Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade*

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Abstract

We develop a multi-sector gravity model with heterogeneous workers to quantify the aggregate and group-level welfare effects of trade. The model generalizes the specific-factors intuition to a setting with labor reallocation, leads to a parsimonious formula for the group-level welfare effects from trade, and nests the aggregate results in Arkolakis et al. (2012). We estimate the model using the structural relationship between China-shock driven changes in manufacturing employment and average earnings across US groups defined as commuting zones. We find that the China shock increases average welfare but some groups experience losses as high as five times the average gain. Adjusted for plausible measures of inequality aversion, gains in social welfare remain positive and deviate only slightly from those according to the standard aggregation method. We also develop and estimate an extension of the model that endogenizes labor force participation and unemployment, finding similar welfare effects from the China shock.

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1 Introduction

The recent empirical literature has made economists less sanguine about the overall benefits from increased trade integration. Although the notion that there are losers from trade is one of the oldest propositions in the field, recent empirical work exemplified most prominently by Autor, Dorn and Hanson (2013) has shown that the distributive implications of trade shocks in developed countries are stronger and more persistent than previously believed. In their survey of this work, Autor, Dorn and Hanson (2016) conclude that "it is incumbent on the literature to more convincingly estimate the gains from trade, such that the case for free trade is not based on the sway of theory alone, but on a foundation of evidence that illuminates who gains, who loses, by how much, and under what conditions." In this paper we take a step in this direction – we develop and estimate a multi-sector gravity model of trade with heterogeneous labor and use it to quantify the group-level and aggregate welfare effects of the China shock and overall trade in the United States.

Our baseline model combines three components: a multi-sector version of the Eaton and Kortum (2002) model as in Costinot, Donaldson and Komunjer (2012); a Roy model of the allocation of heterogeneous labor to sectors with a Fréchet distribution as in Lagakos and Waugh (2013); and the existence of different labor groups differing in their pattern of comparative advantage across sectors. The model yields a simple expression for the group-level welfare effects of trade that generalizes the formula previously shown by Arkolakis, Costinot and Rodríguez-Clare (2012) (henceforth ACR) to be valid for a wide class of gravity models. Compared to the ACR formula, ours has an extra term that captures the group-level effects of trade through changes in the vector of sector-specific wages. Thus, following a logic similar to that in the specific-factors model, groups with high employment shares in sectors that experience strong increases in import competition will fare worse than other groups. The strength of these distributional effects depends on the shape parameter of the Fréchet distribution, κ, which governs the degree of labor heterogeneity across sectors: if $\kappa \to 1$ then our model yields the same welfare implications as the one with sector-specific labor and distributional effects are strongest, while if $\kappa \to \infty$ then we are back to the single ACR formula applying to all groups.

Inspired by Autor et al. (2013) (henceforth ADH), our quantitative analysis focuses on the effect of the China shock on United States workers grouped according to commuting zone. Not only is the focus on local labor markets important in its own right, but it also allows us to build on the empirical strategy developed by ADH to arrive at a credible estimate of κ. We employ an instrumental variable approach where the first stage estimates the group-level effect of the China shock on manufacturing employment, as in the reduced-form of one of the central regressions in ADH. The second stage then exploits the model-implied relationship between the projected change in the share of employment in non-manufacturing (one of the sectors in the model) and group-level average earnings. The estimation yields a value for κ around 1.5, which is in line with estimates of this Roy-Fréchet parameter in related contexts (e.g., Burstein, Morales and Vogel 2019 and Hsieh, Hurst, Jones and Klenow 2013).

Armed with our estimate of κ, we calibrate the China shock following a strategy similar to that in Caliendo, Dvorkin and Parro (2019) and then use the comparative-statics methodology in Dekle, Eaton and Kortum (2008) to compute the group-level and aggregate welfare effects of the China shock in the United States. We find that a modest but non-negligible number of groups representing 15.9% of the population suffer welfare losses, and that those losses can be up to five times as high as the average gains. The welfare effects are spatially correlated, implying the existence of regions such as Southern Appalachia where most groups tend to experience low or negative effects. To compute the aggregate welfare effects of the trade shock, we ignore the possibility that losers are compensated and use a social welfare function with inequality aversion as in Atkinson (1970).[1] We obtain the standard aggregation as a special case with no inequality aversion. Initially poorer groups fare slightly worse after the shock, implying a downward pull in the inequality-adjusted welfare gains. However, for plausible measures of inequality aversion, social welfare still increases with the China shock and this increase is only slightly below the welfare gains without inequality aversion.

Moving beyond the China shock, we also use our model to compute the group-

[1] Recent papers that pursue a similar strategy in the trade context are Antras, de Gortari and Itskhoki (2016), Carrère, Grujovic and Robert-Nicoud (2015) and Artuc, Porto and Rijkers (2019). Antras et al. (2016) also considers the distortions associated with compensation and quantifies the associated effect on the gains from trade. While we do not address the issue of how to optimally compensate losers from trade in this paper, our results on the substantial losses from trade for certain groups highlight the importance of this question for future research.

level and aggregate gains from trade, defined as in ACR as the negative of the losses from moving to autarky. We again find that a small set of groups lose from trade, with one group experiencing losses of 4.2%, more than two and a half times the mean gain across all groups. Interestingly, however, the results imply that trade lowers inequality, and hence the inequality-adjusted gains from trade are slightly above those with no inequality aversion.

We consider a number of extensions to see how our baseline results change when allowing for tradable intermediate goods, trade costs within countries, imperfect substitability of the labor input from skilled and unskilled labor within a commuting zone, and more dissaggreggation across groups so that they can vary by commuting zone, education, gender and age. Tradable intermediates as in Caliendo and Parro (2015) amplify the gains from the China shock, so fewer groups experience losses, while allowing for trade costs across U.S. states has the opposite effect. Imperfect substitutability between the labor input of college and non-college workers in each sector leads to an endogenous college premium (similar to the Hecksher-Ohlin model, although weakened by Roy heterogeneity), but this turns out not to have significant implications on the results for the welfare effects of the China shock in the baseline model, with most of those changes explained by commuting-zone rather than worker-type fixed effects. Finally, allowing groups to vary by education-by-gender or education-by-age within each commuting zone does not significantly affect the main conclusions derived in the baseline model – most importantly, the commuting zone to which a group belongs remains the main determinant of how it is affected by the China shock.

In a final extension we introduce home production (as in Caliendo et al. (2019)) as well as search and matching frictions (as in Kim and Vogel (2021)), so that trade shocks now lead to endogenous employment changes both because of changes in labor-force participation as well as changes in involuntary unemployment. We estimate the full model again exploiting the instrumental-variables strategy inpired by ADH, but now taking into account the observed changes in labor-force participation and unemployment along with the observed changes in average earnings at the commuting-zone level. The model is now qualitatively and quantitatively consistent with observed employment changes, and yet the implications for welfare remain close to those in the baseline model.

Relative to the reduced-form approach in Autor et al. (2013), our general-equilibrium structural analysis enables us to compute the welfare gains and losses caused by the China shock across groups, rather than only the associated relative income effects. We can also quantify the welfare effects of counterfactual shocks such as a move to autarky or a decline in trade costs. Our framework thus serves to establish a formal connection between the fast-growing empirical literature on the distributional implications of trade shocks and the more theoretical approaches to compute aggregate welfare effects of trade surveyed in Costinot and Rodríguez-Clare (2014).

A growing body of empirical work documents substantial variation in local labor-market outcomes in response to national-level trade shocks. In addition to Autor et al. (2013), see for example Dix-Carneiro and Kovak (2016), Kovak (2013) and Topalova (2010).[2] Additionally, a large empirical and theoretical literature studies the distributional effects of trade – some important recent contributions are Autor, Dorn, Hanson and Song (2014), Burstein and Vogel (2017), Costinot and Vogel (2010), Helpman, Itskhoki, Muendler and Redding (2017) and Krishna, Poole and Senses (2012). A literature focusing specifically on the effect of trade shocks on the reallocation of workers across sectors finds significant effects for developed countries (Artuç, Chaudhuri and McLaren 2010, Pierce and Schott 2016, Revenga 1992), although less so in developing countries (see, e.g., Goldberg and Pavcnik 2007 and Dix-Carneiro 2014).

Artuç et al. (2010), Dix-Carneiro (2014) and Adão (2016) also use a Roy model of the allocation of workers across sectors to offer a structural analysis of the distributional effects of trade shocks, but they focus on exogenous changes in the terms of trade in a small economy.[3] We complement these papers by linking the Roy model of the labor market with a gravity model of trade and by using the resulting framework to provide a transparent way to quantify the aggregate and distributional welfare effects of trade.

Caliendo et al. (2019), Lee (2016), and Adão, Arkolakis and Esposito (2020) combine a gravity model of trade with a Roy model of labor allocation, as we do, but these papers focus on different questions: Caliendo et al. (2019) emphasize the dynamics of

[2]Other empirical papers exploring the effects of trade shocks on local labor markets are Dauth, Findeisen and Suedekum (2014), Hakobyan and McLaren (2016) and Yi, Müller and Stegmaier (2016).

[3]Other structural analyses of trade liberalization and labor market adjustments are Coşar (2013), Coşar, Guner and Tybout (2016), Kambourov (2009) and Kim and Vogel (2021). There is also a literature on the impact of trade on poverty and the income distribution using a Computable General Equilibrium (CGE) methodology – see for example Cockburn, Decaluwé and Robichaud (2008).

adjustment after an unexpected trade shock, Lee (2016) focuses on the implications for the skill premium, and Adão et al. (2020) center on how the effect of the trade shock is affected by the interaction between workers' employment decisions and agglomeration economies at the local level.[4] Relative to these papers, we derive an analytical expression for the group-level welfare effects of trade shocks that nests the ACR welfare formula and highlights the role of κ on the distributional effects of trade, and we introduce the concept of inequality-adjusted gains from trade to the gravity literature. On the empirical side, our paper provides a link between the reduced-form results of ADH and the estimation of κ that is needed to compute the group-level welfare effects of trade.[5]

The rest of this paper is structured as follows. Section 2 describes the baseline model and presents our theoretical results. The data is described in Section 3, and Section 4 discusses the structural estimation of the model. Section 5 presents the results of the calibrated China shock for welfare of US groups, while Section 6 computes the aggregate and group-level gains from trade. Sections 7 and 8 present several exensions of the baseline model, and Section 9 offers some concluding thoughts.

2 Theory

We present a multi-sector, multi-country, Ricardian model of trade with heterogeneous workers. There are N countries and S sectors. Each sector is modeled as in Eaton and Kortum (2002) - henceforth EK; there is a continuum of goods, preferences across goods within a sector s are CES with elasticity of substitution σ_s, and technologies have constant returns to scale with productivities that are distributed Fréchet with shape parameter $\theta_s > \sigma_s - 1$ and level parameters T_{is} in country i and sector s. Preferences across sectors are Cobb-Douglas with shares β_{is}. There are iceberg trade costs $\tau_{ijs} \geq 1$ to export goods in sector s from country i to country j, with $\tau_{iis} = 1$.

[4] While all the papers cited so far focus on the differential impact of trade through the earnings channel, another set of papers focuses on the expenditure channel – see Atkin and Donaldson (2015), Faber (2014), Fajgelbaum and Khandelwal (2016) and Porto (2006). More recent contributions by Borusyak and Jaravel (2018) and Artuc et al. (2019) consider both channels simultaneously.

[5] Our paper is also related to Hsieh and Ossa (2016), who use a gravity framework to conduct a comparative-statics analysis in the style of Dekle et al. (2008) to quantify the aggregate effects of the China shock, and to Amiti, Dai, Feenstra and Romalis (2017) and Bai and Stumpner (2019), both of which estimate the effect of the China shock on the U.S. consumer price index.

On the labor side, we assume that there are G_i groups of workers in country i. A worker from group g in country i (henceforth simply group ig) has a number of efficiency units z_s in sector s drawn from a Fréchet distribution with shape parameter $\kappa_{ig} > 1$ and scale parameters A_{igs}. Thus, workers within each group are ex-ante identical but ex-post heterogeneous due to different ability draws across sectors, as in Roy (1951), while workers across groups also differ in that they draw their abilities from different distributions. The number of workers in a group is fixed and denoted by L_{ig}. In Section 8 we extend the model to allow for non-employment and unemployment by introducing home production and search-and-matching frictions, respectively.

If $\kappa_{ig} \to \infty$ for all ig and $A_{igs} = 1$ for all igs, the model collapses to the multi-sector EK model developed in Costinot et al. (2012), while if $\kappa_{ig} \to 1$ for all ig then the model has the same welfare and counterfactual implications as the model in which labor is sector specific.[6] On the other hand, if $\tau_{ijs} \to \infty$ for all $j \neq i$ and $G_i = 1$ then economy i is in autarky and collapses to the Roy model in Lagakos and Waugh (2013) (see also Hsieh et al. (2013)).[7]

2.1 Equilibrium

To determine the equilibrium of the model, it is useful to separate the analysis into two parts: the determination of labor demand in each sector in each country as a function of wages, which comes from the EK part of the model; and the determination of labor supply to each sector in each country as a function of wages, which comes from the Roy part of the model.

Since workers are heterogeneous in their sector productivities, the supply of labor to each sector is upward sloping, and hence wages can differ across sectors. However, since technologies and goods prices are national, wages cannot differ across groups.

