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 US states, including many that experience unemployment during the transition. However, nominal rigidities reduce the overall US 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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I. 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) and others indicating that US 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), 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 Autor, Dorn, and Hanson (2013) on how labor force participation, unemployment, and population across US 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 onward. 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 the transition through both an increase in unemployment and a decline in labor force

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[1] Davidson, Martin, and Matusz (1999), Helpman, Itskhoki, and Redding (2010), Kim and Vogel (2021), and Galle, Rodríguez-Clare, and Yi (2023) 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.

participation. These employment effects have significant welfare implications, as they lead to a two-thirds reduction in the US 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 US relative wage. DNWR prevents this adjustment from taking place through a large decline in the US nominal wage, and a nominal anchor (described below) prevents it from occurring through a large increase in the Chinese wage in US dollars. The result is temporary unemployment in the United States. 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 II, 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, Hurst, and Yildirmaz 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 US regions with more stringent preshock measures of DNWR experienced significantly higher unemployment effects from the China shock.

Section III 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. On the basis of 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 nonbinding.[2] We assume that world nominal gross domestic product (GDP) in US dollars grows at a constant and 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

[2] Our baseline analysis also assumes that third countries have flexible exchange rates against the US dollar, 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 (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.

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 US dollars from increasing—while the United States 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 IV 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 United States. The resulting dataset contains 87 regions (50 US states, 36 additional countries, and the rest of the world) and 15 sectors (home production, 12 manufacturing sectors, services, and agriculture).

Section V 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 US imports from China match those predicted in the data and the Autor, Dorn, and Hanson (2013)–style regression coefficients in the model match those obtained by Autor, Dorn, and Hanson (2013) 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 VI 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 unemployment 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 US states, including many that experience unemployment during the transition. For the United States 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 DNWR 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 Autor, Dorn, and Hanson (2013). This stands in contrast to previous quantitative trade models, such as Caliendo, Dvorkin, and Parro (2019) and Galle, Rodríguez-Clare, and Yi (2023), which deliver too little dispersion, as shown in Adao, Arkolakis, and Esposito (2023).

Section VII 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, Dorn, and Hanson (2021), and use alternative migration assumptions across US 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 nonparticipation 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 VIII discusses two additional topics. First, we argue that, assuming that labor supply is a function of the real wage, Autor, Dorn, and Hanson's (2013) exposure measure to the China shock becomes a relevant statistic in the model only because of DNWR. Second, we explore the model-implied trade-off between unemployment and inflation. For a neighborhood around our baseline, decreasing cumulative unemployment generated by the shock by 1 percentage point over 10 years requires accepting roughly 2 percentage points more 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 Caliendo, Dvorkin, and Parro (2019), Adao, Arkolakis, and Esposito (2023), and Galle, Rodríguez-Clare, and Yi (2023) focus on the effects of the China shock on regions of the United States. 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, Itskhoki, and Redding 2010; Carrere, Grujovic, and Robert-Nicoud 2020; Kim and Vogel 2021; Dix-Carneiro et al. 2023; Galle, Rodríguez-Clare, and Yi 2023; Gurkova, Helpman, and Itskhoki 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, Itskhoki, and Redding (2010), or by changing the profitability of posting vacancies, as in Kim and Vogel (2021). Galle, Rodríguez-Clare, and Yi (2023) focus on the second of these mechanisms and show that US 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 United States 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 multisector 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 US unemployment is negligible, and there are no region-level results connecting to the evidence in Autor, Dorn, and Hanson (2013).

Also related to our paper is Eaton, Kortum, and Neiman (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 multisector model with migration and to quantify the effect of the China shock on unemployment and nonemployment across US states from 2000 onward.

II. A Case for DNWR

A. *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, Hurst, and Yildirmaz (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 US data from the Current Population Survey (CPS). Fallick, Vallenas, and Wascher (2020) find a significant amount of DNWR in the United States 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 US data, whereas in a version that incorporates wage rigidity these fluctuations match the data. Dupraz, Nakamura, and Steinsson (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, Herkenhoff, and Schymik (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-à-vis the euro, suggesting that DNWR in the presence of a fixed exchange rate is the main explanation for these results. Costinot, Sarvimaki, and Vogel (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 sections II.B and II.C, 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.

B. *DNWR and Persistence in the Employment Effects of the Shock*

Recent evidence (e.g., Dix-Carneiro and Kovak 2017; Autor, Dorn, and Hanson 2021) has found that regions more exposed to import competition experienced persistent decreases in employment. Since DNWR can lead to only 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, Dorn, and Hanson (2021) as a baseline and implement four changes (described below) so that the regression results are comparable to those in Autor, Dorn, and Hanson (2013), which use different data and regression specification.[6] The resulting exercise mimics Autor, Dorn, and Hanson (2013) 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, Dorn, and Hanson (2021) but that would allow us to stack the changes in the outcomes for the 1990–2000 period, as in Autor, Dorn, and Hanson (2013). Our main regression specification is

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

where $\Delta Y_{i,t+h}$ is a vector of 10-year equivalent changes in outcome Y for commuting zone i between 1990 and 2000 stacked with the changes in the same outcome between 2000 and $2000 + h$ for $h = 1, \ldots, 20$. The term $\mathrm{IP}^{\mathrm{cu}}_{i,\tau}$ 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 data.[7] Third, we use the exact import exposure definition in Autor, Dorn, and Hanson (2013). Autor, Dorn, and Hanson (2021) use the growth in imports from China between 2000 and 2012 divided by domestic absorption, whereas Autor, Dorn, and Hanson (2013) 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 Autor, Dorn, and Hanson (2013), which we take from their replication.

[5] While Autor, Dorn, and Hanson (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 nonparticipation. 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 nonparticipation.

