-2000}_{C,OC,s}$ is the corresponding change in imports from China by the other high-income countries, and b_2 is the coefficient of interest. The predicted values from this regression are denoted $\{\widehat{\Delta X^{end-2000}_{C,US,s}}\}$.[19] We choose $\{\hat{A}^1_{China,t}\}$ and $\{\hat{A}^2_{China,s}\}$

[17] We use the subset of ADH countries that are also present in the 2013 version of the WIOD, namely Australia, Germany, Denmark, Spain, Finland, and Japan.

[18] As pointed out in Autor et al. (2021), the China shock approached peak intensity around 2010 and plateaued shortly after. Because of this, their baseline definition of the trade shock is the period 2000-2012. We use 2011 as the final year because this is the last year in the WIOD 2014 data release.

[19] We exclude the constant in this regression because it can lead to negative predicted imports from China,

such that the total productivity changes in China $\{\hat{A}_{China,s,t}\}$ deliver changes in imports in our model that match the values of $\{\widehat{\Delta X_{C,US,t}}\}$ and the values of $\{\widehat{\Delta X^{end-2000}_{C,US,s}}\}$.[20]

The calibration of the key model parameters (described below) is based on matching moments that capture the relative effect of the China shock on labor force participation, unemployment, and population. These moments come from regressions of changes in these variables across regions differentially exposed to the China shock, as captured by an exposure measure that follows the one proposed by ADH:

$$\text{Exposure}_i \equiv \sum_{s=1}^{S} \frac{L_{i,s,2000}}{L_{i,2000}} \frac{\widehat{\Delta X^{2007-2000}_{C,US,s}}}{R_{US,s,2000}}, \tag{20}$$

where $R_{US,s,2000}$ is total U.S. output in sector s in the year 2000 and $L_{i,s,2000}$ is employment of region i in sector s in year 2000, $L_{i,2000} \equiv \sum_s L_{i,s,2000}$.

For our baseline specification, we assume that only the manufacturing sectors are subject to DNWR so that $\delta_{i,k} = 0$ if k is services or agriculture.[21] We also assume that all countries outside the U.S. have a flexible exchange rate that adjusts in such a way that they retain full employment, implying that $\delta_{i,k} = 0$ for all $i > M$. Therefore, we have a single δ parameter that applies to all manufacturing sectors in all U.S. states. We do not calibrate γ and δ separately – since only their relative value matters – and instead assume that γ is 1, so that the burden of adjustment falls on δ.

We use dynamic hat algebra as described in Section 3.6 to simulate the economy's response to the calibrated China shock, and then choose values of δ, ν, and κ so that OLS coefficients on the simulated data match three estimates from ADH: a \$1,000 per worker increase in import exposure to China increases the unemployment-to-population ratio by 0.22 percentage points, the NILF-to-population ratio by 0.55 percentage points, and leads

which is impossible. While the regression only has 12 observations, it has an R^2 of 0.99.

[20] The multiplicative nature of $\hat{A}_{China,s,t} = \hat{A}^1_{China,t}\hat{A}^2_{China,s}$, implies that their level is not identified. We use the normalization $\sum_{s=1}^{S} \hat{A}^2_{China,s} = 1$. For more details see Appendix B.9.

[21] There are a few papers documenting a substantial degree of heterogeneity in wage rigidity across sectors and occupations (Radowski and Bonin, 2010; Du Caju et al., 2012). Hazell and Taska (2023) find that production workers face a higher degree of DNWR than workers in non-production occupations. Since production workers are a higher share of total labor in manufacturing compared to non-manufacturing, this could explain why the DNWR could bind more strongly in manufacturing. Another explanatory element could be the presence of stronger unionization in manufacturing.

to a 5 basis-points decrease in population.[22] This leads to calibrated values of $\delta \approx 0.99$, $\nu = 0.54$, and $\kappa = 6.5$.[23] The value of δ implies that nominal wages can fall around 1% annually, and lands within the ballpark described by Schmitt-Grohe and Uribe (2016) who obtain an annual δ of 0.984 (after "normalizing" γ to one as we do). Our estimates for ν and κ compare to a value of $\nu = \kappa = 2.02$ in CDP.[24,25] Imposing $\nu = \kappa = 2.02$ would lead to effects on labor force participation and population that are too small relative to those estimated by ADH. Alternatively, we could constrain our model to satisfy $\nu = \kappa$, but without setting this single elasticity to the CDP value of 2.02. Calibrating $\nu = \kappa$ and δ to match the unemployment and participation targets from ADH leads to a population response that is over four times greater than the population response in ADH.

Finally, we assume that the trade-elasticity parameter σ_s is constant across sectors and takes the value of 6, consistent with the trade literature (e.g. Costinot and Rodriguez-Clare, 2014). We also set the discount factor β equal to 0.95 and the risk sharing parameter z equal to 0.5, implying 50% risk sharing within a given region-sector.

6 Effects of the China Shock in the Baseline Model

6.1 Comparison of Cross-Sectional results with ADH

We now use the calibrated model to study the effects of the China shock across U.S. states. We first obtain the changes in employment, unemployment, labor participation, real wages, and population for all the 87 regions included in our model. Then we run OLS

[22] These results correspond to the ones in panel B of Table 5 and panel C of Table 4 in ADH. Some recent papers such as Borusyak et al. (2021) have cast doubt on the statistical significance of some of ADH's results. Despite that, we focus on these results as targets since ADH is the most influential paper in this literature. That said, our quantitative analysis can be accommodated to match alternative targets.

[23] Identification relies on the assumption that the China shock is the only shock affecting the model economy. Thus, unlike the approach in Caliendo et al. (2019), we do not saturate the model with shocks to match all the data.

[24] In a static setup, our estimate of $\nu = 0.54$ implies a labor supply elasticity at the sector level of around 2 (for small enough sectors). This is just slightly higher than the estimate for this elasticity in Galle et al. (2023). Hsieh et al. (2019) estimate a labor supply elasticity at the level of occupations, finding also a value of 1.5, although they end up using a value of 2 in their quantitative analysis to come closer to estimates of the labor supply elasticity in the meta analysis of Chetty et al. (2013). Similar values are obtained for mobility across occupations in Burstein et al. (2019).

[25] Our model is annual, so we compare our estimates with the annualized version of CDP's single elasticity.

regressions across U.S. states of the model-implied changes in the variables of interest on the exposure measure in equation (20). We present the resulting coefficients in Table 1, along with the analogous coefficients from ADH.

Column (1) of Table 1 reports the results of ADH presented in their panel C of Table 4, panel B of Table 5, and panel B of Table 7. Rows one, two and five correspond to the ADH regression coefficients that we used as targets in our calibration. Column (2) of Table 1 presents the results of our baseline model, where the changes in productivity in China last from the year 2001 to 2007. We focus on the results related to employment and wages in this section, and discuss the welfare effects in Section 6.3.[26] We postpone the discussion of columns (3) and onwards to Section 7.

The results in column (2) show that exposure to China measured as in ADH leads to a fall in manufacturing and non-manufacturing employment of 0.61 and 0.17 percentage points, respectively. These are moments that we did not target in our calibration.[27] Nevertheless, they are very close to the corresponding ADH coefficients. Regarding the effect of exposure to China on wages, our baseline specification indicates that manufacturing wages remain roughly unchanged while non-manufacturing wages fall by 118 basis points. This is qualitatively consistent with the empirical evidence, which finds that the non-manufacturing wage falls more than the manufacturing wage in response to more exposure to the shock.[28]

Our results imply a dispersion in the impacts of the China shock on employment and income per capita across U.S. states that is comparable to the one predicted by the ADH specification in the 2000-2007 data. To assess this, we first compute the predicted vari-

[26] We focus on a state-level analysis because this is the level at which one can construct bilateral trade matrices and mobility flows without having to impose further strong assumptions on how the state-level flows are split between different commuting zones. Moreover, running simple ADH state-level regressions without controls yields similar response-to-exposure coefficients.

[27] The only restriction is that the coefficients have to add up to 0.77 since this is the sum of the targeted unemployment and NILF coefficients in ADH.

[28] We emphasize that average wages are not targeted in our calibration. Instead, the three key parameters (δ, ν, κ) are identified solely from observed changes in unemployment, nonemployment, and population. Although our model does not incorporate heterogeneous wage responses (which could be important as highlighted by Autor et al., 2014 and Chetverikov et al., 2016) and thus cannot capture adjustments across the wage distribution, this limitation does not affect our calibration strategy. The contrast between the untargeted average wage change in the model and the empirical evidence in ADH is still a potentially interesting additional piece of evidence.

Table 1: Employment, population, wage, and welfare effects of exposure to China across U.S. regions and associated parameters generating them

	ADH (1)	Baseline (2)	Longer (3)	NM (4)	$\nu = \kappa$ (5)
Change in Population Shares					
Unemployment (targeted)	0.221**	0.221	0.221	0.221	0.221
NILF (targeted)	0.553**	0.553	0.553	0.553	0.553
Mfg Employment	-0.596**	-0.605	-0.578	-0.602	-0.613
Non-mfg Employment	-0.178	-0.169	-0.196	-0.172	-0.161
Percentage Changes					
Population (targeted)	-0.050	-0.050	-0.050	0.000	-0.211
Mfg Wage	0.150	0.023	0.209	0.016	0.039
Non-mfg Wage	-0.761**	-1.177	-0.966	-1.204	-1.182
Welfare					
Welfare vs exposure		-0.091	-0.134	-0.081	-0.099
Mean welfare change		0.126	0.011	0.138	0.124
Mean welf. change no DNWR		0.312	0.450	0.314	0.313
Parameters					
ν		0.537	0.706	0.611	0.606
κ		6.548	13.53		0.606
δ		0.991	0.994	0.990	0.991

Notes: The changes for the first four coefficients are measured from 2000 to an average of 2006-2008, multiplied by 10/7 to turn into decadal changes. Population and wages are simply measured in percentage change (between 2000 and 2006-2008), still turned into decadal changes. Welfare is obtained as described at the end of Section 3.6. ν is the parameter that governs substitution between sectors, κ is the one that governs substitution between regions, and δ governs the DNWR. Column 1 reproduces the ADH results from their Tables 4 (panel C, first column), 5 (panel B, first row) and 7 (panel B, columns 1 and 4), stars denote significance, one star for 5%, and two for 1%. Column 2 gives the results in our baseline specification. Column 3 describes a longer shock that lasts until 2011 instead of until 2007. Column 4 eliminates migration across U.S. states. Column 5 imposes $\nu = \kappa$. In column (4) κ is not reported, because, without migration, this parameter is irrelevant.

ation in the employment-to-population ratio and income per capita by running ADH's main regression specification on their data at the commuting zone level.[29] We then compute the population-weighted average of these predicted values across all commuting zones within the same state. Finally, we compare these empirical predictions to their model-implied counterparts. The standard deviation (s.d.) of the changes in the state-level employment to population ratio predicted by the model is 1.11, which is similar to the s.d. of 1.18 implied by the empirical estimates. In turn, the s.d. of the changes in income per capita predicted by the model is 2.1, while the one associated with the empirical

[29] For the variation in employment rate we focus on the change in the ratio of total employment to working age population using data from ADH. For the variation in income per capita we follow the left hand side of equation 8 in Autor et al. (2021) to compute the deviation in changes in income per capita of each commuting zone relative to the national weighted average. We use the total salary income per adult from column 2 of Table 9 in ADH as the measure of income per capita.

estimates is 1.9.

These results stand in contrast to previous quantitative models such as CDP and Galle et al. (2023), which imply too little spatial heterogeneity in the employment and income effects relative to ADH (as shown by Adao et al., 2023; Autor et al., 2021). There are two reasons why our model generates more dispersion in employment and income effects. First, because of DNWR, our model leads to much larger declines in employment in the most exposed regions, both directly through higher unemployment, and indirectly through discouraging labor participation. Second, by allowing for a difference between the elasticity of moving across sectors and that of moving across regions, we arrive at lower mobility across states and a higher labor supply elasticity than CDP.

6.2 Aggregate Employment Effects

We now use our general equilibrium model to go beyond cross-sectional implications and obtain the implied aggregate effects of the China shock on unemployment and other variables. Figure 3 plots the aggregate U.S. unemployment generated by the China shock according to our model. It increases gradually at first, reaching 1.25 percent in 2007, and then falls to a level near zero by 2016. Notice that all excess unemployment generated by the DNWR eventually disappears if shocks are no longer hitting the economy. This occurs

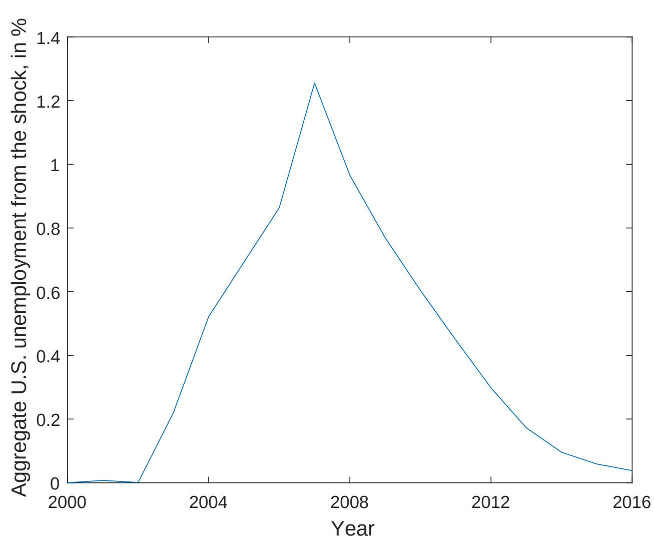


Figure 3: Path of aggregate U.S. unemployment generated by the China shock in the baseline specification between 2000 and 2016.

because, since the nominal wage can fall approximately 1% per year, wages eventually reach the level required to make all unemployment disappear. This is a feature of the model that squares well with the evidence presented in Section 2.2, as well as with the historically low levels of unemployment observed in the U.S. between 2016 and 2019.

Regarding aggregate labor force participation, there is a sign reversal throughout the transition. On impact, the China shock leads to a temporary decline in participation, stemming from the fact that unemployment discourages participation due to the risk of engaging in the labor market but not being able to obtain a job. U.S. labor force participation falls by up to 1.2% in 2007. However, when the China shock stops hitting the economy and the nominal wage has room to fully adjust, labor force participation ends up increasing relative to its original level. This happens because the China shock is a positive terms-of-trade shock for the U.S., which translates to a higher real wage and an increase in labor supply. By 2015, aggregate labor force participation in the U.S. has already reversed sign and increased roughly 1% relative to its pre-shock value.

The results imply that most states experience both a long-run increase in the real wage and a temporary increase in unemployment. This is a consequence of a shock that implies both an improvement in the terms of trade and a decline in the export price index in a setting with DNWR. To see this most clearly, consider an economy facing a foreign shock and a consequent decline in both the export and import price indices, but with the latter falling by more than the former. Since the terms of trade have improved, the real wage and employment would increase in the absence of nominal frictions. However, the fact that the price index of its exports has fallen requires the nominal wage to decline, and if this decline is higher than $1-\delta$, there would be temporary unemployment.[30]

6.3 Welfare Effects

We find that U.S. states more exposed to the China shock experience lower model-implied welfare gains: a \$1,000 per worker increase in exposure to China decreases welfare by around 9.1 basis points (this is the coefficient in column 2, row 8 of Table 1). Figure 4 presents a scatter plot of the percentage change in welfare across states against expo-

[30] Appendix Figure A.10 provides additional intuition for these results.

sure to China, while Appendix Figure A.9 displays a welfare map across the 50 U.S. states. There are 30 states that gain from the China shock while 20 states suffer welfare losses.

When we consider the U.S. as a whole, and measure welfare by the population-weighted average across U.S. states, we see that the China shock leads to an increase in welfare of roughly 12 basis points. We can compare the results of our baseline model against those from a model without nominal rigidity (i.e., with $\delta = 0$). In this alternative version of the model without DNWR and without recalibrating other parameters (such as ν or κ), the U.S. as a whole experiences gains of 31 basis points.[31] Additionally, all but two states experience welfare gains from the China shock. Comparing these two models, we see that the temporary unemployment due to DNWR reduces the aggregate gains from the China shock by roughly two thirds.

Following our measure of welfare changes in Section 3.6, which is at the sector-region level, we can explore how the welfare effects of the China shock vary across workers initially employed in different sectors and regions. Figure 5 presents a histogram of welfare changes for sector-states of the U.S. There is higher variation in this more disaggregated

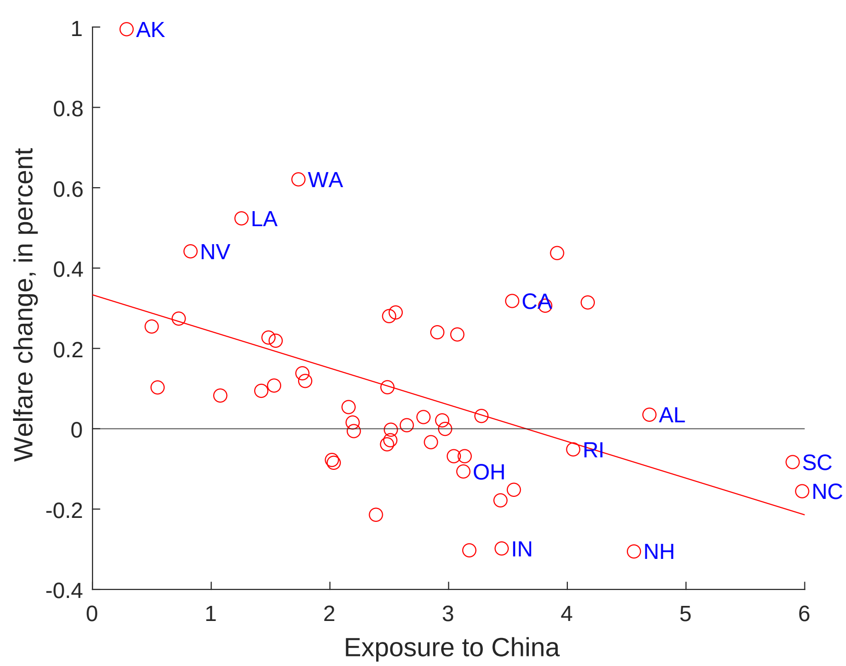


Figure 4: Welfare change vs exposure to China across U.S. states in the baseline specification. Selected states are labelled with the usual two-letter abbreviations.

[31]This is comparable to the gains obtain in other recent papers (e.g., CDP, Galle et al., 2023).

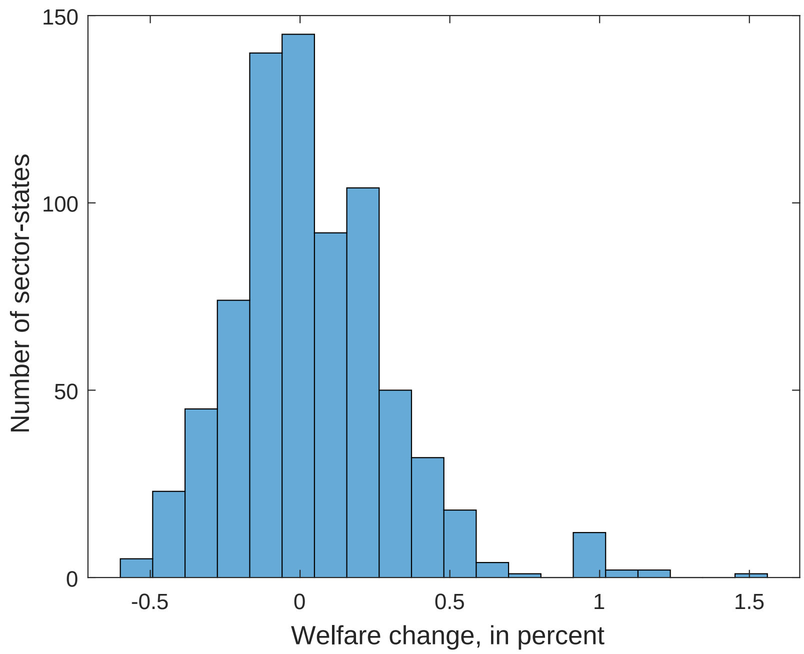


Figure 5: Histogram of welfare changes across different sector-states of the U.S. in the baseline specification.

measure, with welfare effects ranging from -60 to 156 basis points, compared to the measure at the state level, where the welfare effects range only from -31 to 99 basis points.