[6] The only difference between the model with sector-specific labor and ours with $\kappa_{ig} \to 1$ is that in ours the elasticity of labor supply to any particular sector with respect to the wage in that sector goes to one and not zero. However, for $\kappa_{ig} \to 1$ the reallocation of workers across sectors has no effect on the relative supply of efficiency units of labor across sectors – see Equation (4). Note that $\kappa_{ig} \to 1$ implies that mean efficiency units per worker goes to infinity – when we report results for this limit we are implicitly normalizing efficiency units by $\Gamma(1 - 1/\kappa_{ig})$, where $\Gamma()$ is the Gamma function.

[7] There are two sources of comparative advantage in this model: first, as in Costinot et al. (2012), differences in T_{is} drive sector-level (Ricardian) comparative advantage; second, differences in A_{igs} lead to factor-endowment driven comparative advantage. Given the nature of our comparative statics exercise, however, the source of comparative advantage will not matter for the results – only the actual sector-level specialization as revealed by the trade data will be relevant.

Let wages per efficiency unit in sector s of country i be denoted by w_{is}. From EK we know that the demand for efficiency units in sector s in country i is

$$\frac{1}{w_{is}}\sum_{j}\lambda_{ijs}\beta_{js}X_j,$$

where X_j is total expenditure by country j and λ_{ijs} are sectoral trade shares given by

$$\lambda_{ijs}=\frac{T_{is}\left(\tau_{ijs}w_{is}\right)^{-\theta_s}}{\sum_l T_{ls}\left(\tau_{ljs}w_{ls}\right)^{-\theta_s}}. \tag{1}$$

For future purposes, also note that the price index in sector s in country j is

$$P_{js}=\zeta_s^{-1}\left(\sum_i T_{is}\left(\tau_{ijs}w_{is}\right)^{-\theta_s}\right)^{-1/\theta_s}, \tag{2}$$

where $\zeta_s \equiv \Gamma(1-\frac{\sigma_s-1}{\theta_s})^{1/(1-\sigma_s)}$.[8]

Labor supply is determined by workers choices regarding which sector to work in. Let $\boldsymbol{z}=(z_1,z_2,...,z_S)$ and let $\Omega_{is}\equiv\{\boldsymbol{z}\text{ s.t. } w_{is}z_s\geq w_{ik}z_k \text{ for all } k\}$. A worker with productivity vector $\boldsymbol{z}$ in country i will apply to sector s iff $\boldsymbol{z}\in\Omega_{is}$. Let $F_{ig}(\boldsymbol{z})$ be the joint probability distribution of $\boldsymbol{z}$ for workers of group ig. From Lagakos and Waugh (2013) and Hsieh et al. (2013) we know that the share of workers in group ig that apply to sector s is

$$\pi_{igs}\equiv\int_{\Omega_{is}}dF_{ig}(\boldsymbol{z})=\frac{A_{igs}w_{is}^{\kappa_{ig}}}{\Phi_{ig}^{\kappa_{ig}}}, \tag{3}$$

where $\Phi_{ig}^{\kappa_{ig}}\equiv\sum_k A_{igk}w_{ik}^{\kappa_{ig}}$.[9] Under the assumption that efficiency units from different workers are perfect substitutes in production, we just care about the sum of efficiency units supplied to a sector among all workers in a group. For group ig and sector s, this is

$$\mathcal{Z}_{igs}\equiv L_{ig}\int_{\Omega_{is}}z_s dF_{ig}(\boldsymbol{z})=\xi_{ig}\frac{\Phi_{ig}}{w_{is}}\pi_{igs}L_{ig}, \tag{4}$$

[8]As shown in ACR, a multi-sector version of the Armington model would be a workable substitute for the EK-side of the model. The Krugman (1980) model or the Melitz (2003) model with a Pareto distribution (as in Chaney (2008)) would also work, though these models would introduce extra terms because of entry effects – see Costinot and Rodríguez-Clare (2014) and Kucheryavyy, Lyn and Rodríguez-Clare (2018).

[9]This result and the ones below generalize easily to a setting with correlation in workers' ability draws across sectors. In this case, the dispersion parameter κ_{ig} is replaced by $\kappa_{ig}/(1-\rho_{ig})$, where ρ_{ig} measures the correlation parameter of ability draws across sectors for each worker.

where $\xi_{ig} \equiv \Gamma(1 - 1/\kappa_{ig})$. One implication of this result is that even if wages per efficiency unit of labor w_s differ across sectors, expected income per worker is equalized. That is, for each group ig and for all s we have

$$\frac{w_{is}\mathcal{Z}_{igs}}{\pi_{igs}L_{ig}} = \xi_{ig}\Phi_{ig}.$$

This is a special implication of the Fréchet distribution and it implies that the share of income obtained by workers of group ig in sector s (i.e., $w_{is}\mathcal{Z}_{igs}/\sum_k w_{ik}\mathcal{Z}_{igk}$) is also given by π_{igs}. Note also that total labor income in group ig is $Y_{ig} \equiv \sum_s w_{is}\mathcal{Z}_{igs} = \xi_{ig}\Phi_{ig}L_{ig}$, while total labor income in country i is $Y_i \equiv \sum_{g\in G_i} Y_{ig}$.

Allowing for trade imbalances D_j via transfers as in Dekle et al. (2008), we have

$$X_j = Y_j + D_j, \tag{5}$$

with $\sum_j D_j = 0$. Finally, combining the supply and demand sides of the economy, the excess demand for efficiency units in sector s of country i is

$$ELD_{is} \equiv \frac{1}{w_{is}}\sum_j \lambda_{ijs}\beta_{js}X_j - \sum_{g\in G_i}\mathcal{Z}_{igs}. \tag{6}$$

Since λ_{ijs}, Y_j, and $\mathcal{Z}_{igs}$ are functions of the whole matrix of wages $\boldsymbol{w} \equiv \{w_{is}\}$, the system $ELD_{is} = 0$ for all i and s is a system of equations in $\boldsymbol{w}$ whose solution gives the equilibrium wages given some choice of numeraire.

2.2 Comparative Statics

Consider some change in trade costs or technology parameters. We proceed as in Dekle et al. (2008) and solve for the proportional change in the endogenous variables. Formally, using notation $\hat{x} \equiv x'/x$, we consider shocks $\hat{\tau}_{ijs}$ for $i \neq j$, $\hat{D}_j$, $\hat{A}_{igs}$ and $\hat{T}_{is}$. The counterfactual equilibrium entails $ELD'_{is} = 0$ for all i, s. Noting that $w'_{is}\mathcal{Z}'_{igs} = \hat{\pi}_{igs}\hat{Y}_{ig}\pi_{igs}Y_{ig}$, equation $ELD'_{is} = 0$ can be written as

$$\sum_j \hat{\lambda}_{ijs}\lambda_{ijs}\beta_{js}\left(\sum_{g\in G_j}\hat{Y}_{jg}Y_{jg} + \hat{D}_jD_j\right) = \sum_{g\in G_i}\hat{\pi}_{igs}\hat{Y}_{ig}\pi_{igs}Y_{ig} \tag{7}$$

with

$$\hat{Y}_{ig} = \left(\sum_k \pi_{igk} \hat{A}_{igk} \hat{w}_{ik}^{\kappa_{ig}} \right)^{1/\kappa_{ig}}, \tag{8}$$

$$\hat{\lambda}_{ijs} = \frac{\hat{T}_{is} \left(\hat{\tau}_{ijs} \hat{w}_{is} \right)^{-\theta_s}}{\sum_k \lambda_{kjs} \hat{T}_{ks} \left(\hat{\tau}_{kjs} \hat{w}_{ks} \right)^{-\theta_s}}, \tag{9}$$

and

$$\hat{\pi}_{igs} = \frac{\hat{A}_{igs} \hat{w}_{is}^{\kappa_{ig}}}{\sum_k \pi_{igk} \hat{A}_{igk} \hat{w}_{ik}^{\kappa_{ig}}}. \tag{10}$$

Given values for parameters θ_s and κ_{ig}; data on income levels, Y_{ig}, trade imbalances, D_j, trade shares, λ_{ijs}, expenditure shares, β_{is}, labor allocation shares π_{igs}, and labor endowments, L_{ig}; and the shocks to trade costs, $\hat{\tau}_{ijs}$, trade imbalances, $\hat{D}_j$, and productivity levels, $\hat{A}_{igs}$ and $\hat{T}_{is}$, we can solve for changes in wages, $\hat{w}_{is}$, from the system of equations associated with (7)-(10), and then solve for all other relevant changes, including changes in trade shares using (9) and changes in employment shares using (10).

2.3 Group-Level Welfare Effects

Our measure of welfare of individuals in group ig is ex-ante real income, $W_{ig} \equiv \frac{Y_{ig}/L_{ig}}{P_i}$.[10] We are interested in the change in W_{ig} caused by a shock to trade costs or foreign technology levels, henceforth simply referred to as a "foreign shock." Cobb-Douglas preferences imply that $P_i = \prod_s P_{is}^{\beta_{is}}$, and hence

$$\hat{W}_{ig} = \hat{Y}_{ig} \prod_s \hat{P}_{is}^{-\beta_{is}}. \tag{11}$$

From (2) and (9) and given $\hat{T}_{is} = 1$ for all s in domestic country i, we have $\hat{P}_{is} = \hat{w}_{is} \hat{\lambda}_{iis}^{1/\theta_s}$ while from (8) and (10) we have $\hat{Y}_{ig} = \hat{w}_{is} \hat{\pi}_{igs}^{-1/\kappa_{ig}}$. Combining these two results with (11) we arrive at the following proposition:

Proposition 1. *Given some shock to trade costs or foreign technology levels, the percent-*

[10] This is the same as utility if there were no trade imbalances. In the presence of trade imbalances, utility would instead be $(1 + d_{ig})W_{ig}$, where $d_{ig} \equiv D_{ig}/Y_{ig}$ and D_{ig} is the trade deficit of group ig. The formulas below would need to be adjusted to capture changes in d_{ig} by multiplying by $\frac{1+\hat{d}_{ig} d_{ig}}{1+d_{ig}}$. Since we do not know how a country's trade imbalance is allocated to groups, we do not observe d_{ig}. Our approach in the quantitative analysis will be to first use the model to shut down trade imbalances and then use the resulting data for our quantitative analysis.

age change in the real wage of group g in country i is given by

$$\hat{W}_{ig} = \prod_{s} \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s} \cdot \prod_{s} \hat{\pi}_{igs}^{-\beta_{is}/\kappa_{ig}}. \tag{12}$$

The RHS of the expression in (12) has two components: $\prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s}$ and $\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa_{ig}}$, with all variation across groups coming from the second term. If $\kappa_{ig} \longrightarrow \infty$ for all $g \in G_i$ then the gains for all groups in country i are equal to $\prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s}$, which is the multi-sector formula for the welfare effect of a trade shock in ACR. It is easy to show that the term $\prod_{s} \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s}$ corresponds to the change in real income given wages while the term $\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa_{ig}}$ corresponds to the change in real income for group ig coming exclusively from changes in wages $\hat{w}_{is}$ for $s = 1, ..., S$.[11]

The term $\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa_{ig}}$ is related to the change in the degree of specialization of group ig. We can use the Kullback-Leibler (KL) divergence as a way to define the degree of specialization of a group. Formally, the KL divergence from $\boldsymbol{\pi}_{ig} \equiv \{\pi_{ig1}, \pi_{ig2}, ..., \pi_{igS}\}$ to $\boldsymbol{\beta}_i \equiv \{\beta_{i1}, \beta_{i2}, ..., \beta_{iS}\}$ is given by

$$D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}_{ig}) \equiv \sum_{s} \beta_{is} \ln(\beta_{is}/\pi_{igs}).$$

If group ig was in group-level autarky (i.e., not trading with any other group or country) then $\pi_{igs} = \beta_{is}$ for all s. Thus, $D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}_{ig})$ is a measure of the degree of specialization as reflected in the divergence from the actual distribution, $\boldsymbol{\pi}_{ig}$, to what it would be in

[11]The result in Proposition 1 can alternatively be derived by first applying the envelope theorem to the consumption and labor allocation problem at the group level,

$$d\ln W_{jg} = \sum_{s} \pi_{jgs} d\ln w_{js} - \sum_{i,s} \beta_{js}\lambda_{ijs} d\ln(w_{is}\tau_{ijs}).$$

We can then proceed as in ACR to substitute for $d\ln w_{js}$ and $d\ln(w_{is}\tau_{ijs})$ in this expression. From the trade side of the model we have $\frac{d\ln\left(\lambda_{ijs}/\lambda_{jjs}\right)}{d\ln\left(w_{is}\tau_{ijs}/w_{js}\right)} = -\theta_s$, while from the labor side we have $\frac{d\ln\left(\pi_{jgs}/\pi_{jgk}\right)}{d\ln\left(w_{js}/w_{jk}\right)} = -\kappa_{jg}$. Solving for $d\ln(w_{is}\tau_{ijs})$ and $d\ln w_{js}$ from these two equations, respectively, and then plugging back into the expression for $d\ln W_{jg}$ above yields $d\ln W_{jg} = -\sum_s \beta_{js}\left[\frac{d\ln\pi_{jgs}}{\kappa_{jg}} + \frac{d\ln\lambda_{jjs}}{\theta_s}\right]$. Integration leads to the result in (12).

autarky, $\boldsymbol{\beta}_i$.[12] We can now write

$$\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa_{ig}} = \exp\left(\frac{1}{\kappa_{ig}}\left[D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}'_{ig}) - D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}_{ig})\right]\right). \tag{13}$$

This implies that, apart from the common term $\prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s}$, the welfare effect of a trade shock on a particular group in country i is determined by the change in the degree of specialization of that group as measured by the KL divergence, multiplied by the degree of heterogeneity in worker productivity across sectors as captured by $1/\kappa_{ig}$. For example, a group with high employment in textiles would become less specialized and gain less (or even lose) from trade if a foreign shock leads the country to import disproportionally more textiles. On the other hand, groups specialized in exporting sectors gain more from trade than the country as a whole.