[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 Autor, Dorn, and Hanson (2013) associated with the 2000–2007 change, which are well known in the literature and which we use as our main calibration targets.

[7] The ACS allows one to compute consistent measures of unemployment and nonparticipation. However, it does not include full geographic information for 2001–5. Therefore, we start the analysis with the 2000–2006 change. We follow Autor, Dorn, and Hanson (2013) in pooling a moving average of three ACS years.

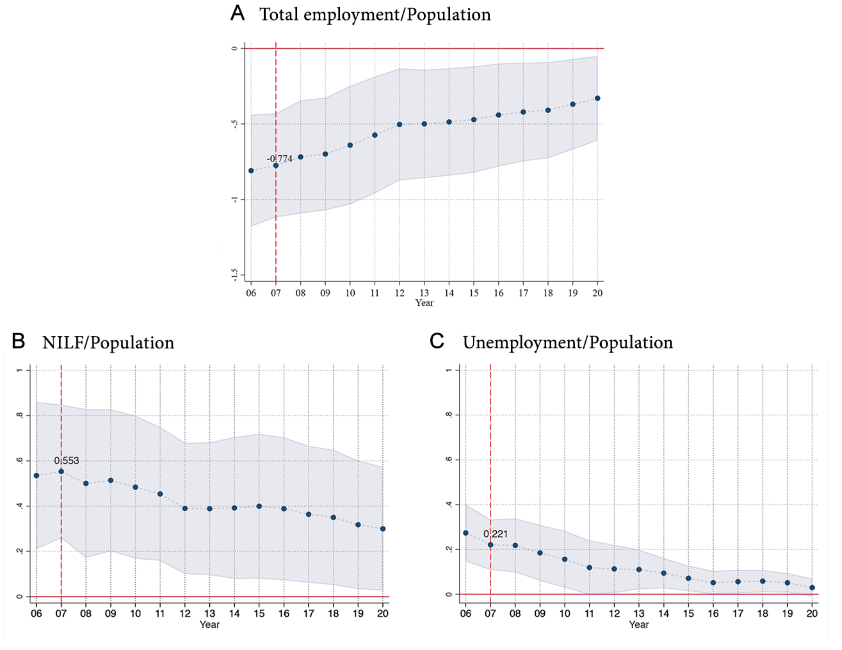

FIG. 1.—Effects of China shock on employment and nonemployment. The figure reports two-stage least squares coefficient estimates for β_{1h} in equation (1) and 95% confidence intervals for these estimates. Each coefficient comes from a separate instrumental variable regression following equation (1). Each regression stacks the change in the specified outcome between 1990 and 2000 and between 2000 and the year indicated on the horizontal axis. The coefficients for 2007 (dashed vertical line) match those from table 5 in Autor, Dorn, and Hanson (2013).

We estimate one regression per year using equation (1) for $h = 6, \ldots, 20$, implementing the same two-stage least squares strategy as in Autor, Dorn, and Hanson (2013; that is, we instrument $\Delta \mathrm{IP}^{\mathrm{cu}}_{i,\tau}$ with $\Delta \mathrm{IP}^{\mathrm{cu}}_{oi,\tau}$, which differs from $\Delta \mathrm{IP}^{\mathrm{cu}}_{i,\tau}$ only 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 (fig. 1*A*), not in the labor force (NILF) to population (fig. 1*B*), and unemployment to population (fig. 1*C*). Note that the coefficients for 2007 coincide with those in Autor, Dorn, and Hanson (2013).[8]

Figure 1*A* suggests that the China shock has long-term employment effects. Even by 2020, commuting zones that were more exposed to the

[8] Specifically, the coefficients for 2007 from fig. 1*B* and 1*C* match those from table 5, panel B, cols. 3 and 4 in Autor, Dorn, and Hanson (2013). The equivalent coefficient for fig. 1*A* is not directly presented in Autor, Dorn, and Hanson (2013), but it matches the sum of the effects for manufacturing and nonmanufacturing employment (divided by working-age population) found in Autor, Dorn, and Hanson (2013).

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, Dorn, and Hanson 2021).[9]

We uncover the separation of the employment effects into NILF and unemployment effects in figure 1*B* and 1*C*. Figure 1*B* shows that by 2020, the effect on NILF is still around half the effect found by Autor, Dorn, and Hanson (2013) for 2007 and continues to be statistically significant. By contrast, figure 1*C* shows that the unemployment effects diminish more rapidly. In particular, the unemployment effect became statistically nonsignificant in 2011, and while the effect became statistically significant again in some other years after 2011, it remained economically small.[10] By 2020, the unemployment effect was around one-tenth of what Autor, Dorn, and Hanson (2013) 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.

C. 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 (commuting zones or states) with more stringent preshock 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:

$$\begin{aligned}\Delta U_{i,t+h} = \gamma_t &+ \beta_{1,h}\Delta \mathrm{IP}^{\mathrm{cu}}_{i,\tau} + \beta_{2,h}\mathrm{Rig}_{s(i),\tau} + \beta_{3,h}\mathrm{Rig}_{s(i),\tau} \times \Delta \mathrm{IP}^{\mathrm{cu}}_{i,\tau} \\ &+ X'_{i,t}\beta_4 + \varepsilon_{i,t+h},\end{aligned} \tag{2}$$

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

[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 nonemployment is small and nonsignificant.

[10] Figure A.1 (figs. A.1–A.10 are available online) presents regression results using an alternative construction of the unemployment to population ratio based on US Bureau of Labor Statistics (BLS) county-level unemployment data and Surveillance, Epidemiology, and End Results working-age population data. The estimates remain both quantitatively and qualitatively consistent with those reported in fig. 1.