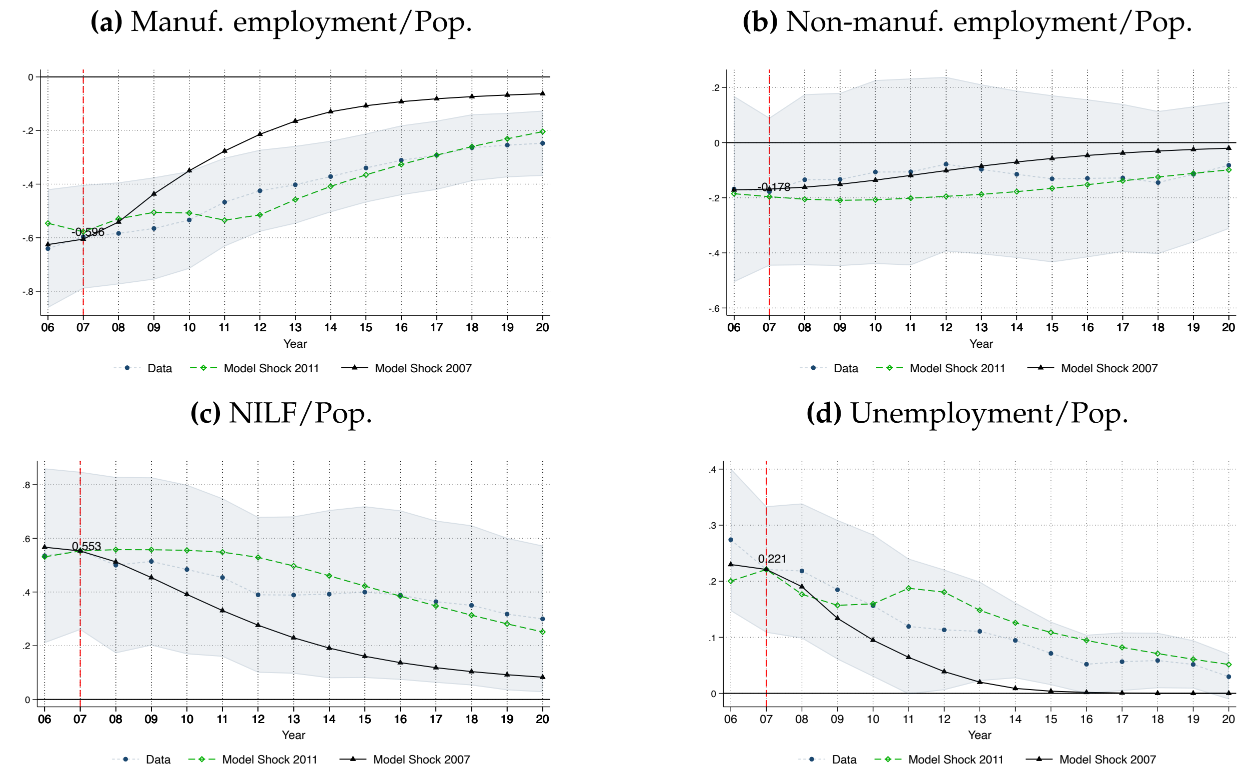
7 Alternative Specifications

In this section, we discuss the implications of the China shock through the lens of the model under alternative specifications. First, we describe the results if the China shock lasts until 2011 instead of 2007. Second, we discuss how different migration assumptions impact the results.

7.1 Longer Shock

As described in Section 5, our baseline specification incorporates a productivity shock in China that lasts from 2001 to 2007. In this section, we discuss a specification where the China shock lasts instead from 2001 to 2011. This variant accounts for the fact that the real-world shock might not have stopped in 2007. For instance, Autor et al. (2021) point out that Chinese import penetration continued to grow after 2007, reaching

Figure 6: Effects of the China Shock on employment and non-employment



Note: Each panel reports three lines. The blue line with circular markers shows the two-stage least squares coefficient estimates for β_{1h} in equation (1) and the shaded area represents their 95% confidence intervals. These coefficients are the same as in Figure 1 with the exception that the total employment to population effects in Figure 1 panel (a) are separated into manufacturing to population (panel a) and non-manufacturing to population (panel b). The green dashed line displays the effects in our model when the China shock lasts between 2001 and 2011 (labeled as "Model Shock 2011"), while the black line with triangular markers displays the effects in our baseline model when the China shock lasts between 2001 and 2007 (labeled as "Model Shock 2007"). The three lines coincide in 2007 for panels (c) and (d) by construction.

peak intensity around 2010 and plateauing shortly thereafter. This motivated them to use a definition of the China Shock that stops in 2012. We use 2011 as our final year because it is the last year available in the WIOD-2014 release, which is one of our main data sources. Column (3) of Table 1 reports some results under the specification with the longer shock. We still target the unemployment, NILF, and population responses in 2007 from ADH. The results for manufacturing and non-manufacturing employment do not change much compared to the baseline, but the wage changes become closer to those in ADH.

To explore how the model-implied persistence of the shock relates to the empirical evidence, Figure 6 shows how the cross-sectional effects of the China Shock evolve over time. The figure's structure is similar to that of Figure 1 but with the total employment effects split into manufacturing and non-manufacturing. The blue line shows the empirical estimates for β_{1h} in equation (1) (the same ones as in Figure 1), the green line displays the equivalent effects in our model when the China shock lasts until 2011, and the black line displays the effects in our baseline specification. The green and black lines match the blue line in 2007 for panels (c) and (d) by construction; these are two of our three targeted moments, the other one being the ADH population effect in 2007. Besides the targeted coefficients in 2007, neither the baseline nor the longer-shock specification use any other targets related to the dynamic path of the cross-sectional empirical results.[32]

Figure 6 illustrates that, qualitatively, the baseline specification does a decent job at matching some of the dynamic properties of the cross-sectional responses in the data, as it is within the confidence intervals for all panels except the manufacturing employment one. Quantitatively, however, the manufacturing employment, NILF, and unemployment results in the baseline are not as persistent as in the data, undershooting for all of the 2010's. By contrast, the dynamic pattern of the cross-sectional results in the longer-shock specification is very close to the one in the data. This is reassuring, as we do not target any of these results. Specifically, the green dashed line for the longer-shock specification is within the confidence interval of the empirical estimates in all panels, and it is also very close to the specific point estimates for almost all years.

It is also worth noting that in the longer-shock specification, the aggregate welfare effect of the China shock in the U.S. becomes very close to zero. Namely, the extended period of unemployment and general dislocation generated by the longer shock, depicted in Figure 7 (which mimics Figure 3 but for the longer-shock specification instead of the baseline), manages to extinguish nearly all the welfare gains that the U.S. would have experienced in the absence of DNWR. As can be seen from Figure 7, aggregate U.S. unemployment generated from the shock peaks at a higher level (1.75% instead of 1.25%) and lasts much longer than in the baseline.

A notable feature of Figure 7 is the decline in unemployment generated by the shock in 2009. This follows naturally from our calibration procedure, which sticks as close as

[32]The longer-shock specification does target the changes in productivity in China in order to match the predicted changes in U.S. imports between 2001 and 2011 as described in Section 5, but this is completely independent from the cross-sectional empirical results we are discussing here.

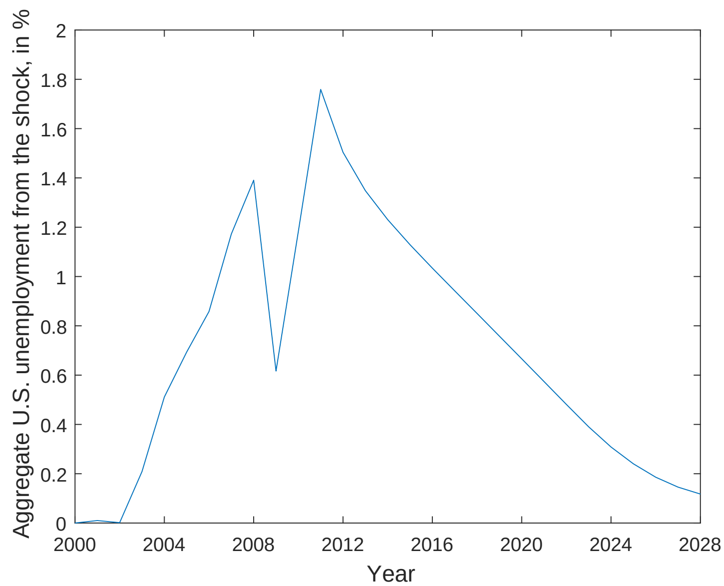


Figure 7: Path of aggregate U.S. unemployment generated by the China shock in the longer-shock specification between 2000 and 2028.

possible to ADH's instrumental-variable strategy. During the Great Recession, imports from China–both by the U.S. and other developed countries used in ADHs instrument–declined significantly. As a result, our calibration infers a negative productivity shock in China for 2009. This leads the model to produce a corresponding decline in the unemployment generated by the shock that year. To avoid complications related to the Great Recession and how it could have interacted with the China Shock, we adopt the shock lasting until 2007 as our baseline. Nevertheless, it is still worthwhile to explore the implications of the longer shock for the dynamic pattern of the cross-sectional effects of exposure (as done in Figure 6).

7.2 Different Migration Assumptions

Given the potential importance of migration for the dispersion of welfare effects across U.S. states, we now study two polar options for migration: no migration and $\nu = \kappa$, which leads to more migration across states in response to the China shock.

In the first case, workers only have the option of moving between sectors within a state. We start from a mobility matrix that matches intra-state migration flows from the CPS data, which has good coverage about employment status and industry of each respondent who stayed in the same state between waves of the survey. We then compute the impacts of the China shock in the same way as in the baseline model except for the fact that migration flows across states have been shut down. The results are described in column (4) of Table 1.[33] The calibrated ν increases relative to our baseline, but the calibrated δ remains similar. In addition, many non-targeted moments, such as the changes in manufacturing and non-manufacturing employment and wages, as well as our inferred welfare changes (with and without DNWR) also stay relatively unchanged.

In our second alternative specification, we impose that $\nu = \kappa$, which is necessarily true in CDP.[34] The results are described in column (5) of Table 1. We find that $\nu = \kappa = 0.606$, similar to our baseline estimate of ν, but less than one tenth of our baseline estimate of κ. This much lower estimate of κ in the restricted model leads to a population response to the China shock that is more than four times greater than the one in the baseline model (and in ADH). Other results, like the calibrated δ and the employment and wage changes are similar to those from the baseline.

8 Discussion

8.1 Different Exposure Measures

The measure of exposure to China that we have been using so far follows the one in ADH. This is a Bartik instrument where the "shift component" is given by the predicted sector-level change in U.S. imports from China and the "share component" is given by sector-level employment shares in a region. As we now discuss, this exposure measure cannot fully capture the welfare effects of the China shock, because it misses the impact through consumer prices.

As we show in Appendix D, in a neoclassical environment with an upward sloping labor supply curve but without nominal rigidities, a sufficient statistic for the first-order changes in employment resulting from the China shock would use net exports as the

[33] Notice that in this case κ is no longer relevant, and we no longer match the response of population to exposure from ADH.

[34] As in the previous extension, we do not target the population response in ADH, and only target the unemployment and participation responses.

"share" component, as in

$$\text{Exposure}_i^{NX} \equiv \sum_{s=1}^{S} \frac{R_{i,s,2000} - E_{i,s,2000}}{R_{i,2000}} \frac{\Delta \widehat{X_{C,US,s}^{2007-2000}}}{R_{US,s,2000}}, \tag{21}$$

where $R_{i,s,2000}$ are total sales of region i in sector s in year 2000, and $E_{i,s,2000}$ is total expenditure of region i on sector s in year 2000. This captures the effect of the shock on the economy's terms of trade. By contrast, when the wage does not adjust because of DNWR, employment shares become directly relevant, since the change in employment is determined entirely by the shift in the demand curve. Of course, if wages are sticky in the short run due to DNWR but can eventually adjust to their frictionless level, then both measures of exposure are expected to be relevant.

To illustrate this point, we regress the state-level changes in welfare and employment generated by the model with and without DNWR on both exposure measures (normalized to have the same mean and standard deviation) and a constant. As shown in Appendix Table D.1, without DNWR, only the net export exposure measure is significant for employment and welfare, while ADH exposure is not significant. By contrast, columns (2) and (4) show that in the model with DNWR both ADH exposure and net export exposure are significant. Combined with the findings in ADH, these results indicate that a mechanism similar to DNWR is likely to be active in the U.S. economy.

8.2 Nominal Considerations

While the nominal anchor described in equation (19) allows us to efficiently solve our model, we acknowledge that it is relatively simplistic.[35] Importantly, we would obtain similar results if we assumed instead that China used a combination of monetary and exchange rate policies to prevent both an appreciation of its currency and large inflationary pressures — thereby preventing its wage in dollars from increasing — while the U.S. did not fully offset this with its own policies (perhaps due to inattentiveness, or due to

[35]For an extended discussion of alternative specifications where we 1) incorporate part of the increases in the Chinese trade surplus that occurred between 2000 and 2007 as part of the China Shock and 2) explore alternative exchange-rate arrangements for third-countries, please see the 2024 vintage of the NBER working paper version of this paper, Rodríguez-Clare et al. (2020).

the fact that because of other shocks, like the 2002-2006 housing bubble, unemployment from other causes was particularly low during that time).

The case of China preventing an appreciation of the renminbi during the early 2000's is a particularly relevant one, as this was something that the Chinese government was widely regarded as doing (c.f., Bergsten and Gagnon, 2017). While the richness in the trade structure of our model prevents us from solving it under this alternative nominal anchor, there are papers that have performed related exercises. Kim et al. (2024), for example, solve a model that is similar to ours but where deficits are endogenous and China uses a currency peg. The added realism in the macro assumptions comes at the cost of richness in the trade structure, as they only have six countries (with no internal regions) and six sectors. Nevertheless, their model's implications for the unemployment and welfare effects of the China shock on the U.S. are qualitatively similar to ours in that a significant amount of aggregate unemployment is generated and the welfare gains of the shock are reduced by a large fraction due to the presence of wage rigidities.

Apart from the form of the nominal anchor assumed in our model, we also explore the tradeoff between unemployment and inflation that arises in response to the shock. As discussed in Section 6.2, DNWR implies that the China shock leads to aggregate unemployment during a transition period. According to our baseline specification, the cumulative effect is roughly 6 year-points of unemployment over the 2001-2010 decade.[36] In principle, monetary policy could have prevented this outcome, but only at the cost of higher inflation. We explore this by computing a "sacrifice ratio". This measure answers the question: if the central bank wanted to have one fewer year-point of unemployment between 2001 and 2010 relative to our baseline specification, how many more year-points of inflation over the same 10 years relative to the baseline would have been necessary?

As can be seen in Figure 8, this sacrifice ratio is highly non-linear. Around the baseline calibration, lowering unemployment by one year-point would require accepting 1.63 year-points higher inflation. This increases to 2.2 year-points when unemployment is 3 year-points lower than in the baseline calibration, and shoots off toward infinity when unemployment is around 6 year-points lower than in the baseline calibration. The sacrifice

[36] This is the area under the curve between 2001 and 2010 in Figure 3.

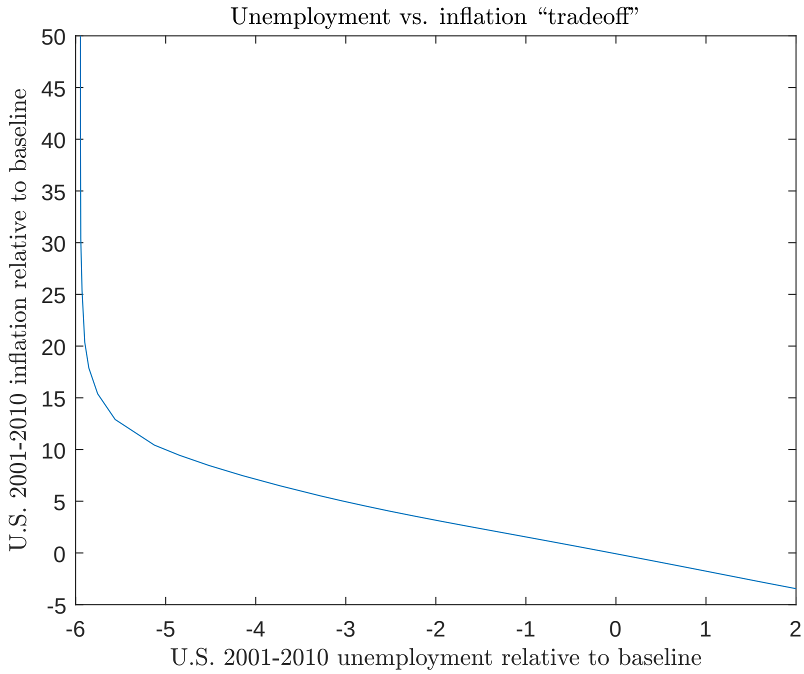


Figure 8: This figure displays aggregate U.S. unemployment between 2001 and 2010, in year-points, relative to the baseline value, in the x-axis. The y-axis displays aggregate U.S. inflation between 2001 and 2010, in year-points, relative to the baseline value. The figure provides a notion of the "sacrifice ratio" between unemployment and inflation that is implicit in the model.

ratio is lower near the baseline because a monetary expansion there makes DNWR less binding and lowers unemployment, leading to higher output and a weaker inflationary effect. By contrast, for lower unemployment levels DNWR is less binding and there is not much additional output forthcoming from a further monetary expansion, so most of the effect is inflationary. While our model does not have all the necessary macro ingredients to properly study the relationship between unemployment and inflation in a way that is robust to the Lucas critique, this analysis highlights the tradeoff involved and indicates that the inflation costs of reducing the unemployment generated by the China shock are not trivial through the lens of the model.

9 Conclusion

In this paper, we propose a dynamic quantitative trade and migration model with downward nominal wage rigidity and use it to study the adjustment path after a large trade shock. We show that even a shock that improves an economy's terms of trade can increase unemployment if it requires a fall in the nominal wage that is larger than the one permitted by nominal frictions. We calibrate the model to match the reduced-form evidence in Autor et al. (2013) and find that, although the U.S. as a whole still gains from the China shock, these gains are approximately two thirds lower than without rigidities.

We acknowledge that we have captured nominal forces and trade imbalances in our model via relatively simple rules. We have done this so that we can have a rich trade structure with the U.S. composed of many regions, as in Caliendo et al. (2019), allowing us to match the empirical results in Autor et al. (2013). Our aim is that this exercise serves to identify the key elements that future models need to incorporate.

Another limitation of our approach is that all employed workers in a given sector-region earn the same wage and have the same expected future earnings. This is inconsistent with evidence in Autor et al. (2014) and Chetverikov et al. (2016) that lower-wage workers in sectors most affected by the China shock experience worse earnings trajectories. This could be incorporated into our framework by including low- and high-skilled workers, with low-wage workers less willing to move away from the most negatively affected sector-regions, leading them to experience larger wage and employment losses.

Our approach also has the drawback that it implies workers' employment status is independent across periods, contrary to empirical evidence and to what one could get in a search and matching framework. A fruitful direction for future research would be to introduce search frictions into a quantitative trade model with many regions and DNWR. Finally, it is important to note that our model does not incorporate mechanisms such as human capital depreciation, hysteresis, or agglomeration forces that could amplify the persistent employment losses of heavily exposed regions in response to trade shocks.

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Trade with Nominal Rigidities: Understanding the Unemployment and Welfare Effects of the China Shock

Andres Rodriguez-Clare, Mauricio Ulate, and Jose P. Vasquez

Appendix for Online Publication

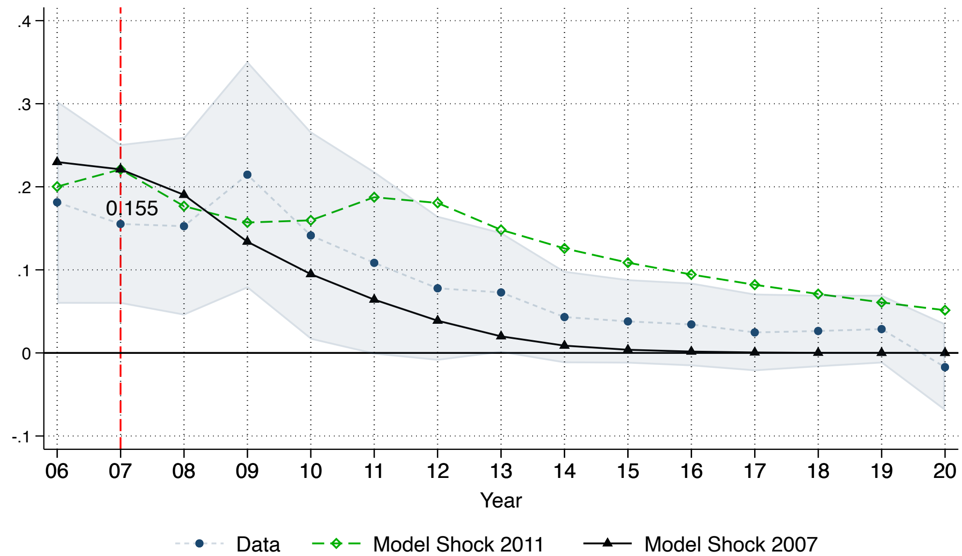
March 2025

This online appendix supplements the paper "Trade with Nominal Rigidities: Understanding the Unemployment and Welfare Effects of the China Shock" with the following material:

- Appendix A provides additional tables and figures referenced in the main text.
- Appendix B presents the details of the model presented in Section 3.
- Appendix C contains more details about the construction of the datasets necessary for the model's calibration, which are described in Section 4.
- Appendix D presents theory and quantification for the alternative exposure measure discussed in Section 8.