Of course, Proposition 1 cannot in general be used to go from observables and elasticities to welfare. We first need to use the model to compute $\{\hat{\lambda}_{iis}\}$ and $\{\hat{\pi}_{igs}\}$ for whatever shock we are interested in. This is also true in ACR, where the formula $\hat{W}_i = \hat{\lambda}_{ii}^{-\theta}$ is only directly applicable to find the gains from trade relative to autarky. Still, we highlight the formula as Proposition 1 because it shows clearly how our model extends the results in ACR, and because it is informative about the way in which the model works, in particular by pointing out the role of the elasticities and the changes in trade and employment shares. In Section 2.6 below we show an approximate formula that uses observables and elasticities to compute the effect of trade on a group's relative income.[13]

[12]The KL divergence was introduced by Kullback and Leibler (1951) and is also known as relative entropy. The KL divergence from q to p, $D_{KL}(p|q) = \sum_i p_i \ln(p_i/q_i)$, is equal to the difference between the cross entropy from q to p, $H(p,q) = -\sum_i p_i \ln(q_i)$, and the entropy of p, $H(p) = -\sum_i p_i \ln(p_i)$, $D_{KL}(p|q) = H(p,q) - H(p)$. Substracting $H(q)$ ensures that $D_{KL}(p|p) = 0$.

[13]We comment briefly on how our model relates to the one in ADH. They derive their regression equations from a log-linear approximation of the equilibrium conditions of a multi-sector gravity model of trade with homogeneous and perfectly mobile workers across sectors, but with each group modeled as a separate economy. In this case all the variation in the effects of a shock across groups arises because of different terms of trade effects. In our baseline model technologies are national and there are no trade costs among groups within countries, so with homogenous and perfectly mobile workers across sectors the terms of trade effects would be the the same for all groups. Instead, worker heterogeneity implies that some groups of workers are more closely attached to some sectors, and it is this that generates variation in the effect of trade shocks across groups.

2.4 Aggregate Welfare Effects

We define aggregate welfare as aggregate real income, $W_i \equiv Y_i/P_i$.[14] The aggregate welfare effect can be obtained from Proposition 1 as $\hat{W}_i = \hat{Y}_i/\hat{P}_i = \sum_{g\in G_i} (Y_{ig}/Y_i)\,\hat{W}_{ig}$, leading to

$$\hat{W}_i = \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s} \cdot \sum_{g\in G_i} \left(\frac{Y_{ig}}{Y_i}\right) \prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa_{ig}}. \tag{14}$$

The welfare effect of a trade shock is no longer given by the multi-sector ACR term (i.e., $\hat{W}_i \neq \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s}$). This is because a trade shock will affect sector-level wages w_{is}, and this in turn will affect welfare through its impact on income and sector-level prices.

2.5 Aggregate and Group-Level Gains from Trade

Following ACR, we define the gains from trade as the negative of the proportional change in real income for a shock that takes the economy back to autarky: $GT_i \equiv 1 - \hat{W}_i^A$ and $GT_{ig} \equiv 1 - \hat{W}_{ig}^A$. A move to autarky for country i entails $\hat{\tau}_{ijs} = \infty$ for all s and all $i \neq j$ and $\hat{D}_i = 0$. Conveniently, solving for changes in wages in country i ($\hat{w}_{is}$ for $s = 1, ..., S$) from Equation (7) only requires knowing the values of employment shares, income levels and expenditure shares for country i, namely β_{is} for all s, Y_{ig} for all g, and π_{igs} for all g, s. This can be seen by letting $\hat{\tau}_{ijs} \to \infty$ in Equation (7), which yields

$$\beta_{is} \sum_{g\in G_i} \hat{Y}_{ig} Y_{ig} = \sum_{g\in G_i} \hat{\pi}_{igs} \hat{Y}_{ig} \pi_{igs} Y_{ig}. \tag{15}$$

Let $r_{is} \equiv \sum_{g\in G_i} \pi_{igs} Y_{ig}/Y_i$ be the share of sector s in total output in country i and note that country i engages in inter-industry trade as long as $r_{is} \neq \beta_{is}$ for some s.

Proposition 2. *Assume that $\kappa_{ig} = \kappa_i$ for all $g \in G_i$. If $\kappa_i < \infty$ and country i engages in inter-industry trade, then the aggregate gains from trade are strictly higher than those that arise in the limit as $\kappa_i \longrightarrow \infty$.*

Online Appendix B.1 has the proof. To understand this result, it is useful to consider the simpler case with a single group of workers, $G_i = 1$. In this case, a move back to

[14] Aggregate real income gives the utility level of all agents if income is shared equally among all individuals in the economy. Also, if there is no risk sharing, W_i gives utility "behind the veil of ignorance" if agents are risk neutral, as further explained in Section 2.7.

autarky would imply

$$\hat{W}_i^A = \prod_s \lambda_{iis}^{\beta_{is}/\theta_s} \cdot \exp\left[-\frac{1}{\kappa_i} D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{r}_i)\right].$$

If there is inter-industry trade then $D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{r}_i) > 0$ so (given $\boldsymbol{r}_i$) a finite κ_i implies a lower $\hat{W}_i^A$ than in the multi-sector ACR formula. Intuitively, a finite κ_i introduces more "curvature" to the PPF, making it harder for the economy to adjust as it moves to autarky. This implies higher losses if the economy were to move to autarky, and hence higher gains from trade. Proposition 2 establishes that this result generalizes to the case $G_i > 1$.

Turning to the group-specific gains from trade, we again use the KL measure of specialization to understand whether a group gains more or less than the economy as a whole. The results of the previous section imply that the gains from trade for group ig are

$$GT_{ig} = 1 - \prod_s \lambda_{iis}^{\beta_{is}/\theta_s} \cdot \exp\left(\frac{1}{\kappa_{ig}}\left[D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}_{ig}^A) - D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}_{ig})\right]\right).$$

The term $D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}_{ig}^A) - D_{KL}(\boldsymbol{\beta}_i \parallel \boldsymbol{\pi}_{ig})$ could be positive or negative, depending on whether group ig becomes more or less specialized with trade as measured by the KL divergence.

Consider a group ig that happens to have efficiency parameters $(A_{ig1}, ..., A_{igS})$ that give it a strong comparative advantage in a sector s for which the country as a whole has a comparative disadvantage, as reflected in positive net imports in that sector. Group ig would be highly specialized in s when the country is in autarky but that specialization would diminish as the country starts trading with the rest of the world. As a consequence, the KL degree of specialization falls with trade for group ig, implying lower gains relative to other groups in the economy.

2.6 A Bartik Approximation

Focusing on the implications of a foreign shock on a group's relative income, equation (8) implies that

$$\frac{\hat{Y}_{ig}}{\hat{Y}_i} = \left(\sum_s \pi_{igs}\left(\frac{\hat{w}_{is}}{\hat{Y}_i}\right)^{\kappa_{ig}}\right)^{1/\kappa_{ig}}. \tag{16}$$

Since wages are not observable, it is convenient to derive an approximation for this expression that uses changes in output shares, $\hat{r}_{is}$ rather than $\hat{w}_{is}$. Assuming that $\kappa_{ig} = \kappa_i$ for all $g \in G_i$ and recalling that $r_{is} \equiv \sum_{g \in G_i} \pi_{igs} Y_{ig}/Y_i$, equations (8) and (10) imply:

$$\hat{r}_{is} = \left(\frac{\hat{w}_{is}}{\hat{Y}_i}\right)^{\kappa_i} \sum_{g \in G_i} \frac{(Y_{ig}/Y_i)\pi_{igs}}{r_{is}} \left(\frac{\hat{Y}_{ig}}{\hat{Y}_i}\right)^{1-\kappa_i}.$$

The term $\frac{(Y_{ig}/Y_i)\pi_{igs}}{r_{is}}$ captures group ig's share of country i's total output of sector s, and $(\hat{Y}_{ig}/\hat{Y}_i)^{1-\kappa_i}$ is an adjustment to take into account how $(\hat{Y}_{ig}/\hat{Y}_i)\hat{\pi}_{igs}$ deviates from $(\hat{w}_{is}/\hat{Y}_i)^{\kappa_i}$ for group ig. The sum on the RHS of the previous equation is then an overall adjustment for how $\hat{r}_{is}$ may deviate from $(\hat{w}_{is}/\hat{Y}_i)^{\kappa_i}$. For κ close to 1 or for shocks that do not lead to large differences in $\hat{Y}_{ig}/\hat{Y}_i$ from 1 for groups with large weights in sector s, that adjustment will be small, and $\hat{r}_{ik} \approx (\hat{w}_{is}/\hat{Y}_i)^{\kappa_i}$, so Equation 16 yields

$$\frac{\hat{Y}_{ig}}{\hat{Y}_i} \approx \left(\sum_k \pi_{igk} \hat{r}_{ik}\right)^{1/\kappa_i}. \tag{17}$$

In the quantitative analysis in Sections 5 and 6 we will see that this equation provides a very good approximation of the model implied group-level relative income effects of the China shock and the move back to autarky for the United States. The benefit of this result is that $\hat{r}_{is}$ is observable in the data. Thus, if we can identify the impact of a foreign shock on output shares, then we can use this Bartik-style result to compute approximate relative income changes across groups.

This result is particularly useful for the shock that takes country i back to autarky. For that case we have $\hat{r}_{is} = \beta_{is}/r_{is}$ and hence we obtain an approximate sufficient statistic for a group's gains from trade relative to the aggregate gains:

$$\frac{\hat{Y}^A_{ig}}{\hat{Y}^A_i} \approx I_{ig}^{1/\kappa_i} \equiv \left(\sum_s \pi_{igs} \frac{\beta_{is}}{r_{is}}\right)^{1/\kappa_i}. \tag{18}$$

We can think of β_{is}/r_{is} as an index of the degree of import competition in industry s and I_{ig} as an index of import competition faced by group g. Thus, for a move back to autarky, the change in relative income levels across groups is approximated by the index of import competition that we can directly observe in the data elevated to the power $1/\kappa_i$. Since a foreign shock does not affect the autarky equilibrium, we can also use the result in (18) to rewrite the approximation in (17) for any foreign shock in terms of the change in the index of import competition, $\frac{\hat{Y}_{ig}}{\hat{Y}_i} \approx \hat{I}_{ig}^{-1/\kappa_i}$.[15]

2.7 Inequality-Adjusted Welfare Effects

We follow Atkinson (1970) and think about social welfare as a (geometric) average of welfare across all individuals with a constant inequality aversion parameter $\rho > 0$ (with $\rho \neq 1$ to simplify the exposition below). Since the z_s for workers in group ig is distributed Fréchet with scale parameter A_{igs} and shape parameter κ_{ig}, then income $\max_s w_{is} z_s$ for workers in group ig is distributed Fréchet with scale parameter $\Phi_{ig}^{\kappa_{ig}}$ and shape parameter κ_{ig}. Social welfare in country i is then

$$U_i = \frac{1}{P_i} \left(\sum_{g \in G_i} \int_0^\infty y^{1-\rho} l_{ig} dH_{ig}(y) \right)^{\frac{1}{1-\rho}},$$

with $H_{ig}(y) = \exp\left(-\Phi_{ig}^{\kappa_{ig}} y^{-\kappa_{ig}}\right)$. Integrating and assuming that $\kappa_{ig} = \kappa_i$ yields

$$U_i = \tilde{\xi}_i \left(\sum_g l_{ig} W_{ig}^{1-\rho} \right)^{\frac{1}{1-\rho}}, \tag{19}$$

where $l_{ig} \equiv L_{ig}/L_i$ and $\tilde{\xi}_i \equiv \frac{\Gamma\left(1-\frac{1-\rho}{\kappa_i}\right)^{\frac{1}{1-\rho}}}{\Gamma\left(1-\frac{1}{\kappa_i}\right)}$.

The inequality-adjusted welfare effect of a foreign shock is defined as $\hat{U}_i - 1$ whereas the inequality-adjusted gains from trade are defined as $IGT_i \equiv 1 - \hat{U}_i^A$. If $\rho = 0$ then these measures correspond to those defined above, namely $\hat{W}_i - 1$ and $GT_i \equiv 1 - \hat{W}_i^A$.[16] To write these results in terms of observables and the endogenous group-level welfare changes $\hat{W}_{ig}$, let $\omega_{ig} \equiv \frac{l_{ig}(Y_{ig}/L_{ig})^{1-\rho}}{\sum_h l_{ih}(Y_{ih}/L_{ih})^{1-\rho}}$ be a modified weight for group ig in country i welfare that appropriately accounts for the social value of income accruing to groups

[15] This result can also be derived directly from (17) by noting that $\sum_k \pi_{igk} \hat{r}_{ik} = \frac{\sum_s \pi_{igs} \beta_{is}/r_{is}}{\sum_s \pi'_{igs} \beta_{is}/r'_{is}} = 1/\hat{I}_{ig}$. See Online Appendix B.2.