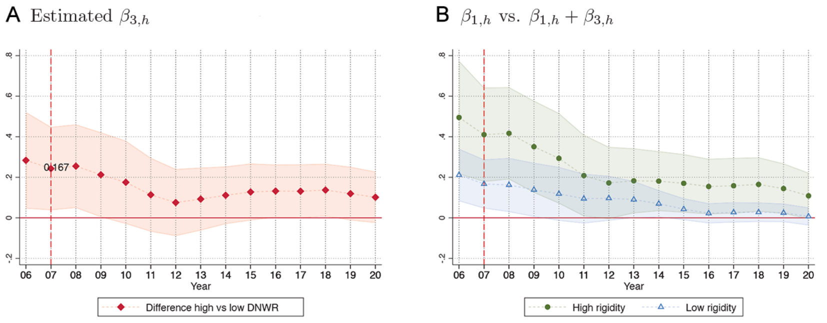

FIG. 2.—China shock and unemployment in commuting zones with high versus low DNWR. The figure reports two-stage least squares coefficient estimates in equation (2) and 95% confidence intervals for these estimates. Coefficients in each year come from a separate instrumental variable regression following equation (2), where the measure $\mathrm{Rig}_{s(i),\tau}$ is a dummy taking a value of 1 in commuting zone i if the share of individuals with negative wage changes in state s is below the mean across all states.

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 on the basis of individual-level year-over-year wage changes from CPS data. We pool observations 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 after 2000.[11] We then define $\mathrm{Rig}_{s\,(i),\tau}$ as a dummy taking a value of 1 if a given state is below the mean share. Note that a value of 1 implies a lower share of negative wage changes, which in turn suggests more DNWR.

Figure 2*A* displays the estimates of $\beta_{3,h}$ in equation (2). These estimates show the differential unemployment-to-population ratio increase for commuting zones with high versus low DNWR. For 2007, figure 2*A* shows that commuting zones with high DNWR experienced an additional 0.17 percentage point increase in the unemployment-to-population ratio because of the China shock, a magnitude that is large compared with the average effect (0.22) found in Autor, Dorn, and Hanson (2013). The differential effect is statistically significant at the beginning of the period and loses significance after some years. Figure 2*B* uses the estimates from the same regression to present the unemployment effects separated by category. While commuting zones in the high-DNWR category experienced

[11] These shares are persistent over time. Only eight states switched categories across the two decades.

significantly larger unemployment effects at the beginning of the period, the unemployment effects in both categories fade out over time.[12]

III. A Dynamic Trade and Migration Model with DNWR

Building on Artuc, Chaudhuri, and McLaren (2010) and Caliendo, Dvorkin, and Parro (2019), we consider a dynamic multisector quantitative trade model with an input-output structure and forward-looking agents who decide in which region and sector to work. Given our goals of matching the results in Autor, Dorn, and Hanson (2013), we introduce two key extensions to Caliendo, Dvorkin, and Parro (2019): (1) DNWR as a mechanism that can generate unemployment and (2) 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 details to appendix B.

A. 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 United States (i.e., the 50 US states) plus $I - M$ regions (countries) outside of the United States. We assume that there is no labor mobility across different countries but allow for mobility across different US states. There are $S + 1$ sectors in the economy (indexed by s or k), with sector 0 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 multisector Armington trade model, consumption in each market sector is a constant elasticity of substitution 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 $\phi_{j,s} + \Sigma_k \phi_{j,ks} = 1$. 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

[12] Appendix A (apps. A–D are available online) shows that the findings in fig. 2 are robust to several alternative proxies of DNWR.

$W_{i,s,t}$ 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, Eaton, and Kortum (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 $\Sigma_j D_{j,t} = 0$, 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:

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

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

An agent who 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

[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 US state would add additional state variables to our model in a way that becomes quickly intractable.

and the idiosyncratic shocks. Denoting with $v_{j,s,t}$ the lifetime utility of an agent who is in (j, s, t), we have

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

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

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

with $\kappa > \nu$. This allows us to have different elasticities of moving across regions and sectors, which will be useful to match the empirical evidence in Autor, Dorn, and Hanson (2013). Let $V_{j,s,t} \equiv E(v_{j,s,t})$ be the expected lifetime utility of a representative agent in labor market j, s. As shown in appendix section B.2, denoting the Euler-Mascheroni constant with γ, we have

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

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

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

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

The share of agents in js who 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

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

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 the model in Caliendo, Dvorkin, and Parro (2019).

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

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

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:

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

For home production, we assume that $U_{i,0,t} = \ln(\omega_{i,0,t})$, with $\omega_{i,0,t}$ being the level of (nonmarket) 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 targets in Autor, Dorn, and Hanson (2013) with a reasonable labor supply elasticity.

[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 the insurance scheme is fully funded within each sector-region.

C. *Downward Nominal Wage Rigidity*

In the standard trade model, labor market clearing requires that labor supply and demand equalize for each sector-region, that is, $L_{i,k,t} = \ell_{i,k,t}$. 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 US dollars, but regions face DNWR in terms of their local currency unit. Letting $W_{i,k,t}^{\mathrm{LCU}}$ denote nominal wages in local currency units, the DNWR takes the following form:

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

Letting $E_{i,t}$ denote the exchange rate between i's local currency and the currency in region 1 (which is the US dollar) in period t, then the DNWR for wages in US dollars entails

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

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

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

In our baseline specification, we assume that all regions outside of the United States 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:

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

D. *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 nonbinding. 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 US 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 very fast 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 appendix 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 US 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 US dollars from increasing, while the United States does not offset this with its own policies (perhaps because of inattentiveness). We further discuss alternative nominal assumptions in section VIII.B.

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 downward as required to avoid unemployment. Relatedly, if γ is high enough, then again there would be no unemployment. 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.