A Additional Figures and Tables

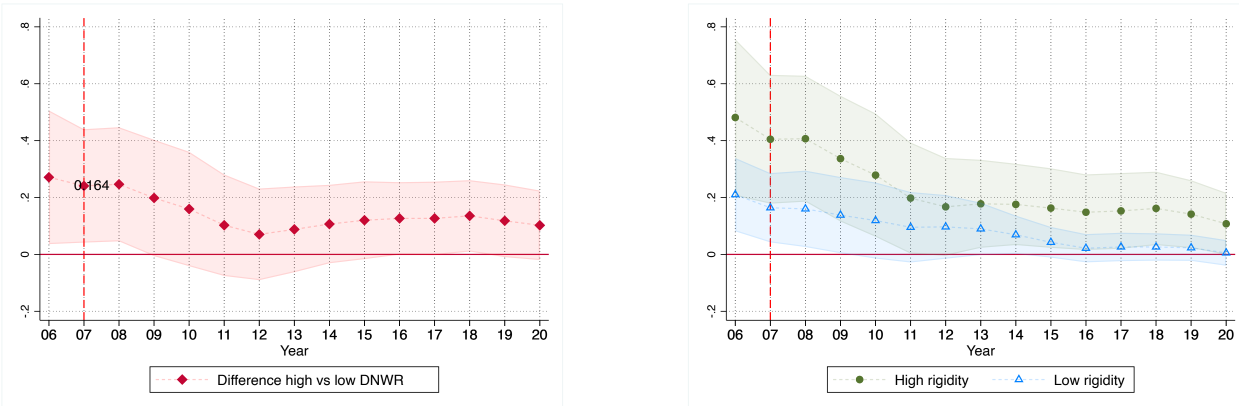
Figure A.1: Baseline empirical analysis using an alternative construction of the unemployment-to-population ratio



Notes: The figure reports three lines. The blue line with circular markers shows the two-stage least squares coefficient estimates for β_{1h} in equation (1) where the outcome variable is the unemployment-to-population ratio, and this variable is constructed using BLS data for unemployment and SEER data for population (in contrast to the ACS data used in ADH). The shaded area represents the 95% confidence interval. The regression estimates are analogous to those in Figure 1, differing only in the data source used to compute the unemployment-to-population ratio. The green dashed line displays the effects in our model when the China shock lasts between 2001 and 2011 (labeled as "Model Shock 2011"), while the black line with triangular markers displays the effects in our baseline model when the China shock lasts between 2001 and 2007 (labeled as "Model Shock 2007").

Figure A.2: China Shock on unemployment in CZs with high vs low DNWR. Share of individuals with negative wage changes in state s is below the median across all states

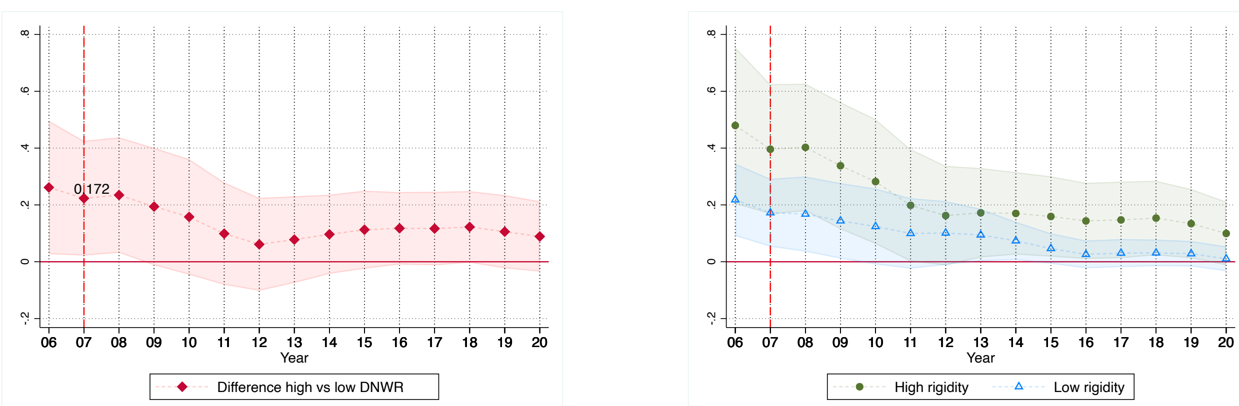
(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2).

Figure A.3: China Shock on unemployment in CZs with high vs low DNWR. Share of individuals with negative wage changes among non-zero wage changes in state s is below the mean across all states

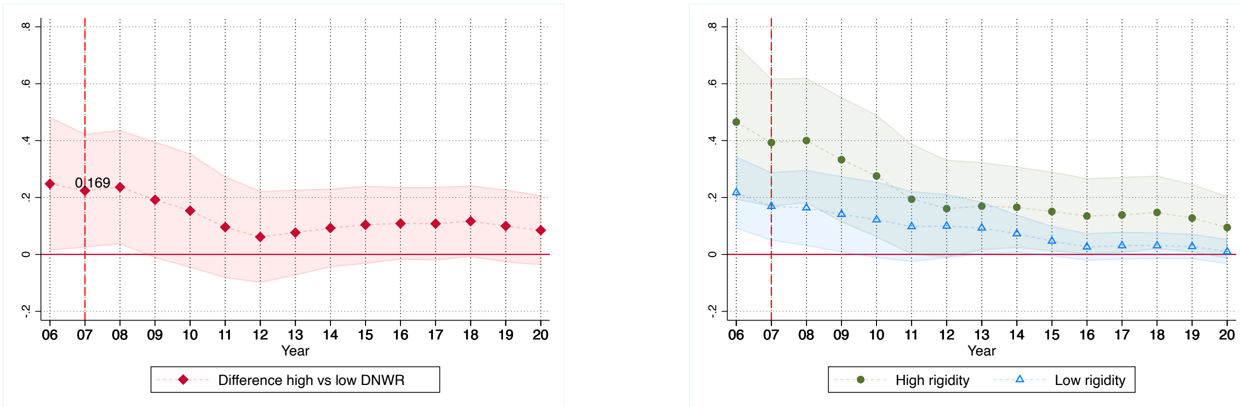
(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2).

Figure A.4: China Shock on unemployment in CZs with high vs low DNWR. Share of individuals with negative wage changes among non-zero wage changes in state s is below the median across all states

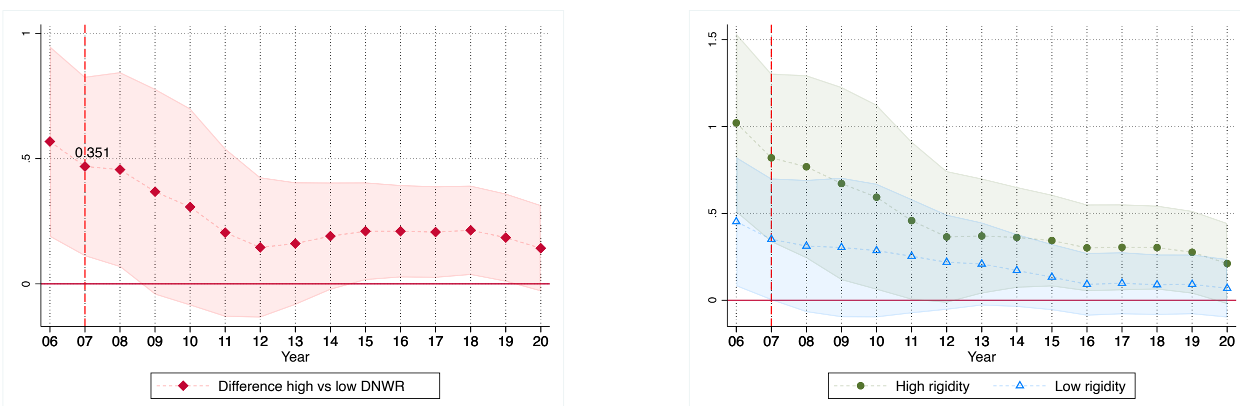
(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2).

Figure A.5: China Shock on unemployment in States with high vs low DNWR. Share of individuals with negative wage changes in state s is below the mean across all states

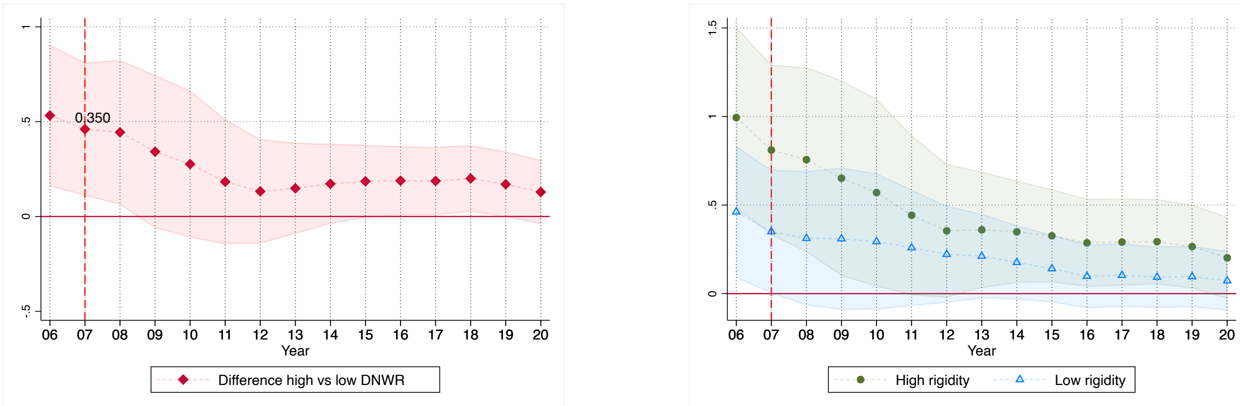
(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2).

Figure A.6: China Shock on unemployment in States with high vs low DNWR. Share of individuals with negative wage changes in state s is below the median across all states

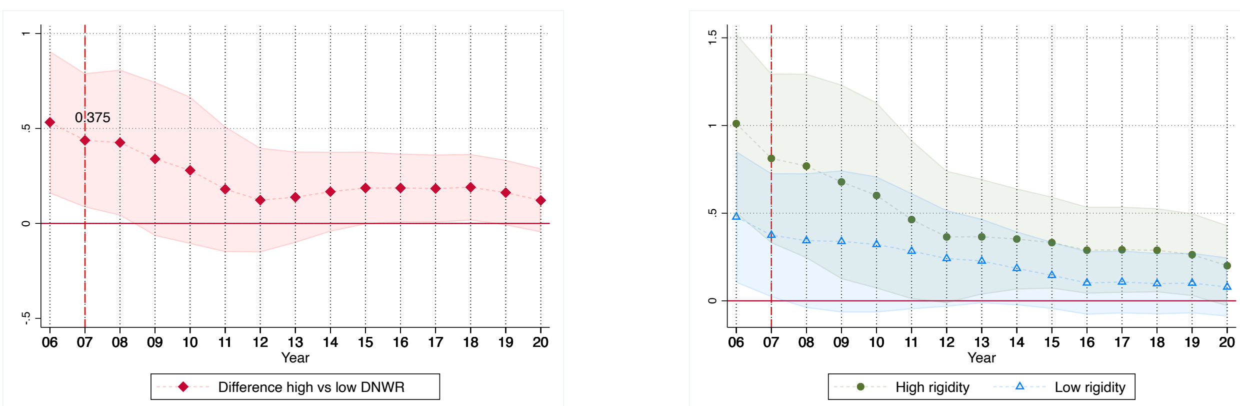
(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2).

Figure A.7: China Shock on unemployment in States with high vs low DNWR. Share of individuals with negative wage changes among non-zero wage changes in state s is below the mean across all states

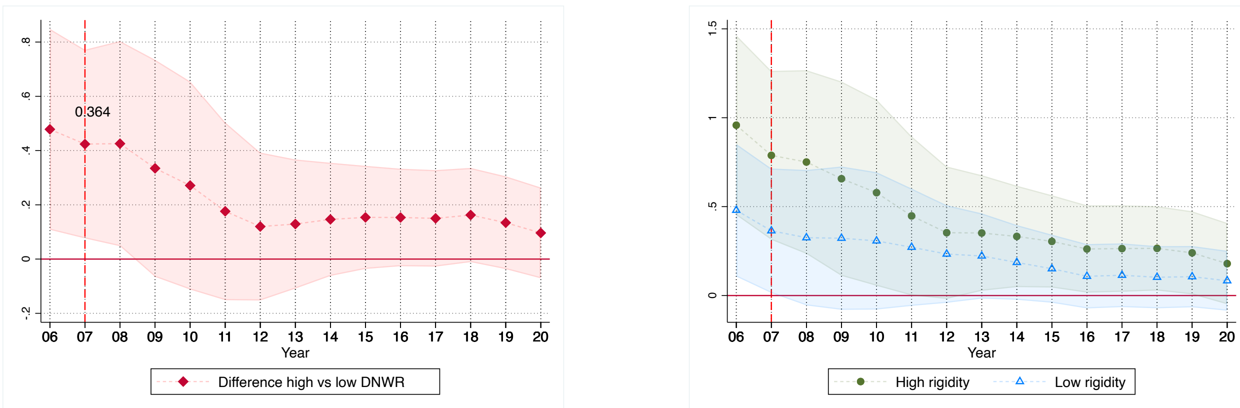
(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2).

Figure A.8: China Shock on unemployment in States with high vs low DNWR.
Share of individuals with negative wage changes among non-zero wage changes in state s is below the median across all states

(a) Estimated $\beta_{3,h}$ **(b)** $\beta_{1,h}$ vs. $\beta_{1,h} + \beta_{3,h}$



Note: The panels report two-stage least squares coefficient estimates in equation (2) and 95 percent confidence intervals for these estimates. Coefficients in each year come from a separate IV regression following equation (2).

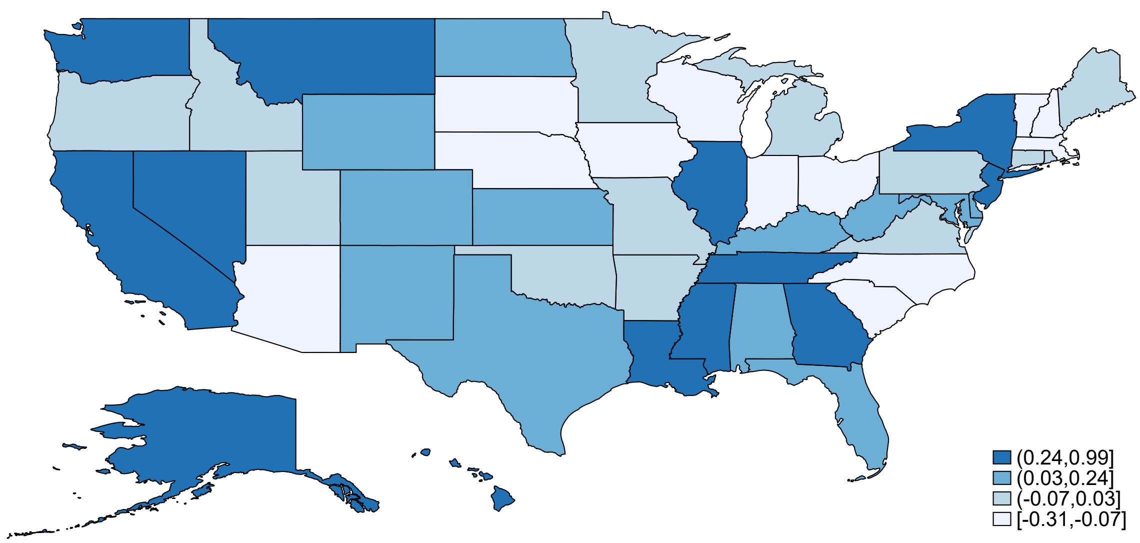
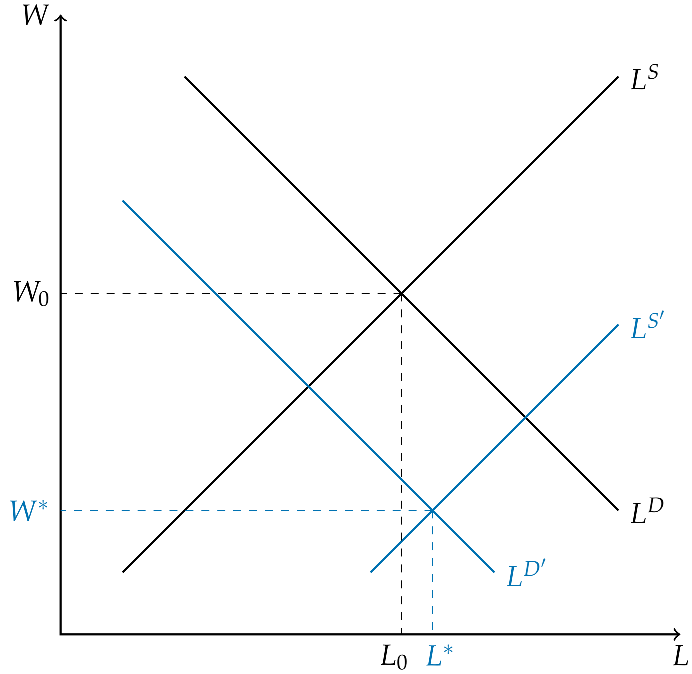


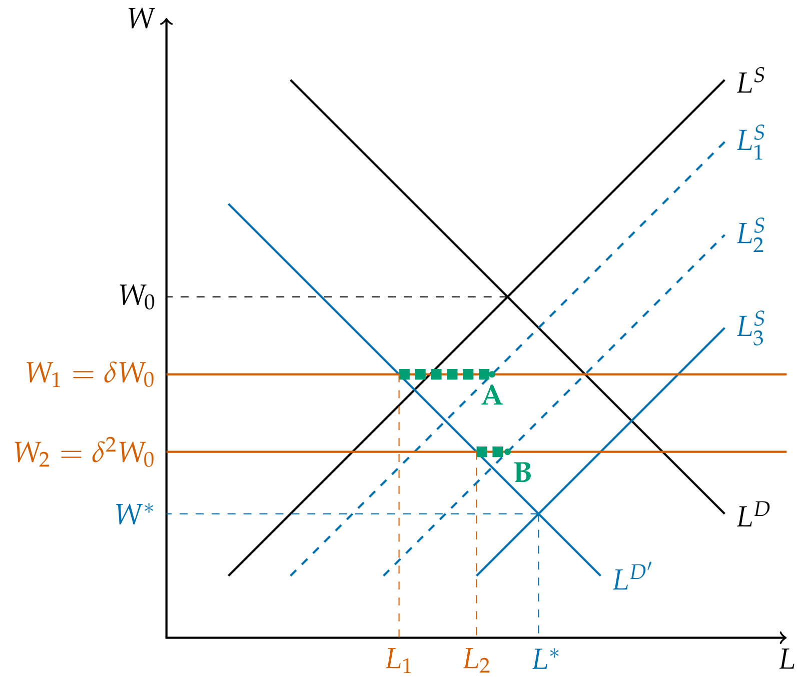
Figure A.9: Welfare change from the China shock across U.S. states in the baseline specification, in percent.

A.1 Additional Intuition for the Results

We illustrate the mechanisms discussed in Section 6.2 in Figure A.10. Both panels have the nominal wage in the vertical axis and employment in the horizontal axis. The China shock leads to a fall in producer prices, shifting labor demand down. At the same time, the shock also leads to



(a) Case without DNWR



(b) Case with DNWR

Figure A.10: Illustration of wage and employment effects, with and without DNWR. The nominal wage is in the vertical axis, hence price movements results in shifts in the labor supply curve. Employment is in the horizontal axis.

a decline in consumer prices, shifting the labor supply to the right. Panel (a) presents the results without nominal frictions. The final result is a fall in the nominal wage from W_0 to W^*, a fall in prices from P_0 to P^* (not illustrated), an increase in the real wage from W_0/P_0 to W^*/P^* (prices fall more than nominal wages), and an increase in the amount of labor supplied from L_0 to L^*.