[16] A Rawlsian approach to social welfare entails $\rho \to \infty$ and $\hat{U}_i = \min_g W'_{ig} / \min_g W_{ig}$. If $\arg\min_g W'_{ig} = \arg\min_g W_{ig} = h$ then $\hat{U}_i = \hat{W}_{ih}$, but of course this need not be the case. We discuss plausible values for ρ in Section 5.

with different income levels. Then simple algebra reveals that

$$\hat{U}_i = \left(\sum_g \omega_{ig} \hat{W}_{ig}^{1-\rho} \right)^{\frac{1}{1-\rho}}. \tag{20}$$

2.8 Extensions

The combination of a stylized model of the labor market with a standard multi-sector gravity model delivers clean analytical results on the group-level welfare effects of trade shocks, while nesting the ACR welfare formula. The implied distributional effects are closely approximated by Bartik-style changes in import competition and can be integrated into an aggregate measure of inequality-adjusted welfare effects. We will show below that this baseline model is sufficient to provide a structural framework for the empirical analysis of changes in import-competition on group-level changes in income and unemployment, and in our counterfactual analysis we will document how the Roy component of our model leads to strong distributional effects of a prominent trade shock, the China shock. In Sections 7-9 we will study several extensions of the baseline model that allow for variation across groups not only by commuting zone but also by gender, age and education, imperfect substitutatiliby between skilled and unskilled labor, endogenous employment levels, tradable intermediate goods, and trade costs within the U.S., studying for each case the associated implications.[17]

3 Data

For our quantitative analysis, we define groups based on geographic location. We follow ADH in using commuting zones (CZs) as geographic units to define local labor markets.[18] This leaves us with a total of 722 groups (CZs). All countries other than the US are assumed to have a single group.

Since our baseline estimation follows ADH as closely as possible, we employ the

[17] In the Online Appendix Section J we also develop an extension with mobility of workers across groups, motivated by the case in which groups correspond to commuting zones. Given the lack of the necessary data, we have not explored the quantitative implications of this extension.

[18] Our assumption of fixed groups applied to this setting implies no mobility across local labor markets. We view this as a reasonable assumption in light of existing literature that finds little evidence of trade exposure causing population shifts across local labor markets. See, for example, ADH for the US, Dauth et al. (2014) for Germany, and Dix-Carneiro and Kovak (2016) for Brazil.

same data sources and definitions. These include labor income and employment status from the American Community Survey (ACS) and decennial censuses, employment shares across industries for each commuting zone from the County Business Patterns database (CBP), and trade flows from the UN Comtrade database.[19] As in ADH, we focus our analysis on the periods 1990-2000 and 2000-2007.[20]

Due to data limitations, our simulation analysis is restricted to the time period 2000-2007 and uses aggregated industry definitions. Our choice of time horizon (2000-2007) resulted from the data requirement on bilateral trade flows from the World Input-Output Database (WIOD), which are only available starting 1995.[21] We chose to have more aggregated sectors in order to link the labor data with WIOD figures in a consistent manner. These aggregated sectors, listed in Appendix Table A.1, are based on the 1987 SIC classification codes. We aggregate all manufacturing industries into 13 sectors which roughly correspond to two-digit ISIC Rev. 3 codes. The remaining sectors, excluding public administration and the non-profit sector, are aggregated to one non-manufacturing sector. [22]

Appendix C describes in detail the construction of our dataset and the definition of our variables. It also details the supplementary data employed in our model extensions and robustness tests.[23]

4 Estimation

The κ parameter is central to our model as it jointly affects the aggregate and the distributional effects from trade. In this section we propose and then implement an es-

[19]In all our estimations, we follow very closely the definitions, sample restrictions and model specifications of ADH. These include industry classification (3-digit SIC codes), same set of covariates, etc. For a detailed description of our data, see Appendix B.

[20]As in ADH, we make adjustments to the data in order to put the two periods on a comparable decadal scale. For the period 2000-2007, we multiply employment, income, and trade changes with a factor of 10/7. Since trade figures are only available from 1991 for the time period 1991 to 2000, we multiplied trade growth with the factor 10/9.

[21]The World Input-Output Database (WIOD) is discussed in Timmer, Dietzenbacher, Los, Stehrer and Vries (2015).

[22]Since we require consistency between the trade and labor data, for US groups we first set $Y_{igs} = \frac{\pi_{igs}^{CBP} Y_{ig}^{CBP}}{\sum_h \pi_{ihs}^{CBP} Y_{ih}^{CBP}} Y_{is}^{WIOD}$, where the superscript denotes the data source, and then focus on π_{igs} as shares of earnings, $\pi_{igs} = \frac{Y_{igs}}{\sum_k Y_{igk}}$. Recall that in our Roy-Fréchet framework the share of workers of any group ig in sector s is the same as the share of earnings derived from working in that sector.

[23]These include data on unemployment, home production and alternative group definitions employed in the extensions presented in Sections 7 and 8.

timation strategy for this parameter that builds on the seminal work of ADH, and in particular on their findings that across commuting zones, the China shock leads to a significant contraction in manufacturing employment and a decline in earnings.

4.1 From Model to Regression Equation

We now restrict attention to the US and therefore drop the country subscript. We estimate a common value for κ_g across groups and hence impose $\kappa = \kappa_g$. From equations (8) and (10) we then obtain $\hat{y}_g = \hat{A}_{gs}^{1/\kappa} \hat{w}_s \hat{\pi}_{gs}^{-1/\kappa}$, where $y_g \equiv Y_g / L_g$ is defined as average income per employed worker in group g. This expression holds for any sector s, and says that, conditional on $\hat{w}_s$ and $\hat{A}_{gs}$, $\hat{\pi}_{gs}^{-1/\kappa}$ serves as a sufficient statistic for the change in a group's income. Intuitively, given $\hat{w}_s$ and $\hat{A}_{gs}$, then $\hat{\pi}_{gs} > 1$ ($\hat{\pi}_{gs} < 1$) implies that wages (or productivity shocks) weighted by employment shares in other sectors must have been negative (positive) for group g, leading workers in that group to move to (out of) sector s. The parameter κ determines how large the loss in relative income is for a given $\hat{\pi}_{gs}$.[24]

Applying this expression to the the non-manufacturing sector, $s = NM$, adding a t subscript to denote time periods, and taking logs yields

$$\ln \hat{y}_{gt} = \delta_t + \beta \ln \hat{\pi}_{gNMt} + \varepsilon_{gt}, \tag{21}$$

where $\delta_t \equiv \ln \hat{w}_{NMt}$, $\beta \equiv -1/\kappa$ and $\varepsilon_{gt} \equiv \ln \hat{A}_{gNMt}^{1/\kappa}$. We can use this equation to estimate κ from a cross-group regression of $\ln \hat{y}_{gt}$ on $\ln \hat{\pi}_{gNMt}$ (pooling across periods), instrumented as in ADH as explained below.[25] Focusing on the non-manufacturing sector allows us to build on the primary finding in ADH, namely the contraction in manufacturing employment caused by the China shock, and leads to a stronger first stage in our IV estimation.

[24]One way to understand why, conditional on $\hat{w}_s$ and $\hat{A}_{gs}$, $\hat{\pi}_{gs}^{-1/\kappa}$ serves as a sufficient statistic for $\hat{y}_g$ is as follows. For any sector s, we know that $\frac{\hat{\pi}_{gk}}{\hat{\pi}_{gs}} = (\frac{\hat{w}_k}{\hat{w}_s})^\kappa$ for all g and k and $\sum_k \pi_{gk} \hat{\pi}_{gk} = 1$ for all g, hence $\hat{\pi}_{gs} \sum_k \pi_{gk} (\frac{\hat{w}_k}{\hat{w}_s})^\kappa = 1$ for all g. This implies that groups more exposed to relative wage declines will have a higher $\hat{\pi}_{gs}$, implying that $\hat{\pi}_{gs}$ acts as a sufficient statistic for such exposure and the associated income change. The same reasoning implies that groups with higher employment shares in sectors experiencing relative wage declines will have higher expansions in sectors that originally had lower employment shares, leading to a larger decline in specialization as measured by the KL divergence and a relative fall in income.

[25]The absence of within-country trade costs is an important assumption in the derivation of this estimation equation, as it ensures that $\ln \hat{w}_{NMt}$ does not vary across commuting zones. We examine the sensitivity of our estimation and simulation results to this assumption in Section 7.3.

4.2 Empirical Strategy

The model implies that the regressor is correlated with the error term in the regression equation (21), i.e. $\mathbb{E}[\ln \hat{\pi}_{gNMt} \cdot \varepsilon_{gt}] \neq 0$. Hence, instead of running a simple OLS regression, we pursue an instrumental-variable strategy to obtain consistent estimates, using the exact same China shock variable as constructed by ADH. Specifically, the instrumental variable we use is

$$Z_{gt} \equiv \sum_{s \in M} \pi_{gst-10} \Delta IP_{st}^{China \to Other}, \tag{22}$$

where M refers to the subset of manufacturing sub-industries and

$$\Delta IP_{st}^{China \to Other} \equiv \frac{\Delta Imports_{st}^{China \to Other}}{L_{st-10}^{US}},$$

where L_{st-10}^{US} denotes US employment in sector s in year $t-10$, $Imports_{st}^{China \to Other}$ are imports from China by a group of countries similar to the US, and Δ refers to the change over period t.[26] We focus on the two time periods used in ADH, namely 1990-2000 and 2000-2007. In the construction of instrument Z_{gt}, the π_{gst-10} are measured for 397 manufacturing subindustries, employing data from the County Business Patterns.[27]

Our estimation of κ from (21) with $\hat{\pi}_{gNMt}$ instrumented by Z_{gt} is consistent if the instrument is relevant, $cov(Z_{gt}, \ln \hat{\pi}_{gNMt}) \neq 0$, and satisfies the exclusion restriction, $cov(Z_{gt}, \varepsilon_{gt}) = 0$, where these covariances are taken with respect to g for each t.[28] Regarding the first condition, large enough technology shocks in manufacturing sectors in China, $\hat{T}_{China,st}$ for $s \in M$, would increase Chinese exports to other countries and to the US, leading to the contraction of the manufacturing sector in the most ex-

[26]The use of countries similar to the US is meant to proxy for changes in sectoral import-competition from China in the US. This set of countries is identical to the set in ADH and consists of Australia, Denmark, Finland, Germany, Japan and Spain, Switzerland and New Zealand. Countries are selected based on having a similar income level as the US, but direct neighbors are excluded.

[27]Although here we have a higher level of disaggregation than in the quantitative analysis below (where we use only 13 manufacturing sectors), it is still the case that $\sum_s \pi_{gst-10}$ equals the total share of employment in manufacturing.

[28]To understand what these conditions entail, think about the model as the data generating process: given initial data, parameters $\{\theta_s\}$ and κ, and a set of exogenous shocks $\{\hat{A}_{igs}\}$ and $\{\hat{T}_{is}\}$, the model in hat changes in Equations (7) - (10) generates $\{\hat{y}_{ig}\}$, $\{\hat{\pi}_{igNM}\}$ and $\{\Delta IP_s^{China \to Other}\}$ (for each period). We think of our data as $\{\Delta IP_s^{China \to Other}\}$ and a subsample $\hat{y}_g$ and $\hat{\pi}_{gNM}$ for $g = 1, ..., \tilde{G} < G$ (again focusing on the US and supressing the country subindex). Consistency is for the limit as $\tilde{G} \to \infty$.

posed groups and implying that $cov(Z_{gt}, \ln \hat{\pi}_{gNMt}) > 0$, as found by ADH and confirmed below. In turn, a sufficient condition for the exclusion restriction to hold is that the shocks $\{\hat{A}_{gNMt}\}$ be mean independent of group g lagged employment shares, $\mathbb{E}(\varepsilon_{gt}|\boldsymbol{\pi}_{gt-10}) = 0$, as this would immediately imply that $cov(Z_{gt}, \varepsilon_{gt}) = 0$.[29]

The condition that the shocks $\{\hat{A}_{gNM}\}$ be mean independent of group g lagged employment shares would fail, for example, if non-manufacturing productivity tended to fall in groups with high employment shares in unskilled-intensive manufacturing sectors. This would create a negative correlation between the instrument and the residual and lead to a downward bias in $\hat{\kappa}$. Similar concerns led ADH to add a set of commuting-zone variables as controls in their estimation. Such controls can be accommodated in our model by assuming that the unobserved productivity shocks are correlated with a vector of group-level variables $\boldsymbol{X}_{gt}$. Formally, assuming that $\varepsilon_{gt} = \boldsymbol{X}'_{gt}\Theta + \epsilon_{gt}$, where Θ is a vector of parameters, then the estimating equation becomes

$$\ln \hat{y}_{gt} = \delta_t + \beta \ln \hat{\pi}_{gNMt} + \boldsymbol{X}'_{gt}\Theta + \epsilon_{gt}. \tag{23}$$

We use the same set of control variables as in ADH.[30] The sufficient condition for the exclusion restriction to hold is now weaker, as we need $\mathbb{E}(\epsilon_{gt}|\boldsymbol{\pi}_{gt-10}, \boldsymbol{X}_{gt}) = 0$ rather than $\mathbb{E}(\varepsilon_{gt}|\boldsymbol{\pi}_{gt-10}) = 0$.