E. Equilibrium

Following Caliendo, Dvorkin, and Parro (2019), 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 $(\Sigma_{i=1}^{I}\Sigma_{s=1}^{S} W_{i,s,0}L_{i,s,0})$, 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 (1) at every period t, $\{W_{i,s,t}, L_{i,s,t}\}$ constitute a temporary equilibrium given $\Sigma_{i=1}^{I}\Sigma_{s=1}^{S} W_{i,s,t-1} L_{i,s,t-1}$, $\{W_{i,s,t-1}\}$, and $\{\ell_{i,s,t}\}$; and (2) $\{\omega_{i,s,t}, \Delta_{i,s,t}, V_{i,s,t}, \mu_{ji,sk|i,t}, \mu_{ji,s\#,t}, \ell_{i,s,t}\}_{t=1}^{\infty}$ satisfy equations (8)–(15).

F. 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 US 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, Eaton, and Kortum (2007) and its extension to dynamic settings proposed by Caliendo, Dvorkin, and Parro (2019). Consequently, our counterfactual exercises require data only 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 0 $(t = t_0)$, 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 section B.3 describes how to express the equilibrium in dots and leave it in terms of observables in period 0. We assume that the economy starts from a point where every region had full employment.[15] Appendix section 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 $(\dot{x}_t)$, that is, $\hat{x}_t = \dot{x}'_t/\dot{x}_t$ for any variable x. Then we compare a counterfactual economy where the knowledge of the China shock is unexpectedly introduced in 2001 (and agents have perfect foresight about the path of the shock) with a baseline economy where no

[15] Assuming that the United States had full employment in 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.

shocks occur. Appendix sections 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 III.B, 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 workers originally employed in region j in sector s, so $V'_{j,s,0} = V_{j,s,0} + \mathcal{V}_{j,s}/(1-\beta)$.[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.

IV. 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 US 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

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

data from the Bureau of Economic Analysis (BEA) for US 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 US state in the total value added of the United States so that the sum of value added across states matches the aggregate value added of the United States according to the 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 the WIOD. Second, we follow Caliendo, Dvorkin, and Parro (2019) to calculate the bilateral trade flows in manufacturing among US states by combining data from the WIOD and the Commodity Flow Survey. Third, we use the import and export merchandise trade statistics to compute—for manufacturing and agriculture—the sector-level bilateral trade flows between each US 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 the 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 the WIOD.

Labor flows across sectors and regions.—For the US states, we combine data from the CPS, the ACS, the state-to-state migration data from the Internal Revenue Service (IRS) Statistics of Income 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 (1) satisfies that the total movements between states across sectors add up to the total state-to-state movements in the IRS data and (2) 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 United States, there are no costs of moving across sectors within a region. Given this, one can infer the matrix of migration flows for non-US countries from the labor distribution in 1999 and 2000, as detailed in appendix section C.3.

V. 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 $\{\hat{A}_{\mathrm{China},s,t}\}$ that apply to only the 12 manufacturing sectors. Inspired by Autor, Dorn, and Hanson (2013) and following Caliendo, Dvorkin, and Parro (2019) and

Galle, Rodríguez-Clare, and Yi (2023), we calibrate these shocks to match the changes in US 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, that is, $\hat{A}_{\mathrm{China},s,t} = \hat{A}^1_{\mathrm{China},t}\hat{A}^2_{\mathrm{China},s}$. The end year will be 2007 in our baseline specification and 2011 in a specification with a longer-lasting China shock.[18] This means that we have to estimate 19 parameters (or 23).

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

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

where $\Delta X_{\mathrm{C,US},t}$ is the change in US imports from China between year $t-1$ and year t in all manufacturing sectors, $\Delta X_{\mathrm{C,OC},t}$ 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 $\{\widehat{\Delta X_{\mathrm{C,US},t}}\}$. The second target is the vector of predicted changes in US imports from China between 2000 and the end year across sectors, obtained from the regression:

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

where $\Delta X^{\mathrm{end}-2000}_{\mathrm{C,US},s}$ is the change in US imports from China between 2000 and our end year in sector s, $\Delta X^{\mathrm{end}-2000}_{\mathrm{C,OC},s}$ 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 $\{\widehat{\Delta X^{\mathrm{end}-2000}_{\mathrm{C,US},s}}\}$.[19] We choose $\{\hat{A}^1_{\mathrm{China},t}\}$ and $\{\hat{A}^2_{\mathrm{China},s}\}$ such that the total productivity changes in China $\{\hat{A}_{\mathrm{China},s,t}\}$ deliver changes in imports in our model that match the values of $\{\widehat{\Delta X_{\mathrm{C,US},t}}\}$ and the values of $\{\widehat{\Delta X^{\mathrm{end}-2000}_{\mathrm{C,US},s}}\}$.[20]

The calibration of the key model parameters (described below) is based on matching moments that capture the relative effect of the China shock

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

[18] As pointed out by Autor, Dorn, and Hanson (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, which is impossible. While the regression has only 12 observations, it has an R^2 of 0.99.

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

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 Autor, Dorn, and Hanson (2013):

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

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

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 United States 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 US 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 III.F, to simulate the economy's response to the calibrated China shock and then choose values of δ, ν, and κ so that ordinary least squares coefficients on the simulated data match three estimates from Autor, Dorn, and Hanson (2013): a US\$1,000 per worker increase in import exposure to China increases the unemployment-to-population ratio by 0.22 percentage points and the NILF-to-population ratio by 0.55 percentage points and leads 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 1 as we do). Our estimates for ν and κ compare with a value of

[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, Fuss, and Wintr 2012). Hazell and Taska (2023) find that production workers face a higher degree of DNWR than workers in nonproduction occupations. Since production workers are a higher share of total labor in manufacturing compared with nonmanufacturing, this could explain why the DNWR could bind more strongly in manufacturing. Another explanatory element could be the presence of stronger unionization in manufacturing.