Panel (b) of Figure A.10 shows the adjustment in the presence of DNWR assuming that $\delta^3 W_0 < W^* < \delta^2 W_0$. In the first year, the nominal wage only falls from W_0 to $W_1 \equiv \delta W_0$ and employment falls from L_0 to L_1, as determined by the demand curve. Since the nominal wage does not fully adjust in the first year, the fall in consumer prices is also smaller than in the frictionless case, and hence the labor supply curve only moves from L^S to L^S_1. The gap between the labor supplied at point A and labor demanded L_1 is the level of unemployment. In the second year, nominal wages adjust further down (to $W_2 \equiv \delta W_1 = \delta^2 W_0$), the labor supply curve moves to L^S_2, employment increases from L_1 to L_2, labor supplied moves from point A to point B, and unemployment decreases. In the third year, nominal wages finally adjust fully and there is no more unemployment.

B Model Details

B.1 Production

Technology to produce the differentiated good of industry s in region i at time t is

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

where $M_{i,ks,t}$ is the quantity of the composite good of industry k used in region i to produce in sector s at time t, $\phi_{i,s}$ is the labor share in region i, sector s, $\phi_{i,ks}$ is the share of inputs that sector s uses from sector k in region i, and $1 - \phi_{i,s} = \sum_{k=1}^{S} \phi_{i,ks}$. The resource constraint for the composite good produced in region j, sector k, at time t is

$$M_{j,k,t} = C_{j,k,t} + \sum_{s=1}^{S} M_{j,ks,t}.$$

In turn, the resource constraint for good s produced by region i is $Y_{i,s,t} = \sum_{j=1}^{I} \tau_{ij,s,t} Y_{ij,s,t}$. The composite in sector k is produced according to

$$M_{j,k,t} = \left(\sum_{i=1}^{I} Y_{ij,k,t}^{\frac{\sigma_k - 1}{\sigma_k}} \right)^{\frac{\sigma_k}{\sigma_k - 1}}.$$

Let $P_{i,s,t}$ be the price of $M_{i,s,t}$, $p_{ij,s,t}$ be the price of $Y_{i,s,t}$ in j at time t, and $W_{i,s,t}$ be the nominal wage in region i, sector s, at time t. We know that $p_{ii,s,t} = A_{i,s,t}^{-1} W_{i,s,t}^{\phi_{i,s}} \prod_{k=1}^{S} P_{i,k,t}^{\phi_{i,ks}}$, $p_{ij,s,t} = \tau_{ij,s,t} p_{ii,s,t}$, and $P_{j,s,t} = \left(\sum_{i=1}^{I} p_{ij,s,t}^{1-\sigma_s} \right)^{1/(1-\sigma_s)}$. Combining these we obtain:

$$P_{j,s,t}^{1-\sigma_s} = \sum_{i=1}^{I} \left(\tau_{ij,s,t} A_{i,s,t}^{-1} W_{i,s,t}^{\phi_{i,s}} \prod_{k=1}^{S} P_{i,k,t}^{\phi_{i,ks}} \right)^{1-\sigma_s},$$

The price of final output in region j at time t is given by $P_{j,t} = \prod_{s=1}^{S} P_{j,s,t}^{\alpha_{j,s}}$. Multiplying the resource constraint for $M_{j,k,t}$ by $P_{j,k,t}$ we get

$$Z_{j,k,t} = P_{j,k,t} C_{j,k,t} + \sum_{s=1}^{S} P_{j,k,t} M_{j,ks,t},$$

where $Z_{j,k,t} \equiv P_{j,k,t} M_{j,k,t}$ denotes the total expenditure of region j in industry k. Let the share of that expenditure spent on imports from i be $\lambda_{ij,k,t} \equiv \frac{p_{ij,k,t} Y_{ij,k,t}}{Z_{j,k,t}}$. We know that

$$\lambda_{ij,k,t} = \frac{p_{ij,k,t}^{1-\sigma_k}}{\sum_l p_{lj,k,t}^{1-\sigma_k}} = \frac{p_{ij,k,t}^{1-\sigma_k}}{P_{j,k,t}^{1-\sigma_k}} = \frac{\left(\tau_{ij,k,t} A_{i,k,t}^{-1} W_{i,k,t}^{\phi_{i,k}} \prod_{s=1}^{S} P_{i,s,t}^{\phi_{i,sk}} \right)^{1-\sigma_k}}{\sum_{r=1}^{I} \left(\tau_{rj,k,t} A_{r,k,t}^{-1} W_{r,k,t}^{\phi_{r,k}} \prod_{s=1}^{S} P_{r,s,t}^{\phi_{r,sk}} \right)^{1-\sigma_k}}.$$

Let $R_{i,k,t} = p_{ii,k,t} Y_{i,k,t}$ represent the sales of good k by region i. Multiplying the resource constraint for $Y_{i,k,t}$ above by $p_{ii,k,t}$ we get $p_{ii,k,t} Y_{i,k,t} = \sum_{j=1}^{I} \tau_{ij,k,t} p_{ii,k,t} Y_{ij,k,t}$, and hence $R_{i,k,t} = \sum_{j=1}^{I} \lambda_{ij,k,t} Z_{j,k,t}$. Plugging in from the resource constraint for $Z_{j,k,t}$ we have

$$R_{i,k,t} = \sum_{j=1}^{I} \lambda_{ij,k,t} \left(P_{j,k,t} C_{j,k,t} + \sum_{s} P_{j,k,t} M_{j,ks,t} \right).$$

Note that $P_{j,k,t} M_{j,ks,t} = \phi_{j,ks} R_{j,s,t}$. Additionally, the total amount available for consumption in region j at time t is the sum of total labor income (denoted $I_{j,t}$, notice $I_{j,t} \equiv \sum_{k=1}^{S} W_{j,k,t} L_{j,k,t}$) and the deficit (denoted $D_{j,t}$). So we get $P_{j,k,t} C_{j,k,t} = \alpha_{j,k} \left(I_{j,t} + D_{j,t} \right)$, hence

$$R_{i,k,t} = \sum_{j=1}^{I} \lambda_{ij,k,t} \left(\alpha_{j,k} \left(I_{j,t} + D_{j,t} \right) + \sum_{s} \phi_{j,ks} R_{j,s,t} \right).$$

We know that a fraction $\phi_{i,k}$ of $R_{i,k,t}$ is paid to labor, hence $W_{i,k,t}L_{i,k,t} = \phi_{i,k}R_{i,k,t}$.

B.2 Labor Supply

As mentioned in the text, an agent's utility in region j, sector s, at time t is given by

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

with the joint distribution of vector $\boldsymbol{\epsilon}$ being i.i.d over time and nested Gumbel,

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

with $\nu \leq \kappa$. If there is an strict inequality such that $\nu < \kappa$, that means that the elasticity across sectors $(1/\nu)$ is greater than the elasticity across locations $(1/\kappa)$. Denote $V_{i,k,t+1} \equiv \mathbb{E}[\mathrm{v}_{i,k,t+1}]$. In this appendix, we will prove two main results. First, the probability that an agent in js will choose to move to ik conditional on moving to region i is

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

while the probability that an agent in js will move to any sector in region i is

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

Second,

$$\mathbb{E}\left[\max_{\{i,k\}_{i=1,k=0}^{I,S}} \{\beta \mathbb{E}(\mathrm{v}_{i,k,t+1}) - \varphi_{ji,sk} + \epsilon_{i,k,t}\}\right] = \ln\left(\sum_{i=1}^{I}\left(\sum_{k=0}^{S}\exp\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)^{1/\nu}\right)^{\nu/\kappa}\right)^{\kappa} + \gamma\kappa,$$

where γ is the Euler-Mascheroni constant. The previous expression implies

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

To show the first result, note that an agent that is in market js at time t will choose to switch to ik if and only if the following expression holds for all mh:

$$\beta V_{i,k,t+1} - \varphi_{ji,sk} + \epsilon_{i,k,t} \geq \beta V_{m,h,t+1} - \varphi_{jm,sh} + \epsilon_{m,h,t},$$

which is equivalent to $\epsilon_{m,h,t} \leq \nu x_{im,kh} + \epsilon_{i,k,t}$, where

$$x_{im,kh} \equiv \frac{\beta \left(V_{i,k,t+1} - V_{m,h,t+1} \right) - \left(\varphi_{ji,sk} - \varphi_{jm,sh} \right)}{\nu}.$$

Denoting

$$\Phi_{j,s,t} \equiv \mathbb{E} \left[\max_{\{i,k\}_{i=1,k=0}^{I,S}} \{ \beta \mathbb{E}(\mathrm{v}_{i,k,t+1}) - \varphi_{ji,sk} + \epsilon_{i,k,t} \} \right]$$

We know that

$$\Phi_{j,s,t} = \sum_{i=1}^{I} \sum_{k=0}^{S} \int_{-\infty}^{+\infty} \left(\beta V_{i,k,t+1} - \varphi_{ji,sk} + \epsilon_{i,k,t} \right) G_{ik}(\epsilon_{i,k,t}, x_{i,k,t}) d\epsilon_{i,k,t}$$

where $G_{ik}(\epsilon_{i,k,t}, x_{i,k,t})$ is the partial derivative of $F(\cdot)$ w.r.t. to the ik element of the vector $\boldsymbol{\epsilon}$, with the ik element of the vector evaluated at $\epsilon_{i,k,t}$ and the generic element in position mh of the vector evaluated at $\nu x_{im,kh,t} + \epsilon_{i,k,t}$. Given our function $F(\boldsymbol{\epsilon})$ above, the partial derivative w.r.t the element in position ik is

$$\frac{\partial F(\boldsymbol{\epsilon})}{\partial \epsilon_{i,k}} = \frac{1}{\kappa} \left(\sum_h \exp\left(-\epsilon_{i,h}/\nu\right) \right)^{\nu/\kappa - 1} \exp\left(-\epsilon_{i,k}/\nu\right) \exp\left[-\sum_m \left(\sum_h \exp\left(-\epsilon_{m,h}/\nu\right) \right)^{\nu/\kappa} \right]$$

We then have

$$\begin{aligned} G_{ik}(\epsilon_{i,k,t}, \boldsymbol{x}_{i,k,t}) &= \frac{1}{\kappa} \left(\sum_h \exp\left(-x_{ii,kh,t}\right) \right)^{\nu/\kappa - 1} \exp\left(-\epsilon_{i,k,t}/\kappa\right) \\ &\cdot \exp\left[-\exp\left(-\epsilon_{i,k,t}/\kappa\right) \sum_m \left(\sum_h \exp\left(-x_{im,kh,t}\right) \right)^{\nu/\kappa} \right] \end{aligned}$$

where we have used the fact that $x_{ii,kk,t} = 0$. Integrating this over $\epsilon_{i,k,t}$ yields

$$\begin{aligned} \int_{-\infty}^{+\infty} G_{ik}(\epsilon_{i,k,t}, x_{i,k,t}) d\epsilon_{i,k,t} &= \frac{\left(\sum_h \exp\left(-x_{ii,kh,t}\right) \right)^{\nu/\kappa - 1}}{\sum_m \left(\sum_h \exp\left(-x_{im,kh,t}\right) \right)^{\nu/\kappa}} \int_{-\infty}^{+\infty} \frac{1}{\kappa} \exp\left(-\epsilon_{i,k,t}/\kappa\right) \\ &\cdot T \exp\left[-\exp\left(-\epsilon_{i,k,t}/\kappa\right) T \right] d\epsilon_{i,k,t}, \end{aligned}$$

where

$$T \equiv \sum_m \left(\sum_h \exp\left(-x_{im,kh,t}\right) \right)^{\nu/\kappa}.$$

But note that

$$\int_{-\infty}^{+\infty} \frac{1}{\kappa} \exp\left(-\epsilon_{i,k,t}/\kappa\right) T \exp\left[-\exp\left(-\epsilon_{i,k,t}/\kappa\right) T \right] d\epsilon_{i,k,t} = 1,$$

because the integrand is the density associated with $\exp\left(-\exp\left(-\epsilon_{i,k,t}/\kappa\right) T\right)$, a univariate Gumbel. Hence, the previous expression simplifies to

$$\int_{-\infty}^{\infty} G_{ik}(\epsilon_{i,k,t}, x_{i,k,t}) d\epsilon_{i,k,t} = \frac{\exp\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)^{1/\nu}}{\sum_h \exp\left(\beta V_{i,h,t+1} - \varphi_{ji,sh}\right)^{1/\nu}} \frac{\left(\sum_h \exp\left(\beta V_{i,h,t+1} - \varphi_{ji,sh}\right)^{1/\nu}\right)^{\nu/\kappa}}{\sum_m \left(\sum_h \exp\left(\beta V_{m,h,t+1} - \varphi_{jm,sh}\right)^{1/\nu}\right)^{\nu/\kappa}}$$

It is easy to see that the first fraction is $\mu_{ji,sk|i,t}$, while the second one is $\mu_{ji,s\#,t}$.

Now we want to solve for

$$\mathbb{E}\left[\max_{\{i,k\}_{i=1,k=0}^{I,S}} \left\{ \beta V_{i,k,t+1} - \varphi_{ji,sk} + \epsilon_{i,k,t} \right\} \right]$$

Let's compute

$$\mathbb{E}\left[\beta V_{i,k,t+1} - \varphi_{ji,sk} + \epsilon_{i,k,t} \middle| \arg\max_{mh} \left\{ \beta V_{m,h,t+1} - \varphi_{jm,sh} + \epsilon_{m,h,t} \right\} = ik \right]$$

To do this, first note that the joint probability that $\beta V_{i,k,t+1} - \varphi_{ji,sk} + \epsilon_{i,k,t} \leq a$ while at the same time $\arg\max_{mh} \left\{ \beta V_{m,h,t+1} - \varphi_{jm,sh} + \epsilon_{m,h,t} \right\} = ik$, is

$$\begin{aligned}
& \int_{-\infty}^{a-\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)} G_{ik}(\epsilon_{i,k,t}, x_{i,k,t}) d\epsilon_{i,k,t} \\
= \quad & \frac{\left(\sum_h \exp\left(-x_{ii,kh}\right)\right)^{\nu/\kappa - 1}}{\sum_m \left(\sum_h \exp\left(-x_{im,kh}\right)\right)^{\nu/\kappa}} \int_{-\infty}^{a-\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)} \frac{1}{\kappa} T \exp\left(-z/\kappa\right) \exp\left(-T \exp\left(-z/\kappa\right)\right) dz
\end{aligned}$$

A change of variables with $y = \exp(z)$ implies that $dy/y = dz$ and

$$\begin{aligned}
& \int_{-\infty}^{a-\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)} \frac{1}{\kappa} T \exp\left(-z/\kappa\right) \exp\left(-T \exp\left(-z/\kappa\right)\right) dz \\
= \quad & \exp\left(-T \exp\left[\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)/\kappa\right] \exp\left(-a/\kappa\right)\right)
\end{aligned}$$

Thus, the **joint** probability we are interested in is

$$\frac{\left(\sum_h \exp\left(-x_{ii,kh}\right)\right)^{\nu/\kappa-1}}{\sum_m \left(\sum_h \exp\left(-x_{im,kh}\right)\right)^{\nu/\kappa}} \exp\left(-T \exp\left[\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)/\kappa\right] \exp\left(-a/\kappa\right)\right)$$

and hence the probability of $(\beta V_{i,k,t+1} - \varphi^{ji,sk} + \epsilon_{i,k,t} \leq a)$ **conditional** on

$$\arg\max_{mh} \left\{\beta V_{m,h,t+1} - \varphi_{jm,sh} + \epsilon_{m,h,t}\right\} = ik,$$

is

$$\exp\left(-\tilde{T} \exp\left(-a/\kappa\right)\right),$$

where now

$$\tilde{T} \equiv T \exp\left[\left(\beta V_{i,k,t+1} - \varphi_{ji,sk}\right)/\kappa\right].$$

In turn, this implies that

$$\begin{aligned} & \mathbb{E}\left[\beta V_{i,k,t+1} - \varphi_{ji,sk} + \epsilon_{i,k,t} \middle| \arg\max_{mh} \left\{\beta V_{m,h,t+1} - \varphi_{jm,sh} + \epsilon_{m,h,t}\right\} = ik\right] \\ = & \int_{-\infty}^{+\infty} a d \exp\left(-\exp\left(-\frac{\left(a - \ln \tilde{T}^{\kappa}\right)}{\kappa}\right)\right), \end{aligned}$$

where we have used

$$\tilde{T} \exp\left(-a/\kappa\right) = \exp\left(-\frac{\left(a - \ln \tilde{T}^{\kappa}\right)}{\kappa}\right).$$

This is the expectation of a variable distributed Gumbel with location parameter $\mu = \ln \tilde{T}^{\kappa}$ and scale parameter $\beta = \kappa$. But we know that the expectation of a variable distributed Gumbel with μ and β is $\mu + \beta\gamma$, where γ is the Euler-Mascheroni constant, hence we have

$$\int_{-\infty}^{\infty} a d \exp\left(-\tilde{T} \left(\exp a\right)^{-1/\kappa}\right) = \ln \tilde{T}^{\kappa} + \gamma\kappa.$$

This implies that

$$\begin{aligned} & \mathbb{E}\left[\beta V_{i,k,t+1} - \varphi_{ji,sk} + \epsilon_{i,k,t} \middle| \arg\max_{mh} \left\{\beta V_{m,h,t+1} - \varphi_{jm,sh} + \epsilon_{m,h,t}\right\} = ik\right] \\ = & \ln\left(\sum_m \left(\sum_h \exp\left(\beta V_{m,h,t+1} - \varphi_{jm,sh}\right)^{1/\nu}\right)^{\nu/\kappa}\right)^{\kappa} + \gamma\kappa \end{aligned}$$

Since this does not depend on ik, then we have

$$\mathbb{E}\left[\max_{\{i,k\}_{i=1,k=0}^{I,S}}\{\beta\mathbb{E}(\mathrm{v}_{i,k,t+1})-\varphi_{ji,sk}+\epsilon_{i,k,t}\}\right]=\ln\left(\sum_{i=1}^{I}\left(\sum_{k=0}^{S}\exp\left(\beta V_{i,k,t+1}-\varphi_{ji,sk}\right)^{1/\nu}\right)^{\nu/\kappa}\right)^{\kappa}+\gamma\kappa,$$

as we wanted to show.