If condition $\mathbb{E}(\epsilon_{gt}|\boldsymbol{\pi}_{gt-10}, \boldsymbol{X}_{gt}) = 0$ holds then any Bartik-type instrument combining employment shares and sector level changes would satisfy the exclusion restriction, even if it were correlated to US sector-level supply or demand shocks. This reveals an important difference between our paper and ADH: whereas the goal in ADH was to identify the causal effect of the China shock on income and employment in the US, our goal is instead to estimate parameter κ. ADH needed to avoid confounding the China shock with US import demand shocks, but in our case those import

[29]In principle, we could also apply estimation equation (21) to each of our 13 manufacturing sectors. Having selected some manufacturing sector s as the basis for the regression (instead of non-manufacturing), we would then construct an instrument as above but leaving out that sector. It turns out that this instrument lacks power regardless of the manufacturing sector s that we consider: changes in imports in manufacturing sectors $s' \neq s$ do not provide a good instrument for the change in the share of employment in manufacturing sector s. This stands in contrast to how changes in imports in all manufacturing sectors affect changes in the share of employment in non-manufacutring, which was one of the key results in ADH.

[30]These controls are lagged manufacturing shares, Census division fixed effects, and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

demand shocks can be part of the variation used to identify κ under the condition $\mathbb{E}(\epsilon_{gt}|\boldsymbol{\pi}_{gt-10}, \boldsymbol{X}_{gt}) = 0$. Accordingly, below we consider two alternative instruments, one using the change in exports by China to the US rather than to other countries, $Z_{gt} \equiv \sum_{s\in M} \pi_{gst} \Delta IP_{st}^{China\to US}$, and the other using the simple Bartik expression $Z_{gt} \equiv \ln \sum_s \pi_{gst} \hat{r}_{st}$, where r_{st} is the share of sector s in total sales in year t.[31,32]

Although $\mathbb{E}(\epsilon_{gt}|\boldsymbol{\pi}_{gt-10}, \boldsymbol{X}_{gt}) = 0$ is a sufficient condition for identification, it is by no means a trivial assumption – see Goldsmith-Pinkham, Sorkin and Swift (2018). Borusyak, Hull and Jaravel (2018), henceforth BHJ, provide an alternative condition for instrument validity by focusing on the exogeneity of the shocks (rather than the shares), and thinking of consistency in terms of the number of sectors rather than the number of groups. This condition is

$$cov(Z_{gt}, \epsilon_{gt}) = \sum_{s\in M} \Delta IP_{st}^{China\to Other} \mathbb{E}\left[\pi_{gst-10}\epsilon_{gt}\right] \to 0$$

as the number of sectors in M goes to infinity. The sector shares π_{gst-10} are now allowed to be correlated with the error term ϵ_{gt}, as long as this correlation is orthogonal to the sector-specific China shocks. This alternative condition to instrument validity has implications for the computation of standard errors as well as additional specification and over-identification tests, which we discuss below when we present the estimation results.

4.3 Estimation Results

Table 1 presents the results of the IV regression described above, with slight variations in the construction of the instrument.[33] The first row shows our second-stage results, while the third row has the corresponding estimate $\hat{\kappa} = -1/\hat{\beta}$, and the fourth row dis-

[31] Due to data limitations, we use contemporaneous shares $\boldsymbol{\pi}_{igt}$ (instead of lagged shares) when contructing the instrument based on Chinese imports to the US. Using lagged shares requires detailed 1980 data, which is difficult to obtain. These instruments correspond to the endogenous regressor in ADH, which is the main source of our data. Identification in this case relies on the assumption that $\mathbb{E}(\epsilon_{gt}|\boldsymbol{\pi}_{gt}, \boldsymbol{X}_{gt}) = 0$.

[32] The assumption that $\mathbb{E}(\epsilon_{gt}|\boldsymbol{\pi}_{gt-10}, \boldsymbol{X}_{gt}) = 0$ also implies that conventional inference methods are valid in our setting. Since this condition can be derived directly from our model's structural assumptions, we present conventional standard errors in our primary results (clustering at the state level to remain consistent with the results in ADH).

[33] Reassuringly, the estimates line up reasonably well across the different columns. We performed a standard Hansen-J overidentification test which fails to reject that the four estimates are statistically the same (our Hansen-J statistic has a p-value of 0.346).

plays the F-statistic from the first stage. The first-stage F-statistics are always sufficiently high, which is not surprising given the central finding in ADH on the contraction of manufacturing due to the China shock. Most importantly, our estimated values for $\hat{\kappa}$ range from 1.42 to 2.79, and these estimates are statistically significant.[34]

Table 1: Estimation of κ

	(1)	(2)	(3)	(4)
	$\ln \hat{y}_g$	$\ln \hat{y}_g$	$\ln \hat{y}_g$	$\ln \hat{y}_g$
$\ln \hat{\pi}_{NM}$	-0.358*	-0.639**	-0.704**	-0.487**
	(0.211)	(0.303)	(0.295)	(0.183)
Implied κ	2.79	1.56	1.42	2.05
	(1.643)	(0.742)	(0.594)	(0.773)
F-First Stage	58.46	24.02	29.52	67.87
Observations	1444	1444	1444	1444
R^2	0.683	0.667	0.662	0.677
Import Penetration	Other (lagged)	Other (no lag)	US (no lag)	US Bartik

IV-estimation results for specification (23), where y_g is average earnings per worker, and π_{gNM} is the employment share in non-manufacturing, measured using the CBP data. The columns differ in the construction of the instrument: column (1) uses the exact instrument borrowed from ADH $Z_{gt} \equiv \sum_{s\in M} \pi_{gst-10} \Delta IP_{st}^{China\to Other}$, column (2) uses $Z_{gt} \equiv \sum_{s\in M} \pi_{gst} \Delta IP_{st}^{China\to Other}$, column (3) uses $Z_{gt} \equiv \sum_{s\in M} \pi_{gst} \Delta IP_{st}^{China\to US}$, and column (4) uses our Bartik variable for the US: $Z_{gt} \equiv \ln \sum_s \pi_{gst} \hat{r}_{st}$. Due to data constraints on π_{gst-10}, we have not constructed $Z_{gt} \equiv \sum_{s\in M} \pi_{gst-10} \Delta IP_{st}^{China\to US}$. Standard errors are clustered at the state level and reported in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. The first row shows the second-stage results, while the third row has the corresponding κ estimates implied by the model and the fifth row displays the F-statistic from the first stage. All regressions include the same controls employed in ADH's preferred specification: lagged manufacturing shares, period fixed effects, Census division fixed effects, and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

Our range of estimated values for κ is consistent with estimates of supply elasticities obtained by Hsieh et al. (2013) and Burstein et al. (2019), across occupations. Despite

[34] Our estimation strategy relies on assuming a Fréchet distribution, which restricts the mechanisms through which the China shock affects inequality (see Adão (2016)). In particular, the Fréchet assumption implies that there will be no effect of the China shock on within-group inequality. In Online Appendix Table D.1 we empirically test whether this is the case. We do so by running reduced form regressions with different measures of within-group inequality as the dependent variables and China shock measures as regressors of interest. The majority of our estimates yield no statistically significant evidence that the China shock increased within-group inequality.

different modeling and estimation approaches, these papers find parameters of productivity dispersion (analogous to our κ) between 1.2 and 3.44.

Our baseline identifying assumption (the exogeneity of employment shares) is not directly testable. We can, however, identify which industry shares are driving our results, and frame our assumptions in terms of those industries. Following Goldsmith-Pinkham et al. (2018) (whose assumptions are analogous to ours), we computed Rotemberg weights for each industry share and found that the China shock instrument is driven by a few industries such as Electronic Computers (see Online Appendix Tables D.2 and D.4). We can then view our orthogonality assumption as stating that CZs with high shares in these industries did not experience better or worse local productivity shocks to the non-manufacturing sector. To alleviate concerns of exogeneity violations for important industries, we constructed different versions of the China shock in a manner inspired by ADH, namely by sequentially leaving each of the top five sectors out. Reassuringly, the estimates for κ do not change significantly and all fall within the range of 1.17 to 3.12 (see Appendix Tables D.3 and D.5).

If assumption $\mathbb{E}(\epsilon_{gt}|\boldsymbol{\pi}_{gt-10}, \boldsymbol{X}_{gt}) = 0$ is violated and identification relies instead on the alternative assumption provided by BHJ, then standard inference methods might not be appropriate[35]. In Online Appendix D, we present our baseline point estimates of Table 1 with standard errors computed as proposed by BHJ (see column 1 of Table D.6). As expected, the standard errors become slightly larger, but our estimates retain conventional levels of statistical significance. In Online Appendix D we also describe additional specification tests suggested by BHJ, and overall find that while results are less precise they nevertheless remain consistent with our baseline findings (see Table D.6). We also find supporting evidence for the orthogonality of the shocks from an overidentification test (see Table D.7).

For the next section, where we will run simulations to analyze the quantitative role of κ in our framework, we will set our preferred value at $\kappa = 1.5$. In addition, we will

[35]As pointed out by Adão, Kolesár and Morales (2019), this is especially true in cases where the error terms are correlated for groups with similar employment shares. In fact the BHJ-corrected standard errors are asymptotically equivalent to those derived by Adão et al. (2019). We present the estimated standard errors in brackets in Appendix Table D.6. We were not able to compute the Adão et al. (2019) standard errors for the instruments constructed using beginning-of-period shares. This was due to the shares not satisifying the necessary rank conditions (a problem that does not apply to the lagged shares employed in their own analysis). This problem has been recently documented by BHJ, who point out that under certain rank conditions their inference approach is feasible whereas Adão et al. (2019)'s is not.

also show results for $\kappa \to 1$ (the theoretical lower bound for κ), and for $\kappa = 3$ (twice our preferred value).

5 Aggregate and Distributional Effects of the Rise of China

While existing research (e.g. ADH) has found strong distributional implications of the "rise of China" across local labor markets in the US, this empirical research remains largely silent on the associated group-level and aggregate welfare effects. We now perform counterfactual simulations with our model to shed light on this question.[36]

5.1 Calibrating the China shock

We model the rise of China as sector-specific technology shocks, $\hat{T}_{China,s}$. We calibrate these shocks such that for each sector, the simulated changes in US expenditure shares on Chinese goods match the change in these expenditure shares that is driven by the rise of China.[37] The first step is to obtain predicted changes in US expenditure shares from running a specification similar to ADH's first-stage regression,

$$\hat{\lambda}_{China,US,s} = \alpha + \beta \hat{\lambda}_{China,Other,s} + \varepsilon_s,$$

where $\hat{\lambda}_{China,Other,s} \equiv \frac{\sum_{j \in Other} \lambda^{2007}_{China,j,s}}{\sum_{j \in Other} \lambda^{2000}_{China,j,s}}$. In a second step we calibrate the technology shocks $\hat{T}_{China,s}$ so that the model-implied changes in the US expenditure shares on imports from China, $\hat{\lambda}_{China,US,s}$, match the predicted values from the first step.

5.2 Aggregate and Distributional Welfare Effects

The results for the US welfare effects of the China shock as calibrated above are shown in Table 2 for four different values of κ: 1, 1.5, 3 and ∞, and for $\theta_s = 5$ for all s.[38] The

[36] In all the ensuing counterfactual exercises, we follow Head and Mayer (2014) and set $\theta_s = 5$ for all s. We perform our counterfactual exercises on data without trade deficits, which we obtain by first simulating the trade equilibrium with balanced trade. This preliminary simulation is always performed with our preferred value of $\kappa = 1.5$.

[37] This calibration is inspired by the procedure in Caliendo et al. (2019), who calibrate $\hat{T}_{China,s}$ to match predicted changes in US imports from China. Instead of imports, we focus on the expenditure shares $\lambda_{China,US,s}$, and thereby avoid any complications arising from matching sectoral deflators for US imports across simulations and data.

[38] To more clearly see the impact of κ on the welfare effects from the China shock, the results for different values of κ correspond to the shock $\hat{T}_{China,s}$ as calibrated for $\kappa = 1.5$. Separately calibrating $\hat{T}_{China,s}$ for each value of κ leads to broadly similar results – see Online Appendix Table E.1.

third row shows standard errors for each statistic based on the estimated $\kappa = 1.5$ in Table 1.[39] The first column shows the aggregate welfare effect for the case with no inequality aversion, $\hat{W}_{US}$, while the next four columns show the mean, the coefficient of variation (CV), and the minimum and maximum for the group-level welfare changes, $\hat{W}_{US,g}$. The last column shows the welfare effect according to the multi-sector ACR formula.

Table 2: The Welfare Effects of the China Shock on the US

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.24	0.30	1.40	-1.73	2.32	0.14
1.5	0.22	0.27	1.16	-1.42	1.64	0.15
	(0.02)	*(0.03)*	*(0.25)*	*(0.35)*	*(0.58)*	*(0.01)*
3.0	0.20	0.24	0.80	-0.90	0.97	0.16
$\to \infty$	0.20	0.20	0	0.20	0.20	0.20

The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms $100(\widehat{W}_{US} - 1)$, and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g} - 1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$\equiv \min_g 100(\widehat{W}_{US,g} - 1)$ and Max.$\equiv \max_g 100(\widehat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s} - 1\right)$. The values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, for each statistic when $\kappa = 1.5$. We provide robustness checks for these numbers in Appendix Tables E.1 and E.2.

Focusing first on the results for our preferred value of $\kappa = 1.5$, the model implies US aggregate welfare gains from the rise of China of 0.22%, with an average gain across groups of 0.27%.[40] The CV is 1.16, and the range is $[-1.42\%, 1.64\%]$, implying a maximum loss that is around 5 times the average gain.[41] While 18 groups lose more than

[39] These standard errors are computed based on the delta method. Each statistic of interest is a function $f(\hat{\beta})$ of our estimated $\hat{\beta}$, and so we compute its standard error as $SE(f(\hat{\beta})) = SE(\hat{\beta})|f'(\hat{\beta})|$, with $SE(\hat{\beta}) = 0.303$ as in column 2 in Table 1, and $f'(\hat{\beta})$ being the numerical derivative computed using simulations.