[22] These results correspond to the ones in panel B of table 5 and panel C of table 4 in Autor, Dorn, and Hanson (2013). Some recent papers, such as Borusyak, Hull, and Jaravel (2021), have cast doubt on the statistical significance of some of the results from Autor, Dorn, and Hanson (2013). Despite that, we focus on these results as targets since Autor, Dorn, and Hanson (2013) 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, Dvorkin, and Parro (2019), we do not saturate the model with shocks to match all the data.

$\nu = \kappa = 2.02$ in Caliendo, Dvorkin, and Parro (2019).[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 Autor, Dorn, and Hanson (2013). Alternatively, we could constrain our model to satisfy $\nu = \kappa$ but without setting this single elasticity to the value of 2.02 in Caliendo, Dvorkin, and Parro (2019). Calibrating $\nu = \kappa$ and δ to match the unemployment and participation targets from Autor, Dorn, and Hanson (2013) leads to a population response that is over four times greater than the population response in Autor, Dorn, and Hanson (2013).

Finally, we assume that the trade elasticity parameter σ_s is constant across sectors and takes a value of 6, consistent with the trade literature (e.g., Costinot and Rodríguez-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.

VI. Effects of the China Shock in the Baseline Model

A. *Comparison of Cross-Sectional Results with Autor, Dorn, and Hanson (2013)*

We now use the calibrated model to study the effects of the China shock across US 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 ordinary least squares regressions across US 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 Autor, Dorn, and Hanson (2013).

Column 1 of table 1 reports the results of Autor, Dorn, and Hanson (2013) presented in their panel C of table 4, panel B of table 5, and panel B of table 7. Rows 1, 2, and 5 correspond to the regression coefficients in Autor, Dorn, and Hanson (2013) 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 2001 to 2007. We focus on the results related to employment and wages in this section and

[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, Rodríguez-Clare, and Yi (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, Morales, and Vogel (2019).

[25] Our model is annual, so we compare our estimates with the annualized version of Caliendo, Dvorkin, and Parro's (2019) single elasticity.

TABLE 1
EMPLOYMENT, POPULATION, WAGE, AND WELFARE EFFECTS OF EXPOSURE TO CHINA ACROSS US REGIONS AND ASSOCIATED PARAMETERS GENERATING THEM

	Autor, Dorn, and Hanson (2013) (1)	Baseline (2)	Longer (3)	No Migration (4)	$\nu = \kappa$ (5)
			A. Change in Population Shares		
1. Unemployment (targeted)	.221*	.221	.221	.221	.221
2. NILF (targeted)	.553*	.553	.553	.553	.553
3. Manufacturing employment	−.596*	−.605	−.578	−.602	−.613
4. Nonmanufacturing employment	−.178	−.169	−.196	−.172	−.161
			B. Percentage Changes		
5. Population (targeted)	−.050	−.050	−.050	.000	−.211
6. Manufacturing wage	.150	.023	.209	.016	.039
7. Nonmanufacturing wage	−.761*	−1.177	−.966	−1.204	−1.182
			C. Welfare		
8. Welfare vs. exposure		−.091	−.134	−.081	−.099
9. Mean welfare change		.126	.011	.138	.124
10. Mean welfare change no DNWR		.312	.450	.314	.313
			D. Parameters		
ν		.537	.706	.611	.606
κ		6.548	13.53		.606
δ		.991	.994	.990	.991

NOTE.—The changes for the first four coefficients are measured from 2000 to an average of 2006–8, multiplied by 10/7 to turn into decadal changes. Population and wages are simply measured in percentage change (between 2000 and 2006–8), still turned into decadal changes. Welfare is obtained as described at the end of sec. III.F. ν governs substitution between sectors, κ governs substitution between regions, and δ governs the DNWR. Column 1 reproduces the Autor et al. (2013) results from their tables 4 (panel C, col. 1), 5 (panel B, row 1), and 7 (panel B, cols. 1 and 4). 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 US states. Column 5 imposes $\nu = \kappa$. In col. 4, κ is not reported because this parameter is irrelevant without migration.
* $p < .01$.

discuss the welfare effects in section VI.C.[26] We postpone the discussion of columns 3–5 to section VII.

The results in column 2 show that exposure to China measured as in Autor, Dorn, and Hanson (2013) leads to a fall in manufacturing and nonmanufacturing employment of 0.61 and 0.17 percentage points, respectively. These are moments that we did not target in our calibration.[27]

[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 Autor, Dorn, and Hanson (2013) 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 Autor, Dorn, and Hanson (2013).

Nevertheless, they are very close to the corresponding coefficients in Autor, Dorn, and Hanson (2013). Regarding the effect of exposure to China on wages, our baseline specification indicates that manufacturing wages remain roughly unchanged, while nonmanufacturing wages fall by 118 basis points. This is qualitatively consistent with the empirical evidence, which finds that the nonmanufacturing 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 US states that is comparable to the one predicted by the specification in Autor, Dorn, and Hanson (2013) in the 2000–2007 data. To assess this, we first compute the predicted variation in the employment-to-population ratio and income per capita by running Autor, Dorn, and Hanson's (2013) 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 of the changes in the state-level employment-to-population ratio predicted by the model is 1.11, which is similar to the standard deviation of 1.18 implied by the empirical estimates. In turn, the standard deviation of the changes in income per capita predicted by the model is 2.1, while the one associated with the empirical estimates is 1.9.

These results stand in contrast to previous quantitative models, such as Caliendo, Dvorkin, and Parro (2019) and Galle, Rodríguez-Clare, and Yi (2023), which imply too little spatial heterogeneity in the employment and income effects relative to the model in Autor, Dorn, and Hanson (2013), as shown by Autor, Dorn, and Hanson (2021) and Adao, Arkolakis, and Esposito (2023). 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

[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, Larsen, and Palmer [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 Autor, Dorn, and Hanson (2013) is still a potentially interesting additional piece of evidence.