B.3 Equilibrium in Relative Time Changes (Dots)

Now we will describe the equilibrium equations in relative changes from one period to the next. We use the notation $\dot{x}_t = x_t/x_{t-1}$. We start by deriving the dot equations for the labor market block of the economy. We will denote $u_{j,s,t} \equiv \exp(V_{j,s,t})$ and assume that the utility function takes log form. We have,

$$\begin{aligned}
\frac{\mu_{ji,sk|i,t+1}}{\mu_{ji,sk|i,t}} &= \frac{\exp\left(\beta V_{i,k,t+2}-\varphi_{ji,sk}\right)^{1/\nu} / \exp\left(\beta V_{i,k,t+1}-\varphi_{ji,sk}\right)^{1/\nu}}{\sum_{h=0}^{S}\exp\left(\beta V_{i,h,t+2}-\varphi_{ji,sh}\right)^{1/\nu} / \sum_{h'=0}^{S}\exp\left(\beta V_{i,h',t+1}-\varphi_{ji,sh'}\right)^{1/\nu}} \\
&= \frac{\exp\left(V_{i,k,t+2}-V_{i,k,t+1}\right)^{\beta/\nu}}{\sum_{h=0}^{S}\mu_{ji,sh|i,t}\exp\left(V_{i,h,t+2}-V_{i,h,t+1}\right)^{\beta/\nu}},
\end{aligned}$$

while

$$\frac{\mu_{ji,s\#,t+1}}{\mu_{ji,s\#,t}} = \frac{\left(\sum_{h=0}^{S}\exp\left(V_{i,h,t+2}-V_{i,h,t+1}\right)^{\beta/\nu}\mu_{ji,sh|i,t}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\mu_{jm,s\#,t}\left(\sum_{h=0}^{S}\exp\left(V_{m,h,t+2}-V_{m,h,t+1}\right)^{\beta/\nu}\mu_{jm,sh|m,t}\right)^{\nu/\kappa}}.$$

Since $u_{j,s,t} \equiv \exp(V_{j,s,t})$ then

$$\begin{aligned}
\dot{u}_{j,s,t+2} &\equiv u_{j,s,t+2}/u_{j,s,t+1} = \frac{\exp(V_{j,s,t+2})}{\exp(V_{j,s,t+1})} = \exp(V_{j,s,t+2}-V_{j,s,t+1}) \\
(\dot{u}_{j,s,t+2})^{\frac{\beta}{\nu}} &= \exp(V_{j,s,t+2}-V_{j,s,t+1})^{\frac{\beta}{\nu}}.
\end{aligned}$$

Introducing this in the previous results and writing the equations for period t instead of $t+1$, we obtain

$$\mu_{ji,sk|i,t} = \frac{\mu_{ji,sk|i,t-1}\dot{u}_{i,k,t+1}^{\frac{\beta}{\nu}}}{\sum_{h=0}^{S}\mu_{ji,sh|i,t-1}\dot{u}_{i,h,t+1}^{\frac{\beta}{\nu}}} \tag{B1}$$

$$\mu_{ji,s\#,t} = \frac{\mu_{ji,s\#,t-1}\left(\sum_{h=0}^{S}\mu_{ji,sh|i,t-1}\dot{u}_{i,h,t+1}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\mu_{jm,s\#,t-1}\left(\sum_{h=0}^{S}\mu_{jm,sh|m,t-1}\dot{u}_{m,h,t+1}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}}. \tag{B2}$$

Take the difference between $V_{j,s,t+1}$ and $V_{j,s,t}$ using equation (8) to get

$$\begin{aligned}
V_{j,s,t+1} - V_{j,s,t} &= U_{j,s,t+1} - U_{j,s,t} \\
&+ \ln\left(\frac{\left(\sum_{i=1}^{I}\left(\sum_{k=0}^{S}\exp\left(\beta V_{i,k,t+2} - \varphi_{ji,sk}\right)^{1/\nu}\right)^{\nu/\kappa}\right)^{\kappa}}{\left(\sum_{m=1}^{I}\left(\sum_{h=0}^{S}\exp\left(\beta V_{m,h,t+1} - \varphi_{jm,sh}\right)^{1/\nu}\right)^{\nu/\kappa}\right)^{\kappa}}\right) \\
e^{V_{j,s,t+1}-V_{j,s,t}} &= \exp(\ln((\omega_{j,s,t+1}\Delta_{j,s,t+1})/(\omega_{j,s,t}\Delta_{j,s,t}))) \\
&\cdot \exp\left(\ln\left(\sum_{i=1}^{I}\left(\sum_{k=0}^{S}\dot{u}_{i,k,t+2}^{\frac{\beta}{\nu}}\mu_{ji,sk|i,t}\right)^{\nu/\kappa}\mu_{ji,s\#,t}\right)^{\kappa}\right).
\end{aligned}$$

Thus, we finally obtain

$$\dot{u}_{j,s,t+1} = \dot{\omega}_{j,s,t+1}\dot{\Delta}_{j,s,t+1}\left(\sum_{i=1}^{I}\mu_{ji,s\#,t}\left(\sum_{k=0}^{S}\mu_{ji,sk|i,t}\dot{u}_{i,k,t+2}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}\right)^{\kappa}. \tag{B3}$$

The equilibrium in changes includes equations (B1), (B2), (B3), together with the dot versions of the remaining equations in (3) - (19).

B.4 Algorithm to Solve the Dot System

Group the equations of the dot equilibrium system into 3 categories:

1. The ones that are needed to obtain new migration and new labor supply from a guess of utilities (block 1):

$$\begin{aligned}
\mu_{ji,sk|i,t} &= \frac{\mu_{ji,sk|i,t-1}\dot{u}_{i,k,t+1}^{\frac{\beta}{\nu}}}{\sum_{h=0}^{S}\mu_{ji,sh|i,t-1}\dot{u}_{i,h,t+1}^{\frac{\beta}{\nu}}} \\
\mu_{ji,s\#,t} &= \frac{\mu_{ji,s\#,t-1}\left(\sum_{h=0}^{S}\mu_{ji,sh|i,t-1}\dot{u}_{i,h,t+1}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\mu_{jm,s\#,t-1}\left(\sum_{h=0}^{S}\mu_{jm,sh|m,t-1}\dot{u}_{m,h,t+1}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}}
\end{aligned}$$

$$\ell_{i,s,t} = \sum_{j=1}^{I}\sum_{k=0}^{S}\mu_{ji,ks|i,t-1}\mu_{ji,k\#,t-1}\ell_{j,k,t-1}$$

With these equations, if one has an initial distribution of labor supply ($\ell_{i,s,0}$), initial mobility matrices ($\mu_{ji,sk|i,0}$ and $\mu_{ji,s\#,0}$) and an initial guess for the utility dots ($\dot{u}^{(0)}_{i,s,t}\ \forall\ t$), one can obtain the entire path of labor supplies ($\ell_{i,s,t}\ \forall\ t > 0$), and the entire path of mobility matrices ($\mu_{ji,sk|i,t}$ and $\mu_{ji,s\#,t}\ \forall\ t > 0$) without needing to use the other equations at all.

2. The ones that are needed to obtain the temporary equilibrium (wages, actual labor, sectoral prices, trade shares, revenue levels) from a given set of shocks and labor supply (block 2):

$$\begin{aligned}
\dot{P}^{1-\sigma_s}_{i,s,t} &= \sum_{j=1}^{I}\lambda_{ji,s,t-1}\left(\dot{\tau}_{ji,s,t}\dot{A}^{-1}_{j,s,t}\dot{W}^{\phi_{j,s}}_{j,s,t}\prod_{k=1}^{S}\dot{P}^{\phi_{j,ks}}_{j,k,t}\right)^{1-\sigma_s} \\
\lambda_{ij,s,t} &= \frac{\lambda_{ij,s,t-1}(\dot{\tau}_{ij,s,t}\dot{A}^{-1}_{i,s,t}\dot{W}^{\phi_{i,s}}_{i,s,t}\prod_{k=1}^{S}\dot{P}^{\phi_{i,ks}}_{i,k,t})^{1-\sigma_s}}{\sum_{r=1}^{I}\lambda_{rj,s,t-1}(\dot{\tau}_{rj,s,t}\dot{A}^{-1}_{r,s,t}\dot{W}^{\phi_{r,s}}_{r,s,t}\prod_{k=1}^{S}\dot{P}^{\phi_{r,ks}}_{r,k,t})^{1-\sigma_s}} \\
R_{i,s,t} &= \sum_{j=1}^{I}\lambda_{ij,s,t}\left(\alpha_{j,s}\left(\sum_{s}\dot{W}_{j,s,t}\dot{L}_{j,s,t}Y_{j,s,t-1}+D_{j,t}\right)+\sum_{k=1}^{S}\phi_{j,sk}R_{j,k,t}\right) \\
\dot{W}_{i,s,t}\dot{L}_{i,s,t}Y_{i,s,t-1} &= \phi_{i,s}R_{i,s,t} \\
\prod_{q=1}^{t}\dot{L}_{i,s,q} &\leq \prod_{q=1}^{t}\dot{\ell}_{i,s,q}\ ,\ \dot{W}_{i,s,t}\geq\delta_{i,s}\ ,\ \text{Complementary Slackness} \\
\gamma\sum_{i=1}^{I}\sum_{s=1}^{S}Y_{i,s,t-1} &= \sum_{i=1}^{I}\sum_{s=1}^{S}\dot{W}_{i,s,t}\dot{L}_{i,s,t}Y_{i,s,t-1}
\end{aligned}$$

3. The ones that are needed to update the guess for the path of utilities (block 3):

$$\begin{aligned}
\dot{P}_{i,t} &= \prod_{s=1}^{S}\dot{P}^{\alpha_{i,s}}_{i,s,t} \\
\dot{\omega}_{i,s,t} &= \frac{\dot{W}_{i,s,t}\dot{L}_{i,s,t}}{\dot{P}_{i,t}\dot{\ell}_{i,s,t}}(\text{but with } \dot{\omega}_{i,s,t}=1 \text{ if } s=0) \\
\dot{u}_{j,s,t+1} &= \dot{\omega}_{j,s,t+1}\dot{\Delta}_{j,s,t+1}\left(\sum_{i=1}^{I}\mu_{ji,s\#,t}\left(\sum_{k=0}^{S}\mu_{ji,sk|i,t}\dot{u}^{\frac{\beta}{\nu}}_{i,k,t+2}\right)^{\nu/\kappa}\right)^{\kappa}
\end{aligned}$$

The algorithm would work as follows:

1. Guess a path for the utility dots (which can be all of them being equal to one).
2. Use block one to obtain paths for the μ's and ℓ's using the guessed path for utility.
3. Use block two to solve the temporary equilibrium using the path for the ℓ's.

4. Use block three to obtain a new guess for the utility dots. This uses the fact that in a far enough point in the future (called T) even the new guess of utility dots should have $\dot{u}^{(1)}_{i,s,T} = 1$. With $\dot{u}^{(1)}_{i,s,T} = 1$, the path for μ's and the sectoral compensations one can obtain $\dot{u}^{(1)}_{i,s,T-1}$. And from those obtain $\dot{u}^{(1)}_{i,s,T-2}$, and so on until $\dot{u}^{(1)}_{i,s,1}$.
5. If the two guessed paths of utility dots $\dot{u}^{(0)}$ and $\dot{u}^{(1)}$ are close enough, stop the algorithm, otherwise return to item one with the new guess and iterate again.

B.5 Equilibrium in Counterfactual Relative to Baseline (Hats)

Now we want to describe the equilibrium equations in ratios of changes in a counterfactual economy relative to the same changes in the baseline economy. We will use the notation $\hat{x}_t = \dot{x}'_t/\dot{x}_t$, where $\dot{x}'_t$ is the relative change from period $t-1$ to t in the counterfactual economy and $\dot{x}_t$ is the same thing but for the baseline economy. First, we want to get the evolution of $\mu'_{ji,sk|i,t}$. Start from equation (B1) for the case of the counterfactual economy,

$$\mu'_{ji,sk|i,t} = \frac{\mu'_{ji,sk|i,t-1}(\dot{u}'_{i,k,t+1})^{\frac{\beta}{\nu}}}{\sum_{h=0}^{S}\mu'_{ji,sh|i,t-1}(\dot{u}'_{i,h,t+1})^{\frac{\beta}{\nu}}}.$$

Divide this by the same expression in the case of the baseline economy and rearrange to get:

$$\mu'_{ji,sk|i,t} = \frac{\mu'_{ji,sk|i,t-1}\dot{\mu}_{ji,sk|i,t}\hat{u}^{\frac{\beta}{\nu}}_{i,k,t+1}}{\sum\limits_{h=0}^{S}\mu'_{ji,sh|i,t-1}\dot{\mu}_{ji,sh|i,t}\hat{u}^{\frac{\beta}{\nu}}_{i,h,t+1}}. \tag{B4}$$

To obtain the evolution of $\mu'_{ji,s\#,t}$, start from equation (B2) for the counterfactual economy,

$$\mu'_{ji,s\#,t} = \frac{\mu'_{ji,s\#,t-1}\left(\sum_{h=0}^{S}\mu'_{ji,sh|i,t-1}(\dot{u}'_{i,h,t+1})^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\mu'_{jm,s\#,t-1}\left(\sum_{h=0}^{S}\mu'_{jm,sh|m,t-1}(\dot{u}'_{m,h,t+1})^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}}.$$

Divide this by the same expression in the case of the baseline economy and rearrange to get:

$$\mu'_{ji,s\#,t} = \frac{\mu'_{ji,s\#,t-1}\dot{\mu}_{ji,s\#,t}\left(\sum\limits_{h=0}^{S}\mu'_{ji,sh|i,t-1}\dot{\mu}_{ji,sh|i,t}\hat{u}^{\frac{\beta}{\nu}}_{i,h,t+1}\right)^{\nu/\kappa}}{\sum\limits_{m=1}^{I}\mu'_{jm,s\#,t-1}\dot{\mu}_{jm,s\#,t}\left(\sum\limits_{h=0}^{S}\mu'_{jm,sh|m,t-1}\dot{\mu}_{jm,sh|m,t}\hat{u}^{\frac{\beta}{\nu}}_{m,h,t+1}\right)^{\nu/\kappa}}. \tag{B5}$$

Now we want to derive an expression for utility in hats. Start from equation (B3) for the counterfactual economy (but for period t instead of $t+1$):

$$\dot{u}'_{j,s,t} = \dot{\omega}'_{j,s,t}\dot{\Delta}'_{j,s,t}\left(\sum_{i=1}^{I}\mu'_{ji,s\#,t-1}\left(\sum_{k=0}^{S}\mu'_{ji,sk|i,t-1}(\dot{u}'_{i,k,t+1})^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}\right)^{\kappa}.$$

Dividing by this equation in the baseline economy and rearranging yields

$$\hat{u}_{j,s,t} = \hat{\omega}_{j,s,t}\hat{\Delta}_{j,s,t}\left(\sum_{i=1}^{I}\mu'_{ji,s\#,t-1}\dot{\mu}_{ji,s\#,t}\left(\sum_{k=0}^{S}\mu'_{ji,sk|i,t-1}\dot{\mu}_{ji,sk|i,t}\hat{u}_{i,k,t+1}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}\right)^{\kappa}. \tag{B6}$$

However, at $t=1$ the equilibrium conditions are slightly different. This is the result of the timing assumption in CDP (which we adopt in this paper too), that the counterfactual fundamentals are unknown before $t=1$. This means that at $t=0$, $\hat{u}_{j,s,0}=1$, $\mu'_{ji,sk|i,0}=\mu_{ji,sk|i,0}$, $\mu'_{ji,s\#,0}=\mu_{ji,s\#,0}$, and $\ell'_{i,k,1}=\ell_{i,k,1}=\sum_{j=1}^{I}\sum_{s=0}^{S}\mu_{ji,sk|i,0}\mu_{ji,s\#,0}\ell_{j,s,0}$. To account for the unexpected change in fundamentals at $t=1$, the right equations are

$$\mu'_{ji,sk|i,1} = \frac{\theta_{ji,sk|i,0}\hat{u}_{i,k,2}^{\beta/\nu}}{\sum_{h=0}^{S}\theta_{ji,sh|i,0}\hat{u}_{i,h,2}^{\beta/\nu}} \tag{B7}$$

$$\mu'_{ji,s\#,1} = \frac{\mu_{ji,s\#,1}\left(\sum_{h=0}^{S}\theta_{ji,sh|i,0}\hat{u}_{i,h,2}^{\beta/\nu}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\mu_{jm,s\#,1}\left(\sum_{h=0}^{S}\theta_{jm,sh|m,0}\hat{u}_{m,h,2}^{\beta/\nu}\right)^{\nu/\kappa}} \tag{B8}$$

$$\hat{u}_{j,s,1} = \hat{\omega}_{j,s,1}\hat{\Delta}_{j,s,1}\left(\sum_{i=1}^{I}\mu_{ji,s\#,1}\left(\sum_{k=0}^{S}\theta_{ji,sk|i,0}\hat{u}_{i,k,2}^{\beta/\nu}\right)^{\nu/\kappa}\right)^{\kappa}, \tag{B9}$$

where

$$\theta_{ji,sk|i,0} \equiv \mu_{ji,sk|i,1}\hat{u}_{i,k,1}^{\beta/\nu}.$$

The equilibrium in hats includes equations (B4), (B5), (B6), together with the hat versions of the remaining equations in (3) - (19).

B.6 Algorithm to Solve the Hat System

As in the previous algorithm, group the equations into 3 categories:

1. The ones that are needed to obtain new mobility shares and new labor supply from a guess of utilities (block 1):

$$
\begin{aligned}
\mu'_{ji,sk|i,t} &= \frac{\mu'_{ji,sk|i,t-1}\dot{\mu}_{ji,sk|i,t}\hat{u}_{i,k,t+1}^{\frac{\beta}{\nu}}}{\sum_{h=0}^{S}\mu'_{ji,sh|i,t-1}\dot{\mu}_{ji,sh|i,t}\hat{u}_{i,h,t+1}^{\frac{\beta}{\nu}}} \\
\mu'_{ji,s\#,t} &= \frac{\mu'_{ji,s\#,t-1}\dot{\mu}_{ji,s\#,t}\left(\sum_{h=0}^{S}\mu'_{ji,sh|i,t-1}\dot{\mu}_{ji,sh|i,t}\hat{u}_{i,h,t+1}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\mu'_{jm,s\#,t-1}\dot{\mu}_{jm,s\#,t}\left(\sum_{h=0}^{S}\mu'_{jm,sh|m,t-1}\dot{\mu}_{jm,sh|m,t}\hat{u}_{m,h,t+1}^{\frac{\beta}{\nu}}\right)^{\nu/\kappa}} \\
\ell'_{i,s,t} &= \sum_{j=1}^{I}\sum_{k=0}^{S}\mu'_{ji,ks|i,t-1}\mu'_{ji,k\#,t-1}\ell'_{j,k,t-1}
\end{aligned}
$$

But period one works differently:

$$
\begin{aligned}
\mu'_{ji,sk|i,1} &= \frac{\theta_{ji,sk|i,0}\hat{u}_{i,k,2}^{\beta/\nu}}{\sum_{h=0}^{S}\theta_{ji,sh|i,0}\hat{u}_{i,h,2}^{\beta/\nu}} \\
\mu'_{ji,s\#,1} &= \frac{\mu_{ji,s\#,1}\left(\sum_{h=0}^{S}\theta_{ji,sh|i,0}\hat{u}_{i,h,2}^{\beta/\nu}\right)^{\nu/\kappa}}{\sum_{m=1}^{I}\mu_{jm,s\#,1}\left(\sum_{h=0}^{S}\theta_{jm,sh|m,0}\hat{u}_{m,h,2}^{\beta/\nu}\right)^{\nu/\kappa}} \\
\theta_{ji,sk|i,0} &\equiv \mu_{ji,sk|i,1}\hat{u}_{i,k,1}^{\beta/\nu}
\end{aligned}
$$

With these equations, if one has an initial distribution of labor supply ($\ell'_{i,s,0}$, which should be the same as $\ell_{i,s,0}$), the mobility matrices in the baseline economy and an initial guess for the utility hats ($\hat{u}_{i,s,t}^{(0)}\ \forall\ t$), one can obtain the entire path of labor supplies ($\ell'_{i,s,t}\ \forall\ t > 0$), and the entire path of mobility matrices without needing to use the other equations at all.

2. The ones that are needed to obtain the temporary equilibrium (wages, actual labor, sectoral prices, trade shares, revenue levels) from a given set of shocks and labor supply (block 2):

$$
\begin{aligned}
\hat{P}_{i,s,t}^{1-\sigma_s} &= \sum_{j=1}^{I}\lambda'_{ji,s,t-1}\dot{\lambda}_{ji,s,t}\left(\hat{\tau}_{ji,s,t}\hat{A}_{j,s,t}^{-1}\hat{W}_{j,s,t}^{\phi_{j,s}}\prod_{k=1}^{S}\hat{P}_{j,k,t}^{\phi_{j,ks}}\right)^{1-\sigma_s} \\
\lambda'_{ij,s,t} &= \frac{\lambda'_{ij,s,t-1}\dot{\lambda}_{ij,s,t}(\hat{\tau}_{ij,s,t}\hat{A}_{i,s,t}^{-1}\hat{W}_{i,s,t}^{\phi_{i,s}}\prod_{k=1}^{S}\hat{P}_{i,k,t}^{\phi_{i,ks}})^{1-\sigma_s}}{\hat{P}_{j,s,t}^{1-\sigma_s}} \\
R'_{i,s,t} &= \sum_{j=1}^{I}\lambda'_{ij,s,t}\left(\alpha_{j,s}\left(\sum_{s}\hat{W}_{j,s,t}\hat{L}_{j,s,t}Y'_{j,s,t-1}\dot{W}_{j,s,t}\dot{L}_{j,s,t}+D'_{j,t}\right)+\sum_{k=1}^{S}\phi_{j,sk}R'_{j,k,t}\right) \\
\phi_{i,s}R'_{i,s,t} &= \hat{W}_{i,s,t}\hat{L}_{i,s,t}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t} \\
\prod_{q=1}^{t}\hat{L}_{i,s,q}\dot{L}_{i,s,q} &\leq \prod_{q=1}^{t}\dot{\ell}'_{i,s,q}\ , \quad \hat{W}_{i,s,t}\dot{W}_{i,s,t}\geq\delta_{i,s}\ , \text{ Complementary Slackness} \\
\sum_{i=1}^{I}\sum_{s=1}^{S}Y'_{i,s,t-1} &= \frac{1}{\gamma}\sum_{i=1}^{I}\sum_{s=1}^{S}\hat{W}_{i,s,t}\hat{L}_{i,s,t}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}
\end{aligned}
$$

With these equations, if we have a set of shocks in hats ($\hat{\tau}$ and $\hat{A}$, as well as deficits in the counterfactual economy D'), together with initial values for the counterfactual economy (like trade shares and nominal incomes) and the solution for the baseline economy (including trade shares dot, wages dot and labor dot), we can solve for hat prices, new trade shares in levels, new revenues in levels, actual labor hats and wages hat.