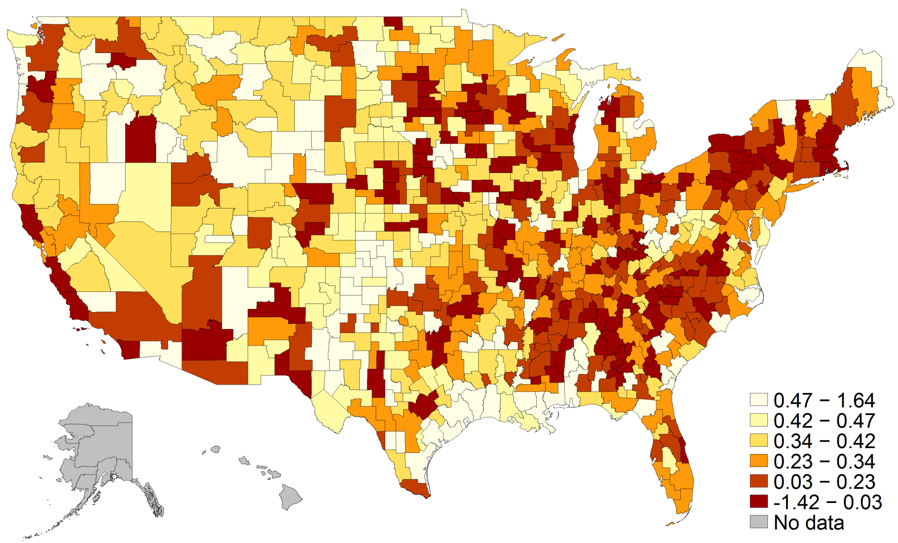
[40] To provide context for this number, Hsieh and Ossa (2016) find welfare gains for the US between 0 and 0.03%. The difference with our results is likely due to the fact that we calibrate Chinese technology growth to fit predicted Chinese exports, whereas Hsieh and Ossa (2016) calculate technological growth based on firm-level data.

[41] The standard errors shown in the table reveal that the aggregate and average results are estimated quite precisely, while this is less so for the results capturing the dispersion of the welfare effects. For example, the maximum loss would be up to 2.12% at the 95% confidence level rather than the estimated 1.41%. To some extent, we will see how this matters for the inequality-adjusted gains from trade by looking

0.5% of their real income, 99 groups gain more than 0.5% of their income. In total, 85% of groups, representing 84% of the population, experience positive gains from the rise of China (see Appendix Figure A.1, panel b).[42]

There is a strong geographical correlation in the gains and losses from the China shock, as is clear from Figure 1, which plots the geographical distribution of the welfare effects from this shock. In the Eastern half of the country, largely excluding the coastal commuting zones, many groups experience below median gains. Particularly in the North East and in Central and Southern Appalachia, there is a strong concentration of commuting zones in the bottom third of the gains distribution.[43]

Figure 1: Geographical distribution of the welfare gains from the rise of China



This figure plots the geographic distribution of $100(\hat{W}_g - 1)$, where $\hat{W}_g$ are the welfare effects for group g in the US from the counterfactual rise of China, for our preferred value of $\kappa = 1.5$.

The distributional impact of the China shock depends on κ, as a lower κ leads to higher dispersion in the gains from trade due to a stronger pattern of worker-level comparative advantage. The simulation results confirm this theoretical prediction, as both

at the case with $\kappa = 1$.

[42]Of course, when a commuting zone experiences positive gains, this does not imply that all workers in that group gain. For instance, workers who stay in a shrinking sector may lose real income. Importantly though, the focus of our model is on group-level average changes in income, not on tracking income changes at the individual level.

[43]Our quantitative analysis assumes that the effect of the China shock on prices is the same across groups. This is consistent with (Bai and Stumpner 2019), who find "no evidence for heterogeneous effects across consumer groups by income or region."

the CV and the difference between maximal and minimal $\hat{W}_{US,g}$ tend to zero as κ approaches infinity (see Table 2). For $\kappa \to 1$, the CV reaches a maximum at 140%, and the range is $[-1.73\%, 2.32\%]$. Table 2 also shows that for $\kappa \leq 3$ there are groups who lose substantially from the rise of China.[44]

5.3 Import Competition and Income

In Section 2.6, we showed that changes in relative income can be approximated by our Bartik measure of import competition: $\ln(\hat{Y}_g/\hat{Y}) \approx \frac{1}{\kappa}\ln\sum_s \pi_{gs}\hat{r}_s = -\frac{1}{\kappa}\ln\hat{I}_g$. We check the accuracy of this approximation for the calibrated China shock by comparing the model-implied values for $\ln(\hat{Y}_g/\hat{Y})$ and $\ln\sum_s \pi_{gs}\hat{r}_s$ across groups in the United States for the impact of the calibrated China shock. As implied by the approximation, the relationship is almost linear, and the slope is virtually undistinguishable from $1/\kappa$ (see Appendix Figures A.4 and A.5).

This finding implies that $\ln\hat{y}_g \approx \ln\hat{y} + \frac{1}{\kappa}\ln\sum_s \pi_{gs}\hat{r}_s$, which is important for two reasons. First, it confirms that $\frac{1}{\kappa}\ln\sum_s \pi_{gs}\hat{r}_s$ (or $-\frac{1}{\kappa}\ln\hat{I}_g$) can serve as an approximate sufficient statistic for a group's welfare change relative to that for the economy as a whole. This is useful because, in contrast to the exact result in Proposition 1, it does not require knowing the group-level employment changes $\hat{\pi}_{gs}$.[45]

Second, we can test this empirical prediction of the model by regressing changes in CZs' average income on $\ln\sum_s \pi_{gs}\hat{r}_s$, instrumented by the ADH shock.[46] In line with the model, trade-induced changes in import-competition lead to strong and statistically significant changes in relative income across groups (see Appendix Table D.8). Although high standard errors on the estimated coefficient prohibit us from making strong inferences for the associated values for κ, the implied value for κ is not signifi-

[44] Appendix Figures A.1 and A.2 visualize how the distributional impact of the China shock diminshes as κ increases, by plotting the full distribution of $\hat{W}_{US,g}$ for different values of κ. To further understand the role of κ, recall that Equation (13) shows how a higher κ directly mitigates the distributional impact of any reallocation, while Appendix Figure A.3 shows that dispersion in $\hat{w}_{US,s}$ across sectors converges to zero as κ increases. Finally, notice also that in the final column 2, κ also indirectly affects the multi-sector ACR term, even though $\hat{T}_{China,s}$ is held constant. This is again because κ affects wage changes in all countries and thereby also the changes in expenditure shares $\hat{\lambda}_{jjs}$.

[45] As in Kovak (2013), the relationship we find between $\ln\hat{y}_g$ and $\ln\sum_s \pi_{gs}\hat{r}_s$ also provides a theoretical foundation for the empirical use of Bartik-style regressors which assign national sectoral changes to groups based on their initial sectoral composition. Relative to Kovak (2013), our model allows for heterogeneous labor and imperfect mobility across sectors.

[46] We employ the same specification we used for our baseline κ estimation (Table 1), except that now the RHS variable is $\ln\sum_s \pi_{gs}\hat{r}_s$ rather than $\ln\hat{\pi}_{NMg}$.

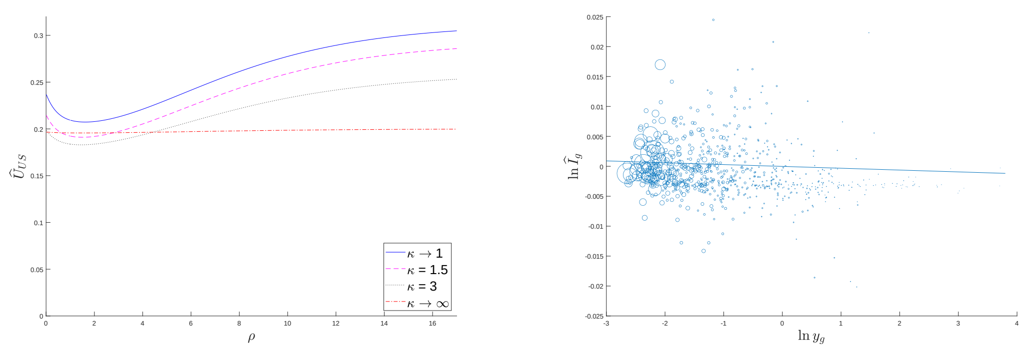
cantly different from our estimated value of $\kappa = 1.5$.

5.4 Inequality-Adjusted Welfare Effect

We summarize the aggregate and distributional welfare effects of the rise of China for the US by computing the inequality-adjusted welfare effect from Equation (19) (see Figure 2a). The consensus in the literature is that plausible values for the coefficient of inequality aversion ρ are between 1 and 3.[47] For these values and for $\kappa = 1.5$, the inequality-adjusted welfare effect of the rise of China is around 0.19%, which is slightly below the inequality neutral welfare gain of 0.22%. This finding is driven by a negative correlation between groups' income and the change in import competition they experience, as is clear from the linear fit between $\ln \hat{y}_g$ and $\ln \hat{I}_g$ in Figure 2b. For higher

Figure 2: Inequality-adjusted welfare effects of the China shock

(a) Inequality-adjusted welfare effects (b) Income and change in import competition



Panel (a) plots the relationship between the inequality-adjusted welfare effects of the rise of China $\hat{U}_{US} \equiv \left(\sum_g \omega_g \hat{W}_g^{1-\rho}\right)^{\frac{1}{1-\rho}}$ and ρ. Here, ρ is the coefficient of relative risk aversion for the agent behind the veil of ignorance and $\omega_g \equiv \frac{l_g (Y_g/L_g)^{1-\rho}}{\sum_h l_h (Y_h/L_h)^{1-\rho}}$ a modified weight for group g. The vertical axis displays $100(\hat{U}_{US}-1)$. Panel (b) plots the relationship between $\ln \hat{I}_g = \ln(\sum_s \pi_{igs} \hat{r}_{is})^{-1}$, our measure for the change in regional import-competition (computed for $\kappa = 1.5$), and the logarithm of a group's average income per worker. The solid line displays the linear fit for this relationship, with each commuting zone weighted by its population size. The size of a circle indicates the population size for that commuting zone.

[47] For instance, using agents' intertemporal elasticity of substitution to estimate the curvature parameter, Lucas 2003 argues that $\rho \approx 1$, while a review of the literature leads Hall (2009) to the conclusion that $\rho = 2$. An alternative approach is to calibrate ρ based on people's aversion to risk. Using an indirect approach based on the labor supply elasticity, Chetty (2006) finds that $\rho < 2$, while more direct estimates based on people's decisions under uncertainty range from $\rho = 1$ in Bombardini and Trebbi (2012) to $\rho \approx 3$ in Paravisini, Rappoport and Ravina (2016).

degrees of inequality aversion, i.e. when $\rho > 3$, $\hat{U}_{US}$ increases monotonically with ρ.[48]

Naturally, higher degrees of inequality aversion put more and more weight on how income changes at the bottom of the income distribution. In the limit as $\rho \to \infty$, only the change in income of the poorest group matters. Interestingly, the groups at the very bottom of the income distribution experience negative changes in import competition, as is clear from Figure 2b. This explains why $\hat{U}_{US}$ is larger than the standard welfare effect for very high values of ρ. Importantly, regardless of the exact value of ρ, $\hat{U}_{US}$ is always positive. Hence, for any degree of inequality aversion, social welfare increases due to the rise of China.

6 Gains from Trade

In this section we compute the aggregate and group-level gains from trade as described in Section 2, i.e., by computing the negative of the proportional gains from a counterfactual move back to autarky. Table 3 summarizes the results. For our estimated value of $\kappa = 1.5$, the aggregate gains from trade with no inequality aversion are 1.56%. As suggested by the theory, the gains from trade decrease with κ, but the effect is small, going from 1.61% for $\kappa = 1$ to 1.45% for $\kappa \to \infty$.

As in the analysis of the China shock, the main effect of κ is on the distribution of the gains from trade across groups, with the CV decreasing from 82% for $\kappa = 1$ to 0 for $\kappa \to \infty$. For our preferred value of $\kappa = 1.5$, the CV is 58%, and the range is [-4.19, 2.97]. The distribution of gains is skewed to the left with a long tail of low gains, but only 6% of the groups lose from trade (see Appendix Figures A.6 and A.7).

As implied by the analysis above (Sections 2.6 and 5.3), our Bartik measure of import competition $I_g \equiv \sum \pi_{gs} \frac{\beta_s}{r_s}$ perfectly ranks groups in terms of winners and losers from trade for all values of κ (see Appendix Figure A.9). The textile industry faces the highest degree of import competition (with $\frac{\beta_s}{r_s} = 1.52$; Appendix Table A.1), so groups particularly specialized in this industry will gain the least. Interestingly, there is a large region with heavy concentration of groups facing particularly strong import-competition - in part due to specialization in the textile industry - centered around the South-Central

[48]The theory does not predict how $\hat{U}_{US}$ changes as function of ρ. Based on the result in equation (20), one could think that the Generalized Mean Inequality (GMI) has implications for how $\hat{U}_{US}$ changes with the power $1-\rho$, but the GMI does not apply to $\hat{U}_{US}$ because the weights ω_g are themselves dependent on the power $1-\rho$.