[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 Autor, Dorn, and Hanson (2013). For the variation in income per capita, we follow the left-hand side of eq. (8) in Autor, Dorn, and Hanson (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 col. 2 of table 9 in Autor, Dorn, and Hanson (2013) as the measure of income per capita.

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 those in Caliendo, Dvorkin, and Parro (2019).

B. 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 US unemployment generated by the China shock according to our model. It increases gradually at first, reaching 1.25% 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 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 II.B, as well as with the historically low levels of unemployment observed in the United States between 2016 and 2019.

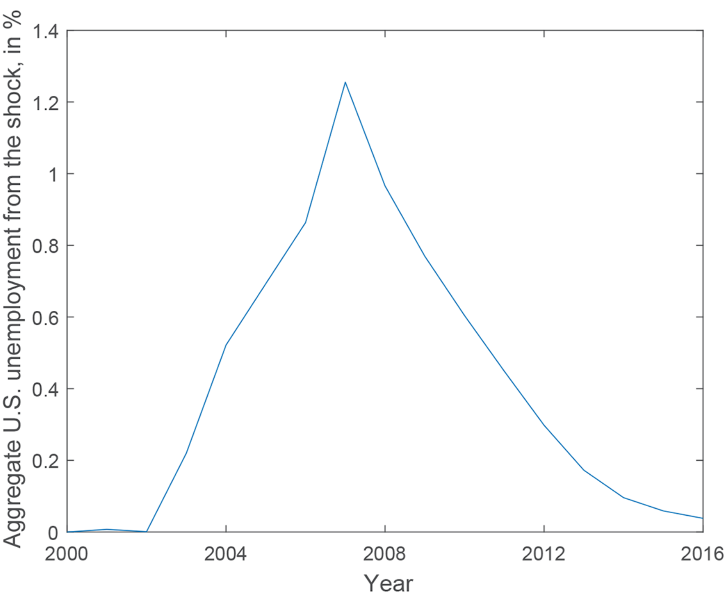

Fig. 3.—Path of aggregate US unemployment generated by China shock in baseline specification between 2000 and 2016.

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. US 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 United States, which translates to a higher real wage and an increase in labor supply. By 2015, aggregate labor force participation in the United States has already reversed sign and increased roughly 1% relative to its preshock 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 the import price indexes 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]

C. *Welfare Effects*

We find that US states more exposed to the China shock experience lower model-implied welfare gains: an increase of US$1,000 per worker in exposure to China decreases welfare by around 9.1 basis points (this is the coefficient in col. 2, row 8 of table 1). Figure 4 presents a scatterplot of the percentage change in welfare across states against exposure to China, while figure A.9 displays a welfare map across the 50 US states. There are 30 states that gain from the shock, while 20 states lose.

When we consider the United States as a whole and measure welfare using the population weighted average across US 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 United States as a whole experiences gains of

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

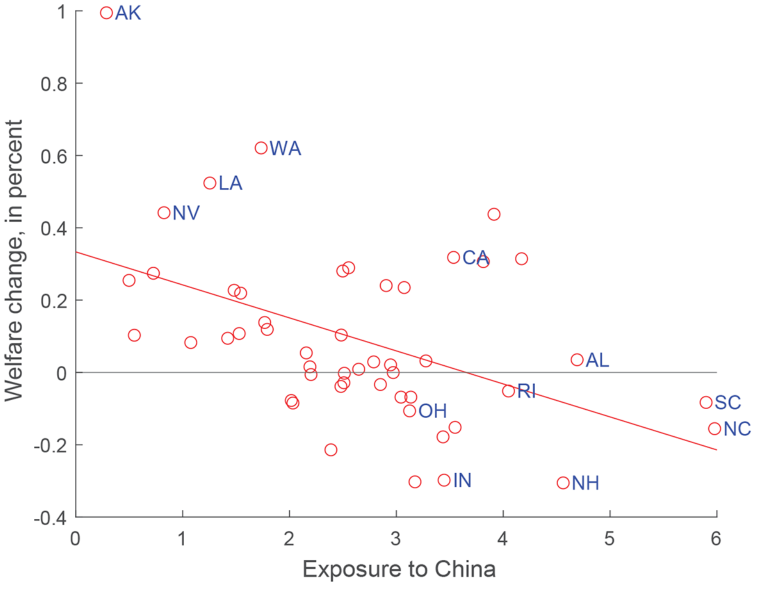

FIG. 4.—Welfare change versus exposure to China across US states in baseline specification. Selected states are labeled with two-letter abbreviations.

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 III.F, 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 US sector-states. There is higher variation in this more disaggregated measure, with welfare effects ranging from −60 to 156 basis points, compared with the measure at the state level, where the welfare effects range only from −31 to 99 basis points.

VII. 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

[31] This is comparable to the gains obtained in other recent papers (e.g., Caliendo, Dvorkin, and Parro 2019; Galle, Rodríguez-Clare, and Yi 2023).

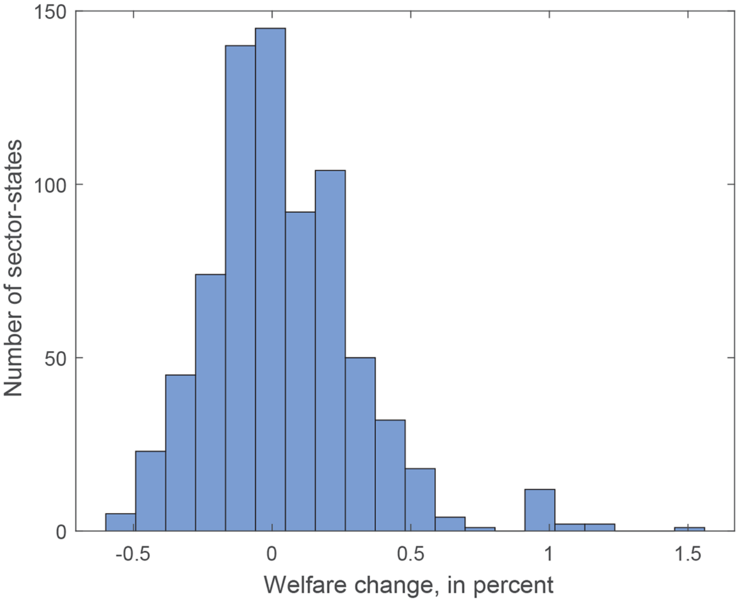

FIG. 5.—Histogram of welfare changes across different US sector-states in baseline specification.

the results if the China shock lasts until 2011 instead of 2007. Second, we discuss how different migration assumptions impact the results.