3. The ones that are needed to update the guess for the path of utilities (block 3):

$$
\begin{aligned}
\hat{P}_{i,t} &= \prod_{s=1}^{S} \hat{P}_{i,s,t}^{\alpha_{i,s}} \\
\hat{\omega}_{i,s,t} &= \frac{\hat{W}_{i,s,t}\hat{L}_{i,s,t}}{\hat{P}_{i,t}\hat{\ell}_{i,s,t}} \quad \text{(but with } \hat{\omega}_{i,s,t} = 1 \text{ if } s = 0\text{)} \\
\hat{u}_{j,s,t} &= \hat{\omega}_{j,s,t}\hat{\Delta}_{j,s,t} \left(\sum_{i=1}^{I} \mu'_{ji,s\#,t-1}\dot{\mu}_{ji,s\#,t} \left(\sum_{k=0}^{S} \mu'_{ji,sk|i,t-1}\dot{\mu}_{ji,sk|i,t}\hat{u}_{i,k,t+1}^{\frac{\beta}{\nu}} \right)^{\nu/\kappa} \right)^{\kappa}
\end{aligned}
$$

But period one works differently:

$$
\begin{aligned}
\hat{u}_{j,s,1} &= \hat{\omega}_{j,s,1}\hat{\Delta}_{j,s,1} \left(\sum_{i=1}^{I} \mu_{ji,s\#,1} \left(\sum_{k=0}^{S} \theta_{ji,sk|i,0}\hat{u}_{i,k,2}^{\beta/\nu} \right)^{\nu/\kappa} \right)^{\kappa} \\
\theta_{ji,sk|i,0} &\equiv \mu_{ji,sk|i,1}\hat{u}_{i,k,1}^{\beta/\nu}.
\end{aligned}
$$

The algorithm would work as follows:

1. Guess a path for the utility hats (which can be all of them being equal to one).
2. Use block one to obtain paths for the μ' and ℓ' using the guessed path for the utility hat and the solution for the baseline economy.
3. Use block two to solve the temporary equilibrium using the path for ℓ', the hat shocks and the solution for the baseline economy.
4. Use block three to obtain a new guess for the utility hats. This uses the sectoral compensations obtained in the previous step and the fact that in a far enough point in the future (called T) the change in utility in the baseline economy should be the same as the change in utility in the counterfactual, so we should have $\hat{u}_{i,s,T}^{(1)} = 1$. With $\hat{u}_{i,s,T}^{(1)} = 1$, the path for the μ' and the sectoral compensations one can obtain $\hat{u}_{i,s,T-1}^{(1)}$. And from those obtain $\hat{u}_{i,s,T-2}^{(1)}$, and so on until $\hat{u}_{i,s,2}^{(1)}$. $\hat{u}_{i,s,1}^{(1)}$ needs to be obtained with a special equation.
5. If the two guessed paths of utility hats $\hat{u}^{(0)}$ and $\hat{u}^{(1)}$ are close enough, stop the algorithm, oth-

erwise return to item one with the new guess and iterate again.

B.7 Algorithm to Solve the Temporary Equilibrium

Block two of the previously described outer algorithms (which solve the equilibrium system in dots or hats) solves for the temporary equilibrium of the baseline or counterfactual economy. Given the presence of an inequality constraint due to DNWR, solving this temporary equilibrium is an unwieldy process that would be infeasible with any traditional solver. To overcome this limitation, we develop an augmented version of Alvarez and Lucas (2007) to be able to handle the existence of DNWR. This inner algorithm is very efficient and allows us to solve the temporary equilibrium of the full model with DNWR extremely fast (provided we use the nominal anchor described in equation 19). In this appendix, we describe this inner algorithm in the case of the hat system. The inner algorithm for the dot system is analogous.

Notice first that, if one knows a given period's wages in hats (as well as the solution for the baseline economy, the previous period's trade shares, and the shocks to trade costs and technology), it is possible to obtain the corresponding prices in hats from the equation:

$$\hat{P}_{i,s,t}^{1-\sigma_s} = \sum_{j=1}^{I} \lambda'_{ji,s,t-1} \dot{\lambda}_{ji,s,t} \left(\hat{\tau}_{ji,s,t} \hat{A}_{j,s,t}^{-1} \hat{W}_{j,s,t}^{\phi_{j,s}} \prod_{k=1}^{S} \hat{P}_{j,k,t}^{\phi_{j,ks}} \right)^{1-\sigma_s},$$

using traditional contraction mapping algorithms. The new trade shares can then easily be obtained from the following equation,

$$\lambda'_{ij,s,t} = \frac{\lambda'_{ij,s,t-1} \dot{\lambda}_{ij,s,t} (\hat{\tau}_{ij,s,t} \hat{A}_{i,s,t}^{-1} \hat{W}_{i,s,t}^{\phi_{i,s}} \prod_{k=1}^{S} \hat{P}_{i,k,t}^{\phi_{i,ks}})^{1-\sigma_s}}{\hat{P}_{j,s,t}^{1-\sigma_s}}.$$

Knowing the previous elements, employment in hats, the previous periods output levels, and the shock to deficits, allows one to solve for revenues using the linear (albeit massive) system described by the following set of equations

$$R'_{i,s,t} = \sum_{j=1}^{I} \lambda'_{ij,s,t} \left(\alpha_{j,s} \left(\sum_{s} \hat{W}_{j,s,t} \hat{L}_{j,s,t} Y'_{j,s,t-1} \dot{W}_{j,s,t} \dot{L}_{j,s,t} + D'_{j,t} \right) + \sum_{k=1}^{S} \phi_{j,sk} R'_{j,k,t} \right).$$

The previous argument implies that we can write revenues in the counterfactual economy in a given period as a function of that same period's wages and employment hats, i.e. $R'_{i,s,t}(\hat{\mathbf{W}}, \hat{\mathbf{L}})$

(where the bold W and L stand for the vector of wages and employment hats in all the regions and sectors).

What remains is to show how to solve the following system in wages and employment hats for all regions and sectors:

$$\begin{aligned} \phi_{i,s} R'_{i,s,t}(\hat{\mathbf{W}}, \hat{\mathbf{L}}) &= \hat{W}_{i,s,t} \hat{L}_{i,s,t} Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t} \\ \hat{L}_{i,s,t} &\leq L^U_{i,s,t} \ , \ \hat{W}_{i,s,t} \geq W^L_{i,s,t} \ , \ \text{Complementary Slackness (C.S.)} \\ \sum_{i=1}^{I} \sum_{s=1}^{S} Y'_{i,s,t-1} &= \sum_{i=1}^{I} \sum_{s=1}^{S} \hat{W}_{i,s,t} \hat{L}_{i,s,t} Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t}. \end{aligned}$$

This is where we will use an augmented version of the Alvarez and Lucas (2007) algorithm that accounts for the presence of DNWR. Imagine that one has an initial guess for wages and employment in hats, denoted $\hat{W}^{(0)}_{i,s,t}$ and $\hat{L}^{(0)}_{i,s,t}$. We use an algorithm that updates this guess as follows:

$$\begin{aligned} \hat{W}^{(1)}_{i,s,t} &= \max \left\{ \frac{(1-\lambda) \hat{W}^{(0)}_{i,s,t} \hat{L}^{(0)}_{i,s,t} + \lambda \frac{\phi_{i,s} R'_{i,s,t}(\hat{\mathbf{W}}^{(0)}, \hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t}}}{L^U_{i,s,t}}, W^L_{i,s,t} \right\} \\ \hat{L}^{(1)}_{i,s,t} &= \min \left\{ L^U_{i,s,t}, \frac{(1-\lambda) \hat{W}^{(0)}_{i,s,t} \hat{L}^{(0)}_{i,s,t} + \lambda \frac{\phi_{i,s} R'_{i,s,t}(\hat{\mathbf{W}}^{(0)}, \hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t}}}{W^L_{i,s,t}} \right\}. \end{aligned}$$

These new guesses obviously satisfy $\hat{L}^{(1)}_{i,s,t} \leq L^U_{i,s,t}$ and $\hat{W}^{(1)}_{i,s,t} \geq W^L_{i,s,t}$. The new guesses also satisfy the C.S. condition. To see this, notice that it cannot happen that:

$$\begin{aligned} \hat{W}^{(1)}_{i,s,t} &= \frac{(1-\lambda) \hat{W}^{(0)}_{i,s,t} \hat{L}^{(0)}_{i,s,t} + \lambda \frac{\phi_{i,s} R'_{i,s,t}(\hat{\mathbf{W}}^{(0)}, \hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t}}}{L^U_{i,s,t}} \\ \hat{L}^{(1)}_{i,s,t} &= \frac{(1-\lambda) \hat{W}^{(0)}_{i,s,t} \hat{L}^{(0)}_{i,s,t} + \lambda \frac{\phi_{i,s} R'_{i,s,t}(\hat{\mathbf{W}}^{(0)}, \hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t}}}{W^L_{i,s,t}}, \end{aligned}$$

since that would require:

$$\begin{aligned} \frac{(1-\lambda) \hat{W}^{(0)}_{i,s,t} \hat{L}^{(0)}_{i,s,t} + \lambda \frac{\phi_{i,s} R'_{i,s,t}(\hat{\mathbf{W}}^{(0)}, \hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t}}}{L^U_{i,s,t}} &\geq W^L_{i,s,t} \\ L^U_{i,s,t} &\geq \frac{(1-\lambda) \hat{W}^{(0)}_{i,s,t} \hat{L}^{(0)}_{i,s,t} + \lambda \frac{\phi_{i,s} R'_{i,s,t}(\hat{\mathbf{W}}^{(0)}, \hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1} \dot{W}_{i,s,t} \dot{L}_{i,s,t}}}{W^L_{i,s,t}}. \end{aligned}$$

Putting the last two inequalities together we get:

$$(1-\lambda)\hat{W}^{(0)}_{i,s,t}\hat{L}^{(0)}_{i,s,t}+\lambda\frac{\phi_{i,s}R'_{i,s,t}(\hat{\mathbf{W}}^{(0)},\hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}}\geq W^{L}_{i,s,t}L^{U}_{i,s,t}\geq(1-\lambda)\hat{W}^{(0)}_{i,s,t}\hat{L}^{(0)}_{i,s,t}+\lambda\frac{\phi_{i,s}R'_{i,s,t}(\hat{\mathbf{W}}^{(0)},\hat{\mathbf{L}}^{(0)})}{Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}},$$

which is impossible unless both inequalities hold with equality (in which case all the relevant conditions are satisfied anyway). This means that unless we are in a knife edge case (where everything works fine) we are going to be either in the point:

$$\left(\hat{L}^{(1)}_{i,s,t},\hat{W}^{(1)}_{i,s,t}\right)=\left(L^{U}_{i,s,t},\frac{(1-\lambda)\hat{W}^{(0)}_{i,s,t}\hat{L}^{(0)}_{i,s,t}+\lambda\frac{\phi_{i,s}R'_{i,s,t}}{Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}}}{L^{U}_{i,s,t}}\right),$$

or in the point:

$$\left(\hat{L}^{(1)}_{i,s,t},\hat{W}^{(1)}_{i,s,t}\right)=\left(\frac{(1-\lambda)\hat{W}^{(0)}_{i,s,t}\hat{L}^{(0)}_{i,s,t}+\lambda\frac{\phi_{i,s}R'_{i,s,t}}{Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}}}{W^{L}_{i,s,t}},W^{L}_{i,s,t}\right),$$

which means that the C.S. condition is satisfied. It is also true that the new guess satisfies the nominal anchor if the previous guess did. To see this, notice that (from the observation that we are always in either of those special points) the following always holds:

$$\hat{W}^{(1)}_{i,s,t}\hat{L}^{(1)}_{i,s,t}=(1-\lambda)\hat{W}^{(0)}_{i,s,t}\hat{L}^{(0)}_{i,s,t}+\lambda\frac{\phi_{i,s}R'_{i,s,t}}{Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}}.$$

Multiplying this by $Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}$ and summing it over i and s we get:

$$\begin{aligned}\sum_{i=1}^{I}\sum_{s=1}^{S}\hat{W}^{(1)}_{i,s,t}\hat{L}^{(1)}_{i,s,t}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t} &= (1-\lambda)\sum_{i=1}^{I}\sum_{s=1}^{S}\hat{W}^{(0)}_{i,s,t}\hat{L}^{(0)}_{i,s,t}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}\\ &+ \lambda\sum_{i=1}^{I}\sum_{s=1}^{S}\frac{\phi_{i,s}R'_{i,s,t}}{Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}.\end{aligned}$$

Focusing on the last term, it is possible to show that:

$$\sum_{i=1}^{I}\sum_{s=1}^{S}\phi_{i,s}R'_{i,s,t}=\sum_{j=1}^{I}\sum_{r=1}^{S}\hat{W}^{(0)}_{j,r,t}\hat{L}^{(0)}_{j,r,t}Y'_{j,r,t-1}\dot{W}_{j,r,t}\dot{L}_{j,r,t}.$$

This makes it clear that:

$$\sum_{i=1}^{I}\sum_{s=1}^{S}\hat{W}_{i,s,t}^{(1)}\hat{L}_{i,s,t}^{(1)}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t} \quad = \quad \sum_{i=1}^{I}\sum_{s=1}^{S}\hat{W}_{i,s,t}^{(0)}\hat{L}_{i,s,t}^{(0)}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}.$$

Therefore, if the initial guess satisfies the nominal anchor the new guess will do so as well. Finally, when the algorithm converges, for example at iteration N, the following holds:

$$\hat{W}_{i,s,t}^{(N)}\hat{L}_{i,s,t}^{(N)} = (1-\lambda)\hat{W}_{i,s,t}^{(N)}\hat{L}_{i,s,t}^{(N)} + \lambda\frac{\phi_{i,s}R'_{i,s,t}}{Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t}},$$

which implies $\hat{W}_{i,s,t}^{(N)}\hat{L}_{i,s,t}^{(N)}Y'_{i,s,t-1}\dot{W}_{i,s,t}\dot{L}_{i,s,t} = \phi_{i,s}R'_{i,s,t}$, indicating that the final guess solves our desired system. We use the following initial guess which satisfies the nominal anchor,

$$\hat{W}_{i,s,t}^{(0)} = \frac{1}{\dot{W}_{i,s,t}}, \qquad \hat{L}_{i,s,t}^{(0)} = \frac{1}{\dot{L}_{i,s,t}}.$$

B.8 Welfare

We start from our previous result that

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

Using

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

we then have

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

Next, using

$$\mu_{jj,ss|j,t} = \frac{\exp\left(\beta V_{j,s,t+1}\right)^{1/\nu}}{\sum_{h=0}^{S}\exp\left(\beta V_{j,h,t+1} - \varphi_{jj,sh}\right)^{1/\nu}},$$

we have

$$\sum_{h=0}^{S}\exp\left(\beta V_{j,h,t+1} - \varphi_{jj,sh}\right)^{1/\nu} = \mu_{jj,ss|j,t}^{-1}\exp\left(\beta V_{j,s,t+1}\right)^{1/\nu},$$

and hence

$$\mu_{jj,s\#,t}^{-1}\left(\sum_{h=0}^{S}\exp\left(\beta V_{j,h,t+1}-\varphi_{jj,sh}\right)^{1/\nu}\right)^{\nu/\kappa} = \mu_{jj,s\#,t}^{-1}\mu_{jj,ss|j,t}^{-\nu/\kappa}\exp\left(\beta V_{j,s,t+1}\right)^{1/\kappa}.$$

This implies that

$$\kappa\ln\left(\sum_{m=1}^{I}\left(\sum_{h=0}^{S}\exp\left(\beta V_{m,h,t+1}-\varphi_{jm,sh}\right)^{1/\nu}\right)^{\nu/\kappa}\right) = \beta V_{j,s,t+1}-\kappa\ln\left(\mu_{jj,s\#,t}\right)-\nu\ln\left(\mu_{jj,ss|j,t}\right).$$

We then write

$$V_{j,s,t}=\ln(\omega_{j,s,t}\Delta_{j,s,t})-\kappa\ln\left(\mu_{jj,s\#,t}\right)-\nu\ln\left(\mu_{jj,ss|j,t}\right)+\gamma\kappa+\beta V_{j,s,t+1}.$$

Iterating this equation forward, we obtain

$$V_{j,s,t}=\sum_{r=t}^{\infty}\beta^{r-t}\left(\ln(\omega_{j,s,r}\Delta_{j,s,r})-\kappa\ln\left(\mu_{jj,s\#,r}\right)-\nu\ln\left(\mu_{jj,ss|j,r}\right)+\gamma\kappa\right).$$

We define the EV in consumption for market js at time $t=0$ to be the scalar $\zeta_{j,s}$ such that

$$V'_{j,s,0}=V_{j,s,0}+\sum_{r=0}^{\infty}\beta^{r}\ln(\zeta_{j,s})=\sum_{r=0}^{\infty}\beta^{r}\left(\ln\left(\frac{\omega_{j,s,r}\Delta_{j,s,r}\zeta_{j,s}}{\left(\mu_{jj,ss|j,r}\right)^{\nu}\left(\mu_{jj,s\#,r}\right)^{\kappa}}\right)+\gamma\kappa\right).$$

Defining $\mathcal{V}_{j,s}\equiv\ln(\zeta_{j,s})$ and rearranging the previous definition, we can write:

$$\begin{aligned}(V'_{j,s,0}-V_{j,s,0}) &= \mathcal{V}_{j,s}\sum_{r=0}^{\infty}\beta^{r}\\ \mathcal{V}_{j,s} &= (1-\beta)(V'_{j,s,0}-V_{j,s,0})\\ &= \sum_{r=1}^{\infty}\beta^{r}\ln\left(\frac{\hat{\omega}_{j,s,r}\hat{\Delta}_{j,s,r}}{\left(\hat{\mu}_{jj,ss|j,r}\right)^{\nu}\left(\hat{\mu}_{jj,s\#,r}\right)^{\kappa}}\right),\end{aligned}$$

which is the expression that we will use for the "welfare change" stemming from the China shock, formally the equivalent variation change in consumption due to the shock. Notice that, since the welfare effects from the China shock will be small in percentage terms, then $\mathcal{V}_{j,s}=\ln(\zeta_{j,s})\approx\zeta_{j,s}-1$.

B.9 More on Calibration

As discussed in the main text, the multiplicative nature of our productivity decomposition, $\hat{A}_{China,s,t} = \hat{A}^1_{China,t}\hat{A}^2_{China,s}$, implies that their level is not identified. For example, if we multiply all the $\hat{A}^2_{China,s}$ by a constant c and we divide all the $\hat{A}^1_{China,t}$ by c, then we would have the same $\hat{A}_{China,s,t}$. Thus, we use the normalization $\sum_{s=1}^{S}\hat{A}^2_{China,s} = 1$. Correspondingly, the model is only able to produce changes in imports that satisfy $\sum_{t=2001}^{end}\Delta X^{model}_{C,US,t} = \sum_{s=1}^{S}\Delta X^{end-2000,model}_{C,US,s}$. This condition is automatically satisfied by the actual changes, i.e. $\sum_{t=2001}^{end}\Delta X_{C,US,t} = \sum_{s=1}^{S}\Delta X^{end-2000}_{C,US,s}$, but not necessarily by the predicted changes, due to the lack of a constant in the second regression. We adjust the predicted changes in manufacturing so that they satisfy: $\sum_{t=2001}^{end}\widehat{\Delta X_{C,US,t}} = \sum_{s=1}^{S}\Delta\widehat{X^{end-2000}_{C,US,s}}$, this adjustment is very small. In all of our applications we match our targets with an accuracy greater than 99.9%.

C Data Construction

In this appendix section, we provide details on the construction of the data we briefly described in Section 4. We divide this appendix into three parts. Appendix C.1 describes all data sources. Appendix C.2 discusses how we combine the different data sources to compute an internally consistent bilateral trade-flow matrix for all sectors for the years when all the data is available. It also discusses how we use the previous step to project bilateral trade flows between states and countries for the years before full data availability. Finally, Appendix C.3 discusses the construction of the initial employment allocations for all regions and the bilateral migration flows between sectors and U.S. states.