Table 3: Aggregate and Group-level Gains from Trade

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	1.61	1.65	0.82	-6.98	3.72	1.45
1.5	1.56	1.59	0.58	-4.19	2.97	1.45
	(0.05)	*(0.06)*	*(0.23)*	*(2.54)*	*(0.68)*	*(0)*
3.0	1.51	1.52	0.31	-1.38	2.22	1.45
$\to \infty$	1.45	1.45	0	1.45	1.45	1.45

The first column displays the aggregate gains from trade for the US, in percentage terms $(100(1-\widehat{W}_{US}))$ and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g 1-\widehat{W}_{US,g})$. Here, $\widehat{W}_{US}$ and $\widehat{W}_{US,g}$ are the aggregate and group-level welfare change from a return to autarky for the US. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$=\min_g 100(1-\widehat{W}_{US,g})$ and Max.$=\max_g 100(1-\widehat{W}_{US,g})$, respectively. The final column displays the multi-sector ACR term $100\left(1-\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s}\right)$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta}=1/\hat{\kappa}$, for each statistic when $\kappa=1.5$. Appendix Table E.3 provides a robustness check with sector-specific θ_s values.

and Southern Appalachia regions (see Appendix Figure A.8).

Appendix Figure A.10 shows that for $\rho > 0$, the inequality-adjusted gains from trade are higher than the standard gains, $IGT > GT$, and that IGT increases with ρ. This is a reflection of the fact that, as illustrated in Appendix Figure A.11, most groups at the bottom of the income distribution experience negative degrees of import-competition ($\ln I_g < 0$), due to their specialization in the non-manufacturing sector.[49]

7 Extensions

7.1 Intermediate Goods

Extending the model to allow for an input-output structure is potentially important because a significant share of the value of production in a sector originates from other sectors, and taking this into account may matter for the effects of trade on wages $\hat{w}_{is}$ and welfare across groups. The labor supply of the model is exactly as in the baseline model (see Equation (3)). On the trade side, the model is identical to Caliendo

[49] Note however that there is no strong systematic relationship between income and trade: in a regression of $\ln I_g$ on $\ln y_g$, employing population weights, the R^2 is only 4.5%.

and Parro (2015), except that wages are now sector-specific (i.e. wages are w_{is} instead of w_i). Hence, trade shares and the price indices are as in equations (1) and (2), but instead of w_{is} we now have c_{is}, where c_{is} is given by $c_{is} = w_{is}^{1-\gamma_{is}} \prod_k P_{ik}^{\gamma_{iks}}$, with $P_{js} = \zeta_s^{-1} \left(\sum_i T_{is} \left(\tau_{ijs} c_{is} \right)^{-\theta_s} \right)^{-1/\theta_s}$. The terms γ_{iks} are Cobb-Douglas input shares: a share γ_{iks} of the output of industry s in country i is used buying inputs from industry k, and $1 - \gamma_{is}$ is the share spent on labor, with $\gamma_{is} = \sum_k \gamma_{iks}$. Given this structure, we derive in Appendix F the following expression for a group's welfare change:

Proposition 3. *Given some trade shock, the percentage change in the real income of group g in country i is given by*

$$\hat{W}_{ig} = \prod_{s,k} \hat{\lambda}_{iik}^{-\beta_{is}\widetilde{a}_{isk}/\theta_s} \cdot \prod_{s,k} \hat{\pi}_{igk}^{-\beta_{is}\widetilde{a}_{isk}(1-\gamma_{ik})/\kappa_{ig}} \tag{24}$$

where $\widetilde{a}_{isk}$ is the typical element of matrix $\left(I - \Upsilon_i^T\right)^{-1}$ with $\Upsilon_i \equiv \{\gamma_{iks}\}_{k,s=1,\ldots,S}$.

For this extended model, for $\kappa = 1.5$ we find a gain from the China shock of 0.37% and gains from trade of 2.86% (see Table 4).[50] These gains are higher than in the baseline model, which is in line with the findings in Costinot and Rodríguez-Clare (2014), who explain that the input-output loop in this model leads to an additional round of welfare gains from a given trade shock.

The distributional effects of both the China shock and opening to trade are mitigated compared to the baseline model. The CV is lower in both cases, and the range of group-level welfare effects is slightly more compressed. Still, the correlation between the group-level welfare effects in the two versions of the model is 95.3% for the China shock and 96.9% for the gains from trade (see Appendix Figure F.1).

7.2 Imperfect Substitutes

In this extension we introduce two worker types, college and non-college educated workers, so that now there are twice as many groups as in the baseline model (two for each commuting zone). We also allow for the possibility that college and non-college labor are imperfect substitutes, leading to an endogenous college premium that will be

[50] Since the labor supply side of the model is unaltered compared to the baseline model, the κ estimation from Section 4 remains valid. This is why we continue to use the same values for κ in the quantification of this model.

Table 4: Counterfactual analysis for the model with intermediates

	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	ACR
Rise of China	0.37	0.43	0.58	-1.07	1.27	0.29
	(0.02)	*(0.03)*	*(0.14)*	*(0.39)*	*(0.41)*	*(0.01)*
Gains from Trade	2.86	2.95	0.26	-1.34	4.06	2.74
	(0.05)	*(0.09)*	*(0.11)*	*(1.84)*	*(0.59)*	*(0)*

The tables show summary statistics for welfare effects of US groups for the model with an input-output structure for $\kappa = 1.5$. The first two rows show results for the counterfactual rise of China, and the final two rows show results for group-level gains from trade. The first column displays the aggregate welfare effect for the US, in percentage terms $100(\widehat{W}_{US} - 1)$ and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g} - 1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$=\min_g 100(\widehat{W}_{US,g} - 1)$ and Max.$=\max_g 100(\widehat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_{s,k}\hat{\lambda}_{US,US,k}^{-\beta_{US,s}\tilde{a}_{US,sk}/\theta_s} - 1\right)$. For the gains from trade we simulate the return to autarky and report the negative of the above statistics for the obtained counterfactual results. Rows 2 and 3 have standard errors, computed using the delta method and the numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, in parentheses. Appendix Table F.1 has results for other κ values.

affected by trade, similar to the Hecksher-Ohlin model. On the labor supply side, the model remains identical to the baseline model, except that employment shares now have an additional subscript for labor of type $m = C, NC$, for college and non-college workers respectively. On the labor demand side, assuming that efficiency units of college and non-college educated workers enter a CES production function with elasticity of substitution η, then wages satisfy $w_{ims} = \frac{\chi_{ims} Y_{is}}{\mathcal{Z}_{ims}}$, where $\chi_{ims} = \frac{\psi_{ims} w_{ims}^{1-\eta}}{\psi_{iCs} w_{iCs}^{1-\eta} + \psi_{iNCs} w_{iNCs}^{1-\eta}}$ is the share of labor type m in total costs in sector s in country i and ψ_{ims} is a corresponding labor-demand shifter.

For the equilibrium analysis, we have market clearing conditions for labor of each type in each industry and country, $ELD_{ims} = 0$, with

$$ELD_{ims} = \chi_{ims} \sum_j \lambda_{ijs} \beta_{js} (Y_j + D_j) - \sum_g w_{ims} \mathcal{Z}_{imgs}.$$

This constitutes a system of equations that we can use to solve for wages, $\{w_{ims}\}$. The following proposition shows the implications for the counterfactual changes in welfare:

Proposition 4. *Given some shock to trade costs or foreign technology levels, the percent-*

age change in the real wage of group mg *in country* i *is given by*

$$\hat{W}_{img} = \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta_s} \cdot \prod_s \hat{\pi}_{imgs}^{-\beta_{is}/\kappa_{ig}} \cdot \prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}. \tag{25}$$

Compared to Proposition 1, we now have the extra term $\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}$, which captures the welfare effect of the change in the college premium. If $\kappa_{ig} \to \infty$ for all ig then the model collapses to the Hecksher-Ohlin model with gravity as analyzed for example in Burstein and Vogel (2011) or Costinot and Rodríguez-Clare (2014). If $\kappa_{ig} \to 1$ for all ig then there is no scope for reallocation across sectors within each group-labor type cell, and so all wage changes are at the sector level, $\hat{w}_{iCs} = \hat{w}_{iNCs}$, implying that $\hat{\chi}_{iCs} = \hat{\chi}_{iNCs} = 1$, as in the case considered in the next subsection.

For our quantitative analysis, we set $\eta = 1.6$, as in Katz and Murphy (1992), and similar to Krusell, Ohanian, Ríos-Rull and Violante (2000) and Acemoglu and Autor (2011). How does lowering η from infinity (i.e., perfect substitutes) to this value $\eta = 1.6$ affect the welfare effects of trade? It is instructive to start by focusing on the results under $\kappa \to \infty$, which implies that there are no changes in the middle, "Roy" term in Equation (25), and the only source of heterogeneity is between college and non-college workers due to changes in the college premium as captured by $\prod_s (\hat{\chi}_{iCs}/\hat{\chi}_{iNCs})^{-\beta_{is}/(\eta-1)}$. As shown in Table 5, the rise of China decreases the college premium by 0.03 percent, while overall trade increases it by 1 percent. The finding that the college premium falls slightly as a consequence of the rise of China is surprising, but it is explained by a large induced contraction of the electrical and optical equipment industry, which has the second highest cost share of college workers. In contrast, opening up to trade leads to a very large contraction of the textile sector, which has a low cost share of college workers.

As discussed above, moving from $\kappa \to \infty$ to $\kappa = 1.5$ brings the Roy term to life and softens the effect of trade on the college premium, which now falls by merely 0.01 percent with the rise of China, and increases by only 0.1 percent with overall trade.[51] In the last row of Table 5 we also show the results with $\kappa = 1.5$ and $\eta \to \infty$, i.e. where

[51] In Appendix Section G we also estimate a separate κ_M for college and non-college workers, and examine how this influences the welfare results. Our point estimate for κ_M is somewhat lower for college workers (see Table G.1), and this κ value slightly increases the college premium for both counterfactual scenarios (see Table G.4). In general though, the welfare results are very close to those for the case with a common $\kappa = 1.5$.

Table 5: College and non-college workers as imperfect substitutes

(a) The rise of China

	$\widehat{W}_{US}$	Mean	CV	Roy gains	College premium
$\kappa \to \infty; \eta = 1.6$	0.15	0.15	0.15	0.00	-0.03
$\kappa = 1.5; \eta = 1.6$	0.22	0.32	0.81	0.07	-0.01
	(0.02)	*(0.05)*	*(0.2)*	*(0.03)*	*(0.02)*
$\kappa = 1.5; \eta \to \infty$	0.22	0.32	0.77	0.07	0.00

(b) Gains from trade

	$\widehat{W}_{US}$	Mean	CV	Roy gains	College premium
$\kappa \to \infty; \eta = 1.6$	1.45	1.48	0.14	0.00	1.00
$\kappa = 1.5; \eta = 1.6$	1.56	1.66	0.44	0.11	0.10
	(0.05)	*(0.08)*	*(0.16)*	*(0.05)*	*(0.09)*
$\kappa = 1.5; \eta \to \infty$	1.56	1.55	0.55	0.11	0.00

The table presents the welfare effects for trade shocks for the model with college and non-college workers as potentially imperfect substitutes. Panel (a) shows results for the rise of China and panel (b) for the gains from trade. The first column provides the parameter values for the simulation results in that row, where $\eta \to \infty$ implies that all labor is perfectly substitutable. Column 2 display the aggregate welfare effect for all workers in the US, in percentage terms $100(\widehat{W}_{US,m} - 1)$, column 3 shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,mg} - 1)$, and column 4 the coefficient of variation (CV). The fifth column shows the aggregate Roy gains $100(\sum_{mg}\left(\frac{Y_{img}}{Y_i}\right)\prod_s \hat{\pi}_{imgs}^{-\beta_{is}/\kappa} - 1)$, and the final column the change in the college premium $100(\prod_s (\hat{\chi}_{iCs}/\hat{\chi}_{iNCs})^{-\beta_{is}/(\rho-1)} - 1)$. The China shock is separately calibrated for the parameter values in each row. For the gains from trade, we simulate the return to autarky, and for that simulation report the negative of the aggregate and mean welfare effect. Standard errors for the benchmark results in the second row, computed using the delta method and the numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, in parentheses. Appendix Tables G.2 and G.3 have results split by education type when $\eta = 1.6$.

education groups are perfect substitutes. Comparing across perfect and imperfect substitutes, we see very similar results for the effects of the rise of China, and slightly larger mean and lower CV for the gains from trade under imperfect substitutes than perfect substitutes.

7.3 Heterogeneity within commuting zones and trade costs

We can easily introduce more worker types within a commuting zone, not only allowing for heterogeneity in education (as in the previous subsection), but also for differences in age and gender. Here we revert to the baseline assumption of perfect substitutability in the labor input from different worker types, but allow each worker type m to have a potentially different value for κ_m. Moreover, we can also relax the assumption that all goods are costlessly tradable across CZs in the United States. This we do by assuming that there are arbitrary trade costs across U.S. states but no trade costs within states, which amounts to treating each U.S. state as if it were a separate country.[52]

Given the presence of different worker types, we can separately estimate κ_m for each m, employing our baseline regression specification (23). However, due to the within-U.S. trade costs, non-manufacturing wages $\hat{w}_{NMt}$ now vary by U.S. state, which requires the addition of state-by-period fixed effects to our estimation. As discussed in detail in Online Appendix H, the new estimates for κ_m turn out quite similar to those in the baseline.

Although we now have four different groups within each commuting zone, we find that 85% of the variance in the simulated welfare changes across groups is explained by the commuting zone to which they belong. This high share arises from the high correlation in π_{gs} across worker types within a CZ. Hence, the baseline model already captures this driver of the distributional effects fairly well. Still focusing on the distributional effects, we find that the presence of trade costs between U.S. states tends to increase dispersion in the welfare effects compared to the baseline model.[53] This is mainly due to the ACR welfare term varying across states.