A. *Longer Shock*

As described in section V, 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, Dorn, and Hanson (2021) point out that Chinese import penetration continued to grow after 2007, reaching 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 Autor, Dorn, and Hanson (2013). The results for manufacturing and nonmanufacturing employment do not change much compared with the baseline, but the wage changes become closer to those in Autor, Dorn, and Hanson (2013).

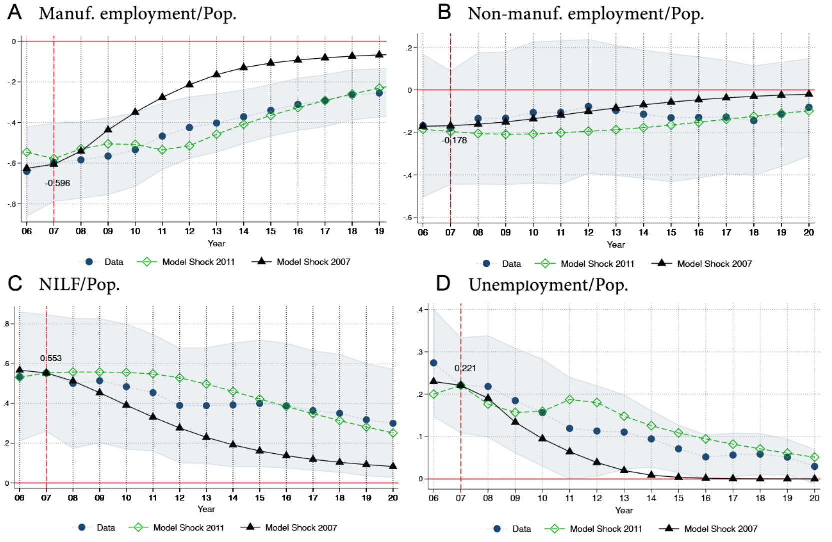

FIG. 6.—Effects of China shock on employment and nonemployment. Lines with circles show the two-stage least squares coefficient estimates for β_{1h} in equation (1), and shaded areas represent their 95% confidence intervals. These coefficients are the same as in figure 1 with the exception that the total employment to population effects in figure 1*A* are separated into manufacturing to population (*A*) and nonmanufacturing to population (*B*). Lines with diamonds display the effects in our model when the China shock lasts between 2001 and 2011 ("Model Shock 2011"), while lines with triangles display the effects in our baseline model when the China shock lasts between 2001 and 2007 ("Model Shock 2007"). The three lines coincide in 2007 for *C* and *D* by construction.

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 structure of figure 6 is similar to that of figure 1 but with the total employment effects split into manufacturing and nonmanufacturing. Lines with circles show the empirical estimates for β_{1h} in equation (1) (the same ones as in fig. 1), lines with diamonds display the equivalent effects in our model when the China shock lasts until 2011, and lines with triangles display the effects in our baseline specification. In figure 6*C* and 6*D*, the lines with diamonds and triangles match the line with circles in 2007 by construction; these are two of our three targeted moments, the other one being the population effect in Autor, Dorn, and Hanson (2013) 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]

[32] The longer-shock specification does target the changes in productivity in China in order to match the predicted changes in US imports between 2001 and 2011, as described in

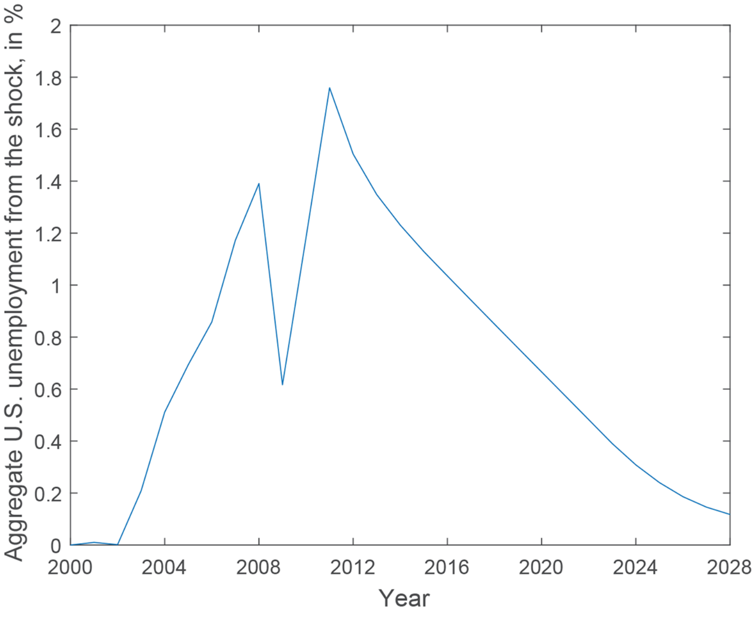

FIG. 7.—Path of aggregate US unemployment generated by China shock in longer-shock specification between 2000 and 2028.