C.1 Data Description and Sources

List of sectors. We use a total of 14 market sectors (plus a home production sector). The list of market sectors includes 12 manufacturing sectors, one catch-all services sector, and one agriculture sector. We follow CDP in the selection of the 12 manufacturing sectors. These are: **1)** Food, beverage, and tobacco products (NAICS 311-312, WIOD sector 3); **2)** Textile, textile product mills, apparel, leather, and allied products (NAICS 313-316, WIOD sectors 4-5); **3)** Wood products, paper, printing, and related support activities (NAICS 321-323, WIOD sectors 6-7); **4)** Mining, petroleum and coal products (NAICS 211-213, 324, WIOD sectors 2, 8); **5)** Chemical (NAICS 325, WIOD sector 9); **6)** Plastics and rubber products (NAICS 326, WIOD sector 10); **7)** Nonmetallic mineral products (NAICS 327, WIOD sector 11); **8)** Primary metal and fabricated metal products (NAICS 331-332, WIOD sector 12); **9)** Machinery (NAICS 333, WIOD sector 13); **10)** Computer and electronic products, and electrical equipment and appliance (NAICS 334-335, WIOD sector 14); **11)** Transportation equipment (NAICS 336, WIOD sector 15); **12)** Furniture and related products, and miscellaneous manufacturing (NAICS 337- 339, WIOD sector 16). There is a **13)** Services sector which includes Construction (NAICS 23, WIOD sector 18); Wholesale and retail trade sectors (NAICS 42-45, WIOD sectors 19-21); Accommodation and Food Services (NAICS 721-722, WIOD sector 22); transport services (NAICS 481-488, WIOD sectors 23-26); Information Services (NAICS 511-518, WIOD sector 27); Finance and Insurance (NAICS 521-525, WIOD sector 28); Real Estate (NAICS 531-533, WIOD sectors 29-30); Education (NAICS 61, WIOD sector 32); Health Care (NAICS 621-624, WIOD sector 33); and Other Services (NAICS 493, 541, 55, 561, 562, 711-713, 811-814, WIOD sector 34).[37]

List of countries: We use data for 50 U.S. states, and 37 other countries, including an aggregated rest of the world. The list of countries is: Australia, Austria, Belgium, Bulgaria, Brazil, Canada, China, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Indonesia, Italy, Ireland, Japan, Lithuania, Mexico, the Netherlands, Poland, Portugal, Romania, Russia, Spain, the Slovak Republic, Slovenia, S. Korea, Sweden, Taiwan, Turkey, the United Kingdom, and the rest of the world.

Data on bilateral trade between countries. World Input-Output Database (WIOD). Release of 2013. We use data for 2000-2007 in our baseline and 2000-2011 in one of our extensions. We map the sectors in the WIOD database to our 14 market sectors in the following way: **1)** Food Products, Beverage, and Tobacco Products (c3); **2)** Textile, Textile Product Mills, Apparel, Leather, and Allied Products (c4-c5); **3)** Wood Products, Paper, Printing, and Related Support Activities (c6-c7); **4)** Petroleum and Coal Products (c8); **5)** Chemical (c9); **6)** Plastics and Rubber Products (c10); **7)** Nonmetallic Mineral Products (c11); **8)** Primary Metal and Fabricated Metal Products (c12); **9)** Machinery (c13); **10)** Computer and Electronic Products, and Electrical Equipment and Appliances (c14); **11)** Transportation Equipment (c15); **12)** Furniture and Related Products, and Miscellaneous Manufacturing (c16); **13)** Construction (c18), Wholesale and Retail Trade (c19-c21), Transport Services (c23-c26), Information Services (c27), Finance and Insurance (c28), Real Estate

[37] The only difference with respect to CDP in the definition of manufacturing sectors is that we include Mining (NAICS 211-213) together with Petroleum and Coal Products (NAICS 324) in our sector 4.

(c29- c30); Education (c32); Health Care (c33), Accommodation and Food Services (c22), and Other Services (c34); **14)** Agriculture and Mining (c1-c2). We follow Costinot and Rodriguez-Clare (2014) to remove the negative values in the trade data from WIOD.

Data on bilateral trade in manufacturing between U.S states. We combine the 2002 and 2007 Commodity Flow Survey (CFS) with the WIOD database. The CFS records shipments between U.S. states for 43 commodities classified according to the Standard Classification of Transported Goods (SCTG). We follow CDP and use CFS 2007 tables that cross-tabulate establishments by their assigned NAICS codes against commodities (SCTG) ship-ped by establishments within each of the NAICS codes. These tables allow for the mapping of SCTG to NAICS.

Data on bilateral trade in manufacturing and agriculture between U.S states and the rest of the countries. We 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, which is compiled by the U.S. Census Bureau. This dataset reports imports and exports in each NAICS sector between each U.S. state and each other country in the world.

Data on sectoral and regional value-added share in gross output. Value added for each of the 50 U.S. states and 14 sectors can be obtained from the 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 equal gross output. For the list of countries, we obtain the share of value added in gross output from WIOD.

Data on services expenditure and production. We compute bilateral trade in services using a gravity approach explained in Appendix C.2. As part of these calculations, we require data on production and expenditure in services by region. We obtain U.S. state-level services GDP from the Regional Economic Accounts of the BEA. We obtain U.S. state-level services expenditure from the Personal Consumption Expenditures (PCE) database of BEA. Finally, for the list of other countries we compute total production and expenditure in services from WIOD.

Data on agriculture expenditure and production. We also compute bilateral trade in agriculture using a gravity approach explained in Appendix C.2. To get production in agriculture for the U.S. states, we combine the 2002 and 2007 Agriculture Census with the National Marine Fisheries Service Census to get state-level production data on crops, livestock and seafood. We infer state-level expenditure in agriculture from our gravity approach explained in Appendix C.2. Finally, for the list of other countries we compute total production and expenditure in agriculture from WIOD.

Data on population and geographic coordinates. As part of the gravity approach to compute bilateral trade in services, we also need to compute bilateral distances between regions. We follow the procedure used in the GeoDist dataset of CEPII to calculate international (and intranational) bilateral trade distances. We thus require data on the most populated cities in each country, the cities' coordinates and population, and each country's population. We obtained this information from the United Nations Population Division website. In particular, we use the population of urban agglomerations with 300,000 inhabitants or more in 2018, by country, for 2000-2007. For Austria, Cyprus, Denmark, Estonia, Hungary, Ireland, Lithuania, Slovakia and Slovenia we use the two most populated cities.[38] For the case of U.S. states, we use population and coordinates data for each U.S. county within each U.S. state. The data for the U.S. counties comes from the U.S. CENSUS.

Data on employment and migration flows. For the case of countries, we take data on employment by country and sector from the WIOD Socio Economic Accounts (WIOD-SEA). For the case of U.S. states, we take sector-level employment (including unemployment and non-participation) from the 5% sample PUMS files of the 2000 Census. 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 American Community Survey (ACS) and the Current Population Survey (CPS). Finally, we abstract from international migration.

C.2 Construction of the Bilateral Trade Flows Between Regions

We follow the notation from Costinot and Rodriguez-Clare (2014) and omit the time subscripts t that are relevant in our quantitative model. Define $X_{ij,ks}$ as sales of intermediate goods from sector k in region i to sector s in region j, and $X_{ij,kF}$ as the sales of sector k in region i to the final consumer of region j. Our final objective is to construct a bilateral trade flows matrix between all regions in our sample with elements equal to $X_{ij,k} = \sum_s X_{ij,ks} + X_{ij,kF}$. This matrix allows us to compute the trade shares $\lambda_{ij,k}$, and the sector-level revenues $R_{j,k} = \sum_l X_{jl,k}$ for each region, which are crucial elements in our hat algebra described in Section 3.6.

As additional definitions, take $E_{j,k} = \sum_i X_{ij,k}$ as the total expenditure of region j in sector k, $F_{j,k} = \sum_i X_{ij,kF}$ as the final consumption in region j of sector k, $F_j = \sum_k F_{j,k}$ as the total final

[38]For the specific case of Cyprus, the cities' information comes from the country's Statistical Service.

consumption of region j, and $X_{j,ks} = \sum_i X_{ij,ks}$ as the total purchases that sector s in region j makes from sector k. We construct $X_{ij,k}$ in the four steps explained below. With some abuse of notation, we refer to a region i as a U.S. state (country) by $i \in US$ ($i \notin US$).

Step 1: Bilateral trade between countries. In the first step we focus on the case where both i and j are countries. Thus, we simply take $X_{ij,k} = X_{ij,k}^{WIOD}$, where $X_{ij,k}^{WIOD}$ are the bilateral trade flows that come directly from the WIOD database.

Step 2: Manufacturing trade among U.S. states. In the second step we focus on manufacturing bilateral trade between U.S. States. For this, we combine the closest Commodity Flow Survey (CFS) for each year with WIOD Data for the total trade of the U.S. with itself. We first compute the shares that each state i exports to state j in sector k represent in the total trade of sector k according to CFS. Then, we calculate the total exports of state i to state j in sector k as WIOD's U.S. trade with itself in sector k multiplied by the share computed in the previous step to ensure that bilateral trade between states adds up to the WIOD total.

Step 3: Manufacturing trade between U.S. states and countries. For the third step, we combine Census and WIOD data to calculate the trade flows between each of the 50 U.S. states and the other 37 country regions. There is limited availability for the state×sector-level trade data coming from the CENSUS. Data for exports at the state×sector-level starts in 2002 and data for imports starts in 2008. We scale state-level imports and exports data from the Import and Export Merchandise Trade Statistics to match the U.S. totals in WIOD. More precisely, the exports (imports) of state i to (from) country j in manufacturing sector k are computed as a proportion of WIOD's U.S. export (imports) to (from) country j in sector k. This proportion is equal to the exports (imports) of state i to (from) country j in sector k relative to the total U.S. exports (imports) to (from) country j in sector k.

Since the Import and Export Merchandise Trade Statistics data for exports starts in 2002 and for imports starts in 2008, the bilateral trade flows between regions for the years before the data starts cannot be computed directly from the data. We adapt our computation method to take into account this issue. All previous procedures remain the same. Denote $X_{ij,k}^{base}$ as the matrix $X_{ij,k}$ for the first year where the exports or imports data is available (the base year). Define the share of exports of U.S. State i in sector k, going to country j in the base year as $y_{ij,k}^{base} \equiv \frac{X_{ij,k}^{base}}{\sum_{h \in US} X_{hj,k}^{base}} \quad \forall i \in US\,,\, j \notin US$. Similarly, define the share of imports of U.S. state j in sector k, coming from country i in the base year as $e_{ij,k}^{base} \equiv \frac{X_{ij,k}^{base}}{\sum_{l \in US} X_{il,k}^{base}} \quad \forall i \notin US\,,\, j \in US$. Finally for each sector k in manufacturing or agriculture; and any year before the base year define $X_{ij,k} = e_{ij,k}^{base} X_{i\,US,k}^{WIOD} \quad \forall i \notin US,\ \forall j \in US$

and $X_{ij,k} = y_{ij,k}^{base} X_{US\,j,k}^{WIOD} \quad \forall i \in US,\ \forall j \notin US$.

Step 4: Trade in services and trade in agriculture. We compute bilateral trade flows for services and agriculture separately using a gravity structure that matches WIOD totals for trade between countries (including the U.S.). We start with the standard gravity equation (for simplicity, we remove the subscript of the sector) $X_{ij} = \left(\frac{w_i \tau_{ij}}{P_j}\right)^{-\varepsilon} E_j$, where $P_j^{-\varepsilon} = \sum_i \left(w_i \tau_{ij}\right)^{-\varepsilon}$. We know that $\sum_j X_{ij} = R_i$ and hence $\sum_j \left(\frac{w_i \tau_{ij}}{P_j}\right)^{-\varepsilon} E_j = R_i$. This implies $w_i^{-\varepsilon} \Pi_i^{-\varepsilon} = R_i$, where $\Pi_i^{-\varepsilon} = \sum_j \tau_{ij}^{-\varepsilon} P_j^{\varepsilon} E_j$. Let $\tilde{P}_j \equiv P_j^{-\varepsilon}$ and $\tilde{\Pi}_i \equiv \Pi_i^{-\varepsilon}$, and $\tilde{\tau}_{ij} \equiv \tau_{ij}^{-\varepsilon}$. Given $\{E_j\}$, $\{R_i\}$, and $\{\tilde{\tau}_{ij}\}$, one we can get $\{\tilde{P}_j\}$ and $\{\tilde{\Pi}_i\}$ from the following system:

$$\tilde{P}_j = \sum_i \tilde{\tau}_{ij} \tilde{\Pi}_i^{-1} R_i$$

$$\tilde{x}_i = \sum_j \tilde{\tau}_{ij} \tilde{P}_j^{-1} E_j \tag{C1}$$

The solution for $\{\tilde{P}_j, \tilde{\Pi}_i\}$ is unique up to a constant (Fally, 2015). This indeterminacy requires a normalization. We thus impose $\tilde{P}_1 = 100$ in each exercise. Then one can compute our outcome of interest $\{X_{ij}\}$ from

$$X_{ij} = \tilde{\tau}_{ij} \tilde{\Pi}_i^{-1} \tilde{P}_j^{-1} R_i E_j. \tag{C2}$$

Computation of the bilateral resistance $\tilde{\tau}_{ij}$. To solve the gravity system, we must first compute $\tilde{\tau}_{ij}\ \forall i,\ j$. We proceed by assuming the following functional form: $\tilde{\tau}_{ij} = \beta_0^{\iota_{ij}} dist_{ij}^{\beta_1} \exp\left(\xi_{ij}\right)$, where ι_{ij} is an indicator variable equal to 1 if $i = j$, and ξ_{ij} is an idiosyncratic error term. β_1 captures the standard distance elasticity and β_0 captures the additional *inverse* resistance of trading with others versus with oneself.

To calculate $dist_{ij}$, we follow the same procedure used in the GeoDist dataset of CEPII to calculate international (and intranational) bilateral trade distances. The idea is to calculate the distance between two countries based on bilateral distances between the largest cities of those two countries, those inter-city distances being weighted by the share of the city in the overall country's population (Head and Mayer, 2002).

We use population for 2010 and coordinates data for all U.S. counties, and all cities around the world with more than 300,000 inhabitants. For those countries with less than two cities of this size, we take the two largest cities. Coordinates are important to calculate the physical bilateral distances in kms between each county r in state i and county s in state j ($d_{rs}\ \forall r \in i\ ,\ s \in$

j and $\forall i, j = 1, ..., 50$), and define $dist\,(ij)$ as:

$$dist\,(ij) = \left(\sum_{r\,\in\,i} \sum_{s\,\in\,j} \left(\frac{pop_r}{pop_i} \right) \left(\frac{pop_s}{pop_j} \right) d_{rs}^{\theta} \right)^{1/\theta}, \tag{C3}$$

where pop_h is the population of country/state h. We set $\theta = -1$.

Given our definition of $\tilde{\tau}_{ij}$ we can write the gravity equation between countries as $X_{ij} = \beta_0^{\iota_{ij}} dist_{ij}^{\beta_1} \exp\left(\xi_{ij}\right) \tilde{\Pi}_i^{-1} \tilde{P}_j^{-1} R_i E_j$. Taking logs we can write the previous equation as:

$$\ln X_{ij} = \delta_i^o + \delta_j^d + \tilde{\beta}_0 \iota_{ij} + \beta_1 \ln dist_{ij} + \xi_{ij}, \tag{C4}$$

where $\tilde{\beta}_0 = \ln \beta_0$ and the δs are fixed effects. We first estimate the equation above separately for services and agriculture using a 2000-2011 panel of bilateral trade flows between countries from WIOD. We present our OLS estimation results in Table C.1. Columns (1) and (2) refer to the estimated coefficients for the case of services and agriculture, respectively. Both regressions include year-by-origin and year-by-destination fixed effects. We take these estimates and compute the bilateral resistance term in each sector as $\hat{\tilde{\tau}}_{ij} = exp(\hat{\tilde{\beta}}_0 \iota_{ij} + \hat{\beta}_1 \ln dist_{ij})$.

Trade in services. As inputs, we need total expenditures in services for each region (E_i), as well as total production in services (R_i). For the case of countries we take this directly from WIOD. For the case of U.S. states we take these variables from the Regional Economic Accounts of the Bureau

Table C.1: Estimation of Own-Country Dummy and Distance Elasticity

Dep. Var.: $\ln X_{ij,t}$	(1) Services	(2) Agriculture
ι_{ij}	7.357***	4.143***
	(0.126)	(0.145)
$\ln dist_{ij}$	-0.376***	-1.745***
	(0.037)	(0.020)
Year×Orig.	Yes	Yes
Year×Dest.	Yes	Yes
Observations	17,328	17,328
Adjusted R^2	0.66	0.76

Notes: This table displays the OLS estimates of specifications analogous to the one in equation (C4). The outcome variable $\ln X_{ij,t}$ is the log exports of country i sent to country j. The own-country dummy ι_{ij} is defined as an indicator function equal to one whenever country i is the same as country j. Finally, $\ln dist_{ij}$ is the log distance between country i and country j. This variable is computed according to equation (C3). Robust standard errors are presented in parenthesis. *** denotes statistical significance at the 1%.

of Economic Analysis. We scale the state-level services production and expenditures so that they aggregate to the U.S. totals in WIOD.

We incorporate the information on bilateral trade in services between countries (including the U.S.) that comes from WIOD to the gravity system of equation (C1) by first writing the system as $\tilde{P}_j = \sum_{i \notin US} \tilde{\tau}_{ij} \tilde{\Pi}_i^{-1} R_i + \sum_{i \in US} \tilde{\tau}_{ij} \tilde{\Pi}_i^{-1} R_i$ and $\tilde{\Pi}_i = \sum_{j \notin US} \tilde{\tau}_{ij} \tilde{P}_j^{-1} E_j + \sum_{j \in US} \tilde{\tau}_{ij} \tilde{P}_j^{-1} E_j$. Then, we define $\tilde{\lambda}_j \equiv 1 - \frac{\sum_{i \notin US} X_{ij}}{E_j}$ for $j \notin US$ (the share of imports of region $j \notin US$ coming from the U.S.) and $\tilde{\lambda}_i^* \equiv 1 - \frac{\sum_{j \notin US} X_{ij}}{R_i}$ for $i \notin US$ (total exports of region $i \notin US$ to other regions not in the U.S.). Using these two definitions and substituting $\tilde{\tau}_{ij} = X_{ij} \tilde{\Pi}_i \tilde{P}_j R_i^{-1} E_j^{-1}$ whenever $i, j \notin US$ in the previous system of equations we have the final system we solve for services:

$$
\begin{aligned}
\tilde{P}_j &= \sum_i \tilde{\tau}_{ij} \tilde{\Pi}_i^{-1} R_i \quad j \in US \\
\tilde{\Pi}_i &= \sum_j \tilde{\tau}_{ij} \tilde{P}_j^{-1} E_j \quad i \in US \\
\tilde{\lambda}_j \tilde{P}_j &= \sum_{i \in US} \tilde{\tau}_{ij} \tilde{\Pi}_i^{-1} R_i \quad j \notin US \\
\tilde{\lambda}_i^* \tilde{\Pi}_i &= \sum_{j \in US} \tilde{\tau}_{ij} \tilde{P}_j^{-1} E_j \quad i \notin US
\end{aligned}
$$

Once we find solutions for $\{\tilde{P}_j, \tilde{\Pi}_i\}$, we compute the final bilateral trade matrix according to equation (C2).

Trade in agriculture. As inputs, we need total expenditures in agriculture for each region (E_i), as well as total production in agriculture (R_i). For the case of countries we take this directly from WIOD. For the case of U.S. states we compute total production (R_i) by combining data from the Agriculture Census and the National Marine Fisheries Service Census. We scale the state-level agriculture production so that it aggregates to the U.S. total in WIOD. However, it is not possible to find state-level agriculture expenditure for U.S. states. To overcome this data unavailability, we combine the U.S. input-output matrix $(\phi_{j,ks})$ together with the shares of value-added in gross production $(\phi_{j,k})$ in order to compute a value of (E_i) that is consistent with the full bilateral trade matrix for all regions and all sectors.

In order to describe our procedure, note that the total expenditure of region j in sector k $(E_{j,k})$ could be written as $E_{j,k} = \sum_s \tilde{\phi}_{j,ks} R_{j,s} + F_{j,k}$, where $\tilde{\phi}_{j,ks} = \phi_{j,ks}(1 - \phi_{j,s})$. We make two assumptions. First, we assume that $\tilde{\phi}_{j,ks} = \tilde{\phi}_{US,ks}\ \forall j \in US$, which means that we assume common input-output matrix and value-added shares across U.S. states and equal to the ones of the U.S. as a whole. Second, we assume identical Cobb-Douglas preferences across U.S. states. This means that when

$j \in US$ we have that $F_{j,k} = \frac{F_j}{F_{US}} F_{US,k} = F_j \gamma_k$, where $\gamma_k \equiv \frac{F_{US,k}}{F_{US}}$. Using these two assumptions we get $F_j = E_{j,k} - \sum_s \tilde{\phi}_{j,ks} R_{j,s} + \sum_{r \neq k} \left(E_{j,r} - \sum_s \tilde{\phi}_{j,rs} R_{j,s} \right)$. Substituting the previous equation in the definition of $E_{j,k}$ for the agriculture sector ($k = AG$), and $j \in US$ we find

$$E_{j,AG} = \sum_s \tilde{\phi}_{j,AG\,s} R_{j,s} + \frac{\gamma_{AG}}{1 - \gamma_{AG}} \sum_{r \neq AG} \left(E_{j,r} - \sum_s \tilde{\phi}_{j,rs} R_{j,s} \right),$$

which can be computed using state-level production of all sectors and state-level expenditure data of all other sectors (excluding agriculture), combined with the U.S.-level input-output matrix, value-added shares, and sector-level consumption shares.

Once we obtain the state-level expenditure values in agriculture, we can proceed with the gravity system in equation (C1). As in the case of services, we incorporate the information on bilateral trade in agriculture between countries that comes from WIOD. We also incorporate the bilateral trade in agriculture between U.S. states and other countries coming from the Import and Export Merchandise Trade Statistics. Thus, we only need to focus on $\{\tilde{P}_j\}_{j \in US}$ and $\{\tilde{\Pi}_i\}_{i \in US}$. Define $\chi_i^* = 1 - \sum_{j \notin US} \frac{X_{ij}}{R_i}$ for $i \in US$ (the share of sales of state i that stay in the U.S.) and $\chi_j = 1 - \sum_{i \notin US} \frac{X_{ij}}{E_{j,k}}$ for $j \in US$ (the share of purchases of state i that come from the U.S.). The final system we solve for agriculture becomes:

$$\begin{aligned} \chi_j \tilde{P}_j &= \Sigma_{i \in US} \tilde{\tau}_{ij} \tilde{\Pi}_i^{-1} R_i, \forall j \in US \\ \chi_i^* \tilde{\Pi}_i &= \Sigma_{j \in US} \tilde{\tau}_{ij} \tilde{P}_j^{-1} E_j, \forall i \in US \end{aligned}$$

As before, once we find solutions for $\{\tilde{P}_j, \tilde{\Pi}_i\}$, we compute the bilateral trade in agriculture between U.S. states according to equation (C2).

C.3 Initial Employment Allocations for each Region and Bilateral Migration Flows between Sectors and U.S. States

Employment allocation in each region and sector. For the case of countries outside of the U.S., we first compute the employment distribution by country-sector from the WIOD-SEA. We treat the unemployed and out-of-labor force as an additional sector. The data for that sector combines WIOD-SEA's worker population and each country's labor force participation rate from World Bank data. Since SEA does not include the RoW directly and since the remaining countries in SEA are too few, we define RoW's employment such that its production to employment ratio equals the respective average ratio of the other 37 countries. This calculation is done separately for each sector.

For the case of U.S. states, we calculate the employment level for each state and sector (including unemployment and non-participation) in the year 2000 from the 5% sample PUMS files of the 2000 Census. We only keep observations type "P" (persons) aged 25 to 65, who are either employed or out of the labor force. Finally, we apply proportionality so that the aggregate employment at the sector level coincides with the totals for the U.S. in WIOD-SEA.

Workers' mobility matrix for U.S. states. Let $L_{ji,sk}$ be the number of workers who move from state j and sector s to state i and sector k between two periods (we ignore the time subscript for simplicity). We want to compute the mobility matrix for the shares $\mu_{ji,sk}$, for each origin state j, origin sector s, destination state i, and destination sector k, with the shares defined as $\mu_{ji,sk} = \frac{L_{ji,sk}}{\sum_{i'}\sum_{k'} L_{ji',sk'}}$. To do this, we combine data from the Current Population Survey (CPS), the American Community Survey (ACS), the IRS state-to-state migration data, and the sector-state employment data from BLS, as explained below.

The CPS provides details of people's employment status and industry each month, but it does not provide information regarding movements across states. This means that we can construct from the CPS data $L^{CPS}_{jj,sk} \quad \forall j \in$ U.S. and any origin or destination sectors s, k (intra-state flows of people between sectors). To remain internally consistent with the model, we only consider employed or out-of-the-labor force workers (i.e., we exclude unemployed workers). [39]

The ACS provides details of workers' current employment status, sector, and state. It also asks the state in which respondents lived the prior year. However, this survey does not provide information regarding people's employment status and sector in the previous year. This means that we can construct from the ACS data $L^{ACS}_{ji,\#k} \quad \forall j, i \in$ U.S. and destination sector k (interstate flows but without knowing the sector of origin, where the unknown component is labeled as #). Finally, the IRS state-to-state migration data allows us to construct the mobility between states regardless of their sector $L^{IRS}_{ji,\#\#} \ \forall j, i \in$ U.S.

[39] The CPS surveys households in a 4-8-4 format; that is, it interviews the household for four consecutive months, gives them an 8-month break, and interviews them again for four straight months. We start with the NBER version of the CPS. The first four monthly interviews are 12 months apart from the final four interviews, and the first four and final four are consecutive months. Since we are interested in recording annual changes, we only keep interview months (1,5) which is equivalent to following individuals for the first twelve months they appear in the survey. To avoid noise in our sample, we pooled observations for the previous two years and the following two years for the year of interest.

We combine these datasets to compute the labor transitions across states and sectors. We also apply proportionality to the flows from CPS and ACS to sum up the total flows of the IRS data (which do not require additional assumptions and are available for interstate movements). In particular, for movements between sectors within the same state we use the following rule:

$$L^{jj,sk} = L^{IRS}_{jj,\#\#} \times \frac{L^{CPS}_{jj,sk}}{\sum_s \sum_k L^{CPS}_{jj,sk}} \quad \forall j, \forall s, k$$

For movements across states, we define:

$$L^{ji,sk} = \frac{L^{CPS}_{jj,sk}}{\sum_s L^{CPS}_{jj,sk}} \times L^{IRS}_{ji,\#\#} \times \frac{\sum_i L^{ACS}_{ji,?k}}{\sum_i \sum_k L^{ACS}_{ji,?k}},$$

where, in the few cases when the diagonal value of the matrix (same state and sector in origin and destination) is zero, we change it to the minimum non-zero diagonal value.

Since the U.S. Census has the highest-quality data on the labor distribution by sector-state, we want our constructed flows to be consistent with sector-state data from the Census. However, this data is only available every ten years. Because of this, we first rely on sector-state data from the BLS (which is available yearly) to get sector-level employment for 1999 and 2000 and make our migration flows consistent with those employment vectors as explained below. One disadvantage of the BLS data is that it is based on a sample of the U.S. population and therefore its levels are less reliable than the ones from the Census (in particular, some sector-states have zero employment in both 1999 and 2000 in the BLS data but non-zero employment in the 2000 Census). To make the employment changes consistent with the 1999-2000 BLS data but the levels in 2000 consistent with the Census data, we construct the ratio of employment in 1999 to employment in 2000 for all sector-states using BLS data (after normalizing the total employment to be constant across time as it is in our model), winsorize these ratios at the 2.5% and 97.5% levels, and then multiply them by the 2000 Census data to generate a 1999 employment vector that is consistent with the levels of the 2000 Census but the changes in BLS, which we denote by "CBLS".

Note that the migration shares imply that $L_{i,k,t+1} = \sum_{j=1}^{I} \sum_{s=0}^{S} \mu_{ji,sk} L_{j,s,t}$, where $L_{j,s,t}$ is the total employment in region j, sector s, at time t. Since we want the migration flows matrix for 1999-2000 to be consistent with the change in the stocks of workers across sector-state pairs that we observe in the data between 1999 and 2000 (which is much more reliable than the direct migration flows), we use the $\mu'_{ji,sk}$s that are the closest to the ones constructed with the steps above but that satisfy that

$L^{Census}_{i,k,2000} = \sum_{j=1}^{I} \sum_{s=0}^{S} \mu'_{ji,sk} L^{CBLS}_{j,s,1999}$. Specifically, we minimize the sum of square differences between the new μ's and the original ones subject to: (1) the new μ's are consistent with the change in the stocks of workers across sector-states from the CBLS data, (2) they are greater than zero: $\mu'_{ji,sk} \geq 0$, and they sum to one for each sender market over all receiver markets: $\sum_{i=1}^{I} \sum_{k=0}^{S} \mu'_{ji,sk} = 1$, and (3) if the original μ matrix has a given flow as zero, then this must still be the case in the new μ' matrix: $\mu'_{ji,sk} = 0 \text{ if } \mu_{ji,sk} = 0$. The change in the flows implied by this procedure is very small. In particular, the correlation between the original $\mu_{ji,sk}$ and the $\mu'_{ji,sk}$ is greater than 99.99%.

Mobility matrix for non-U.S. regions. We do not take the mobility matrix for each country outside of the U.S. from the data, which would be extremely cumbersome because we have 37 other countries. However, it can be shown (details provided upon request), that for a country with a single region (such as non-U.S. countries in our context), the fact that there are no mobility costs can be captured by setting a special mobility matrix between 1999 and 2000. Thus, we compute the elements of that mobility matrix between 1999 and 2000. To do this, we take as given the labor distribution in 1999 ($L_{i,s,0}$) and 2000 ($L_{i,s,1}$) and compute the following formula:

$$\mu_{ii,sk,0} = \frac{L_{i,k,1}}{\sum_{r=1}^{S} L_{i,r,0}}$$

Notice that the flows between sector s and sector k do not depend on information of the sender sector (s), which is implicitly encoding the information that in the countries outside of the U.S., mobility between sectors is frictionless.

C.4 Handling Negative Cobb-Douglas Shares

From our data on bilateral trade flows, labor shares, and input-output coefficients we can back out a set of implied values for the $\alpha_{j,s}$ Cobb-Douglas parameters. However, there may be situations where the implied α's for a small fraction of the region-sectors are slightly negative, which is not consistent with our model. In this case, we modify the bilateral trade flow data to make it consistent with non-negative α's. In order to do this, we first obtain the set of α's implied by the original data, then we set the negative implied α's to zero, and then we re-normalize the α's so that they add up to one again in each region. This process yields a new set of non-negative alphas which we denote $\tilde{\alpha}_{j,s}$.

We then recover the bilateral trade flows that are compatible with the new $\tilde{\alpha}_{j,s}$. The equilibrium system to obtain these bilateral trade flows is a special case of the temporary equilibrium "dot" system described in point (2) of Section B.4 for the year 2000, without DNWR, without mobility, without technology or trade shocks, and with $\gamma = 1$ in the nominal anchor:

$$\begin{aligned}
\dot{P}_{i,s,t}^{1-\sigma_s} &= \sum_{j=1}^{I} \lambda_{ji,s,t-1} \left(\dot{W}_{j,s,t}^{\phi_{j,s}} \prod_{k=1}^{S} \dot{P}_{j,k,t}^{\phi_{j,ks}} \right)^{1-\sigma_s} \\
\lambda_{ij,s,t} &= \frac{\lambda_{ij,s,t-1} (\dot{W}_{i,s,t}^{\phi_{i,s}} \prod_{k=1}^{S} \dot{P}_{i,k,t}^{\phi_{i,ks}})^{1-\sigma_s}}{\sum_{r=1}^{I} \lambda_{rj,s,t-1} (\dot{W}_{r,s,t}^{\phi_{r,s}} \prod_{k=1}^{S} \dot{P}_{r,k,t}^{\phi_{r,ks}})^{1-\sigma_s}} \\
R_{i,s,t} &= \sum_{j=1}^{I} \lambda_{ij,s,t} \left(\tilde{\alpha}_{j,s} \left(\sum_{s} \dot{W}_{j,s,t} Y_{j,s,t-1} + D_{j,t} \right) + \sum_{k=1}^{S} \phi_{j,sk} R_{j,k,t} \right) \\
\dot{W}_{i,s,t} Y_{i,s,t-1} &= \phi_{i,s} R_{i,s,t} \\
\sum_{i=1}^{I} \sum_{s=1}^{S} \dot{W}_{i,s,t} Y_{i,s,t-1} &= \sum_{i=1}^{I} \sum_{s=1}^{S} Y_{i,s,t-1}.
\end{aligned}$$

In this system, the λ_{t-1}, $\tilde{\alpha}_{j,s}$, Y_{t-1}, and D_t's are all known, and the $\dot{W}$, $\dot{P}$, R_t and λ_t's are the outcomes. From these outcomes we can construct the new bilateral trade flow matrix that is consistent with the non-negative $\tilde{\alpha}_{j,s}$. This process changes the original data by a negligible amount; the correlation between the constructed bilateral trade flows and the original ones is above 99.99%. A version of this process is also applied by CDP, who further equalize the α's across regions.

D Exposure Measures

Consider an economy producing a set of homogeneous goods across sectors $s = 1, ..., S$ with prices p_s. Labor is the only factor of production that is mobile across sectors, and there are decreasing returns to labor in each sector so that $q_s = F_s(l_s)$ with $F_s'(\cdot) > 0$ and $F_s''(\cdot) < 0$. Preferences are given by $U(c) - V(l)$, where $l \equiv \sum_s l_s$, $U(c)$ is homogeneous of degree one, and $V'(\cdot) > 0$ and $V''(\cdot) > 0$. We are interested in the effect of a foreign shock on employment in two different cases. In the first case the wage w is fixed and labor is fully determined by labor demand (we assume that labor supply is higher than labor demand at the fixed wage w), while in the second case the wage is fully flexible and clears the labor market. Below we show that further assuming that $\varepsilon(l_s) \equiv -\frac{F_s''(l_s) l_s}{F_s'(l_s)} = \varepsilon$ for all s and $\mu(l) \equiv \frac{V''(l) l}{V'(l)} = \mu$, then in the case of a fixed wage we have

$$d \ln l = \frac{1}{\varepsilon} \sum_{s} \left(\frac{p_s q_s}{I} \right) d \ln p_s \tag{D1}$$

while in the case of flexible wages we have

$$d\ln l = \frac{1}{\varepsilon+\mu}\sum_s \left(\frac{p_s q_s - p_s c_s}{I}\right) d\ln p_s, \tag{D2}$$

where $I \equiv \sum_s p_s q_s$. Thus, if the wage is fixed and if we know the log changes in prices resulting from the foreign shock then we can interact them with revenue shares, $\frac{p_s q_s}{I}$, to construct a Bartik-style sufficient statistic for the first order effect on employment. In contrast, if the wage fully adjusts to equalize labor supply and demand, then the appropriate weights (share components in the Bartik measure) for the price changes are instead given by net exports as a share of GDP, to capture the implied terms-of-trade effects. If the economy is small, then prices are exogenous and one could further replace $d\ln p_s$ by the underlying Chinese productivity shocks.

Let's start with the case where w is fixed. Fully differentiating the equilibrium condition $p_s F_s'(l_s) = w$ implies $d\ln l_s = \frac{d\ln p_s}{\varepsilon_s(l_s)}$, where $\varepsilon(l_s) \equiv -\frac{F_s''(l_s)l_s}{F_s'(l_s)}$. We then have $d\ln l = \sum_s m_s \frac{d\ln p_s}{\varepsilon_s(l_s)}$, where $m_s \equiv \frac{l_s}{\sum_s l_s}$. Assuming that $\varepsilon_s(l_s) = \varepsilon$ we know that $p_s q_s / I = m_s$ and hence we get (D1).

Now let's consider the case with a flexible wage. The equilibrium is given by w, l, λ and $\{l_s, c_s\}_s$ such that the following equations hold

$$p_s F_s'(l_s) = w \tag{D3}$$
$$\frac{\partial U_s}{\partial c_s} = \lambda p_s \tag{D4}$$
$$V'(l) = \lambda w \tag{D5}$$
$$\sum_s l_s = l \tag{D6}$$
$$\sum_s p_s c_s = \sum_s p_s f_s(l_s). \tag{D7}$$

Differentiating equation (D5) yields $\mu(l) d\ln l = d\ln\lambda + d\ln w$, where $\mu(l) \equiv \frac{V''(l)l}{V'(l)}$. Thus

$$d\ln l = \frac{d\ln(w/P)}{\mu(l)}, \tag{D8}$$

with $P \equiv 1/\lambda$. Next, totally differentiating equations (D3) and (D6) yields $d\ln p_s - \varepsilon d\ln l_s = d\ln w$ and $\sum_s m_s d\ln l_s = d\ln l$. Combined, the previous two equations imply $\sum m_s d\ln p_s - \varepsilon d\ln l = d\ln w$, which combined with (D8) implies (after some rearranging):

$$d\ln(w/P) = \frac{\mu}{\mu+\varepsilon}\left(\sum m_s d\ln p_s - d\ln P\right). \tag{D9}$$

But equation (D4) implies that $\sum_s \frac{\partial U_s}{\partial c_s} c_s = \lambda \sum_s p_s c_s$. Since $U(c)$ is homogeneous of degree one this implies $U(c) = \lambda \sum_s p_s c_s$. Totally differentiating this equation yields $\sum_s \frac{\partial U_s}{\partial c_s} dc_s = (\sum_s p_s c_s)\, d\lambda + \lambda \sum_s p_s dc_s + \lambda \sum_s c_s dp_s$. Using equation (D4) we get $\sum_s \lambda p_s dc_s = (\sum_s p_s c_s)\, d\lambda + \lambda \sum_s p_s dc_s + \lambda \sum_s c_s dp_s$, which, after simplifying, implies

$$d \ln P = d \ln (1/\lambda) = \sum_s \theta_s d \ln p_s, \tag{D10}$$

where $\theta_s \equiv \frac{p_s c_s}{\sum_s p_s c_s}$. Plugging into (D9) and combining with (D8) we get

$$d \ln l = \frac{1}{\mu + \varepsilon} \sum (m_s - \theta_s)\, d \ln p_s = d \ln l.$$

Finally, note that $m_s \equiv \frac{l_s}{\sum_s l_s} = \frac{w l_s}{\sum_s w l_s} = \frac{p_s F_s'(l_s) l_s}{\sum_s p_s F_s'(l_s) l_s}$. Using $\varepsilon(l_s) \equiv -\frac{F_s''(l_s) l_s}{F_s'(l_s)} = \varepsilon$, we know that $F_s(l_s) \propto l_s^{1-\varepsilon}$ and $F_s'(l_s) \propto (1-\varepsilon)\, l_s^{-\varepsilon}$, hence $m_s = \frac{p_s F_s(l_s)}{\sum_s p_s F_s(l_s)} = \frac{p_s q_s}{\sum_s p_s q_s} = \frac{p_s q_s}{I}$. On the other hand, using (D7) we have $\theta_s \equiv \frac{p_s c_s}{\sum_s p_s c_s} = \frac{p_s c_s}{I}$. Combining all of this we obtain (D2).

D.1 "Horse Race" Between Different Exposure Measures

Table D.1: "Horse race" between different exposure measures in the baseline model with and without DNWR

	(1) Welf. Flex.	(2) Welf. DNWR	(3) Empl. Flex.	(4) Empl. DNWR
Constant	0.598**	0.555**	2.733**	1.324*
	(0.056)	(0.071)	(0.313)	(0.512)
ADH Exposure	−0.027	−0.066**	−0.079	−0.780**
	(0.016)	(0.020)	(0.090)	(0.147)
NX Exposure	−0.098**	−0.110**	−0.534**	−0.617**
	(0.016)	(0.020)	(0.090)	(0.147)
N	50	50	50	50
R squared	0.500	0.516	0.462	0.557
Mean dep. var.	0.269	0.093	1.121	−2.350

Notes: This table shows the results of regressing several variables on a constant, ADH exposure, and net export exposure (renormalized to have the same mean and standard deviation as ADH exposure). The exposure variables are described in the text. The dependent variables are: welfare change from the China shock in the baseline model without DNWR (column 1), welfare change from the China shock in the baseline model with DNWR (column 2), percentage change in total employment between 2000 and 2007 in the baseline model without DNWR (column 3), and percentage change in total employment between 2000 and 2007 in the baseline model with DNWR (column 4). Stars denote significance, one for 5%, and two for 1%.