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 figure 6*B*–6*D* but not figure 6*A* (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 2010s. 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 line with diamonds for the longer-shock specification is within the confidence interval of the empirical estimates in all of figure 6, 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 United States becomes very close to zero. Namely, the extended period of unemployment and general dislocation generated by the longer shock, depicted in figure 7 (which

sec. V, but this is completely independent from the cross-sectional empirical results we are discussing here.

mimics fig. 3 but for the longer-shock specification instead of the baseline), manages to extinguish nearly all the welfare gains that the United States would have experienced in the absence of DNWR. As can be seen from figure 7, aggregate US 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 possible to Autor, Dorn, and Hanson's (2013) instrumental variable strategy. During the Great Recession, imports from China—by both the United States and other developed countries used in Autor, Dorn, and Hanson's (2013) 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 fig. 6).

B. *Different Migration Assumptions*

Given the potential importance of migration for the dispersion of welfare effects across US 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 have the option of moving only between sectors within a state. We start from a mobility matrix that matches intrastate 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 nontargeted moments—such as the changes in manufacturing and nonmanufacturing employment and wages—as well as our inferred welfare changes (with and without DNWR) also stay relatively unchanged.

[33] Notice that in this case κ is no longer relevant, and we no longer match the response of population to exposure from Autor, Dorn, and Hanson (2013).

In our second alternative specification, we impose that $\nu = \kappa$, which is necessarily true in Caliendo, Dvorkin, and Parro (2019).[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 Autor, Dorn, and Hanson 2013). Other results, like the calibrated δ and the employment and wage changes, are similar to those from the baseline.

VIII. Discussion

A. *Different Exposure Measures*

The measure of exposure to China that we have been using so far follows the one in Autor, Dorn, and Hanson (2013). This is a Bartik instrument where the shift component is given by the predicted sector-level change in US 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 share component, as in

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

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 because of 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 table D.1 (tables C.1 and D.1 are available online), without DNWR, only the net export exposure measure is

[34] As in the previous extension, we do not target the population response in Autor, Dorn, and Hanson (2013) and target only the unemployment and participation responses.

significant for employment and welfare, while exposure in Autor, Dorn, and Hanson (2013) is not significant. By contrast, columns 2 and 4 show that in the model with DNWR, both exposure in Autor, Dorn, and Hanson (2013) and net export exposure are significant. Combined with the findings in Autor, Dorn, and Hanson (2013), these results indicate that a mechanism similar to DNWR is likely to be active in the US economy.

B. *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 US dollars from increasing—while the United States did not fully offset this with its own policies (perhaps because of inattentiveness or the fact that because of other shocks, like the 2002–6 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 2000s is a particularly relevant one, as this was something that the Chinese government was widely regarded as doing (cf. 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, de la Barrera, and Fukui (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 have only 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 United States 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 because of the presence of wage rigidities.

Apart from the form of the nominal anchor assumed in our model, we also explore the trade-off between unemployment and inflation that arises in response to the shock. As discussed in section VI.B, DNWR implies that the China shock leads to aggregate unemployment during a

[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 working paper version of this paper (Rodríguez-Clare, Ulate, and Vásquez 2020).

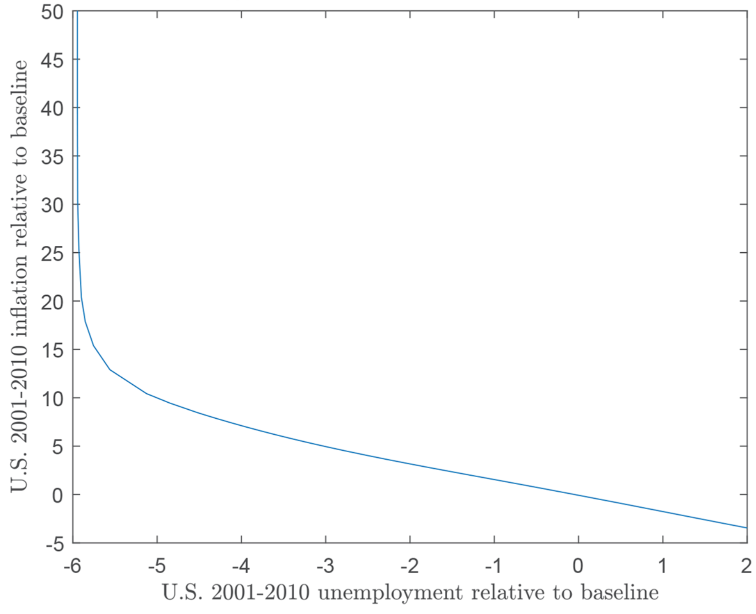

FIG. 8.—Aggregate US unemployment between 2001 and 2010 (in year-points) relative to baseline value (x-axis) and aggregate US inflation between 2001 and 2010 (in year-points) relative to baseline value (y-axis). The figure provides a notion of the sacrifice ratio between unemployment and inflation that is implicit in the model.

transition period. According to our baseline specification, the cumulative effect is roughly 6 year-points of unemployment over the 2001–10 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 nonlinear. Around the baseline calibration, lowering unemployment by 1 year-point would require accepting 1.63 year-points of 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 ratio is lower near the baseline because a monetary expansion there makes DNWR less binding and lowers unemployment, leading to higher output

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

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 trade-off 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.

IX. Conclusion

In this paper, we propose a dynamic quantitative trade and migration model with DNWR 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, Dorn, and Hanson (2013) and find that although the United States 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 United States composed of many regions, as in Caliendo, Dvorkin, and Parro (2019), allowing us to match the empirical results in Autor, Dorn, and Hanson (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, Larsen, and Palmer (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 that 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.

Data Availability

Code replicating the tables and figures in this article can be found in Rodríguez-Clare, Ulate, and Vásquez (2025) in the Harvard Dataverse, https://doi.org/10.7910/DVN/R96X0Z.

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