[52]The quantitative analysis now requires sector-level production and trade data at the level of U.S. states and the other countries, which we borrow from Rodríguez-Clare, Ulate and Vásquez (2019). They build this dataset using data from the Import and Export Merchandise Trade Statistics (from the U.S. Census Bureau), the Commodity Flow Survey (CFS), and the Regional Economic Accounts of BEA Commodity Flow Service. In principle, the model could allow for trade costs between geographical units at an even more disaggregated level, but we are not aware of reliable data at lower levels of disaggregation that cover the entire United States.

[53]This finding comes out clearest in a version of the model where we only add trade costs and don't consider different groups within each CZ, such that we have a clean comparison with the results of the baseline model. The results for this version of the model are discussed in detail in the 2020 version of this paper.

7.4 Mobility across commuting zones

In Online Appendix J, we show how to extend our analysis to allow for mobility of workers across commuting zones. Unfortunately, the data requirements are severe, and we have left this analysis for future work. We note, however, that ADH find insignificant effects of the China shock on population shifts at the commuting zone level, and hence we expect that adding mobility in a way that is consistent with their evidence should not have sizable effects on our results.[54]

In addition to migration, an alternative form of mobility across regions arises from changes in commuting patterns, as in Monte, Redding and Rossi-Hansberg (2018). Extending our model to allow for commuting and exploring the impact of the China shock in that setting is an interesting task but beyond the scope of this paper. Here we simply note that, as shown in Section 5, the regions that are most negatively affected by the China shock tend to be geographically concentrated, and so commuting is unlikely to serve as a significant margin of adjustment.

8 Employment Effects

In this section we extend the model so that total employment is endogenous both because of the possibility of home production, modeled as in Caliendo et al. (2019), and because of involuntary unemployment due to search and matching frictions, modeled as in Kim and Vogel (2021). We then estimate the model and report the group-level and aggregate effects of the China shock.

8.1 Model

There are three periods. In the first one workers learn about their productivity in home production and formal employment and decide whether to seek formal employment based on the expected income in each of those options. In the second period work-

[54] Caliendo et al. (2019) and Adão et al. (2020) allow for mobility across both sectors and regions and quantify the effect of the China shock at the level of US states rather than commuting zones (CZs). Their results also point to weak effects of trade shocks on mobility across regions. Relatedly, the reduced form evidence on the regional migration response to trade shocks in the U.S. is mixed. For instance, Greenland, Lopresti and McHenry (2019) find a substantial impact on CZs' population growth arising from the granting of Permanent Normal Trade Relations to China, primarily driven by adjustments among the younger cohorts. In contrast, Choi, Kuziemko, Washington and Wright (2020) find no local US migration response in the US after the introduction of NAFTA.

ers who chose formal employment learn about their sector-specific productivity realization and decide in which sector to apply for work. This decision depends on the probability of employment and the wage per efficiency unit in each sector. In the third period, workers learn whether they are employed or unemployed.[55]

For each worker, productivity in home production is z_{HP} while productivity in sector s is $z_F z_s$. As in Section 2.1, the productivity terms z_s are drawn independently from a Fréchet distribution with shape and scale parameters κ and A_{igs}, respectively. In addition, z_{HP} and z_F are drawn independently from a Fréchet distribution with shape and scale parameters μ, A_{igHP} and A_{igF}, respectively. Finally, firms can post vacancies at a cost of c in terms of the final good (i.e., aggregating across sectors in the same way that consumers do) and capture an exogenous share $1-\nu$ of the value generated from a match. Here, total sector-level matches (M_{igs}) are a Cobb-Douglas function of vacancies (V_{igs}) and labor supply (L_{igs}): $M_{igs} = A_{igM} V_{igs}^{\alpha} L_{igs}^{1-\alpha}$, with $\alpha \in (0,1)$.[56]

With free entry of firms to posting vacancies in each sector, in equilibrium we must satisfy the zero-profit condition

$$cV_{igs} = (1-\nu)\omega_{is} e_{igs} \mathcal{Z}_{igs} \tag{26}$$

for all s, where e_{igs} is the employment rate ($e_{igs} \equiv M_{igs}/L_{igs}$) in sector s, ω_{is} the real wage in sector s, and $\mathcal{Z}_{igs}$ the total efficiency units of labor supplied to sector s.[57] The results of Section 2.1 still apply so that we have $\omega_{is}\mathcal{Z}_{igs}/L_{igs} = \xi\Phi_{ig}\bar{z}_{igF}$ and $L_{igs} = \pi_{igs}L_{igF}$, with π_{igs}, Φ_{ig} and ξ as in Section 2.1 (except with $\nu\omega_{is}e_{igs}$ now playing the role of w_{is}) and where L_{igF} is the number of workers seeking formal employment and $\bar{z}_{igF} \equiv \frac{\mathcal{Z}_{igF}}{L_{igF}}$ is the corresponding average efficiency units per worker. Combining the expressions for the matching function, the zero-profit condition, the employment rate

[55] An alternative approach is to assume a two-period structure, with a nested Fréchet distribution for productivity draws in home production and in each of the formal sectors. The problem with this specification is that it would require the elasticity of substitution between home production and formal employment to be lower than the one across formal sectors, which is not what the data implies.

[56] Our theoretical results remain valid if the parameters α, μ, κ, ν and c vary across groups. Thus, as in Section 2, we could allow these parameters to vary across groups and write them with the ig subscript. However, here we choose not to do that to ease the notational burden. In any case, when we come to estimation, we will need to assume that α, μ and κ are common across groups in the United States.

[57] We have assumed here that unemployment goes along with no income, so that the surplus of a match is just $\omega_{is}z_s z_F$. We could instead assume that there are unemployment benefits financed from a common tax rate on employed workers. Since being employed is randomly determined, and assuming that the tax rate is common across sectors, these benefits have no distortive effects, and all our results remain valid.

and revenue per applicant, we get that the employment rate is common across sectors, $e_{igs} = e_{ig}$ for all s, and is given by

$$e_{ig} = A_{igM}^{\frac{1}{1-\alpha}} \left(\frac{(1-\nu)\xi}{c} \right)^{\frac{\alpha}{1-\alpha}} \left(\Phi_{ig} \bar{z}_{igF} \right)^{\frac{\alpha}{1-\alpha}} . \tag{27}$$

The result that the employment rate is common across sectors depends of course on our assumption of no cross-sector variation in ν, α, and c within a group.

The only remaining task is to solve for L_{igF} and $\bar{z}_{igF}$. Since workers make these decisions based on the expected value of formal employment, $\eta\nu e_{ig}\Phi_{ig}$, then we know from the standard Fréchet algebra that $L_{igF} = \pi_{igF} L_{ig}$, with

$$\pi_{igF} = \frac{A_{igF} \left(\xi\nu e_{ig}\Phi_{ig} \right)^{\mu}}{A_{igHP}\omega_{iHP}^{\mu} + A_{igF} \left(\xi\nu e_{ig}\Phi_{ig} \right)^{\mu}}, \tag{28}$$

where ω_{iHP} is the exogenous real wage per efficiency unit in home production. Expected welfare (and average real income among all workers) is

$$W_{ig} = \tilde{\xi} \left(A_{igHP}\omega_{iHP}^{\mu} + A_{igF} \left(\xi\nu e_{ig}\Phi_{ig} \right)^{\mu} \right)^{1/\mu} . \tag{29}$$

where $\tilde{\xi} \equiv \Gamma(1 - 1/\mu)$. By the properties of the Fréchet distribution, this is also the average real income among all workers choosing formal employment. Applying the same logic as in Section 2.1, we can show that $W_{ig} = \xi\nu e_{ig}\Phi_{ig}\mathcal{Z}_{igF}/L_{igF}$, and hence $\bar{z}_{igF} \equiv \frac{\mathcal{Z}_{igF}}{L_{igF}} = \frac{W_{ig}}{\xi\nu e_{ig}\Phi_{ig}}$. This implies that

$$e_{ig} = A_{igM} \left(\frac{(1-\nu)}{\nu c} \right)^{\alpha} W_{ig}^{\alpha}. \tag{30}$$

We assume that parameters are such that the solution to this equation entails $e_{ig} \in (0,1)$. The equilibrium system to solve for all wages is very similar to the one for the baseline model (see Online Appendix I.1)

Proposition 5. *Given some trade shock, the percentage change in the real income of group g in country i is given by*

$$\hat{W}_{ig} = \left(\pi_{igHP} + (1 - \pi_{igHP})\hat{e}_{ig}^{\mu}\hat{\Phi}_{ig}^{\mu} \right)^{(1/\mu)}, \tag{31}$$

where $\hat{\Phi}_{ig}$ captures country and group-level gains from specialization

$$\hat{\Phi}_{ig} = \prod_{s \in F} \hat{\lambda}_{iis}^{-\frac{\beta_{is}}{\theta_s}} \prod_{s \in F} \hat{\pi}_{igs}^{-\frac{\beta_{is}}{\kappa}},$$

and where the change in the employment rate comes from the solution to

$$\hat{e}_{ig}^{\mu/\alpha} = \pi_{igHP} + (1 - \pi_{igHP})\, \hat{e}_{ig}^{\mu} \hat{\Phi}_{ig}^{\mu}. \tag{32}$$

It is easy to verify that a trade shock leads to a change in employment in the same direction as in Φ_{ig}, so that $\hat{e}_{ig} < 1$ if $\hat{\Phi}_{ig} < 1$ and $\hat{e}_{ig} > 1$ if $\hat{\Phi}_{ig} > 1$.

Intuitively, a negative trade shock leads to a decline in the real wage, which makes posting vacancies less profitable because the cost is in terms of the final good and the benefit is in terms of the nominal wage. Via the zero-profit condition, this leads to fewer posted vacancies and a higher unemployment rate, amplifying the effect of trade shocks on welfare. We can see this most clearly if we ignore home production by setting $\pi_{igHP} = 0$. In that case we would have $\hat{e}_{ig} = \hat{\Phi}_{ig}^{\frac{\alpha}{1-\alpha}}$ and hence $\hat{W}_{ig} = \Phi_{ig}^{\frac{1}{1-\alpha}}$, implying an amplification of trade shocks on welfare by the factor $\frac{1}{1-\alpha} > 1$.[58]

In contrast, home production softens the effect of trade shocks on welfare. This happens first because workers have the option to engage in home production, where the real wage is not affected by the trade shock, and second because the decline in labor supply reduces the effect of the trade shock on the unemployment rate.[59] Thus, as emphasized by Kim and Vogel (2020), although both home production and frictional unemployment imply that a negative trade shock lowers employment, they have opposite effects on the welfare effects of a trade shock: home production serves as an efficient adjustment mechanism that mitigates the effect whereas frictional unemploy-

[58]Amplification through endogenous unemployment arises in a similar way as with an input-output loop: whereas the factor of amplification there is the inverse of the labor share in the production of final goods, here it is the inverse of the labor share in the production of matches, i.e., $1/(1-\alpha)$. In fact, if we had a single sector then the model above would be isomorphic to the Eaton and Kortum (2002) model with an input-output loop where final output is used together with labor to produce final goods according to a Cobb-Douglas production function with labor share $1 - \alpha$.

[59]To understand this second effect, we can log-linearize Equation (32) around $\hat{\Phi}_{ig} = 1$, which implies

$$\frac{d \ln \hat{e}_{ig}}{d \ln \hat{\Phi}_{ig}} = \frac{\alpha}{1-\alpha} \left(\frac{1 - \pi_{igHP}}{1 + \frac{\alpha}{1-\alpha} \pi_{igHP}} \right).$$

This implies that $\frac{d \ln \hat{e}_{ig}}{d \ln \hat{\Phi}_{ig}}|_{\pi_{igHP} > 0} < \frac{d \ln \hat{e}_{ig}}{d \ln \hat{\Phi}_{ig}}|_{\pi_{igHP} = 0}$.

ment amplifies it.[60]

8.2 Estimation

Dropping the country subscript, we start from the fact that if W_g is real average income among workers in the labor force, then average nominal income among employed workers is $y_g = W_g P/e_g$. Combining this with Equations (29) and (30), we obtain

$$\ln \hat{y}_g = \ln \hat{P} + \frac{1-\alpha}{\alpha} \ln \hat{e}_g - \ln \left(\hat{A}_g^M\right)^\alpha, \tag{33}$$

where without loss of generality we have assumed that $\hat{c} = \hat{\nu} = 1$. Next, combining $y_g = W_g P/e_g$ with Equations (29) and (28), and using $\pi_{gHP} = 1 - \pi_{gF}$ yields

$$\ln\left(\hat{e}_g \hat{y}_g\right) = \ln\left(\hat{P}\hat{\omega}_{HP}\right) - \frac{1}{\mu} \ln \hat{\pi}_{gHP} + \ln \hat{A}_{gHP}. \tag{34}$$

Finally, combining $y_g = W_g P/e_g$ with Equations (29) and (28), and proceeding as in Section 4 to use $\pi_{gNM} = \frac{A_{gNM}\omega_{NM}^\kappa}{\Phi_g^\kappa}$, we get

$$\ln\left(\hat{y}_g \hat{\pi}_{gF}^{1/\mu}\right) = \ln\left(\hat{P}\hat{\omega}_{NM}\right) - \frac{1}{\kappa} \ln \hat{\pi}_{gNM} + \ln\left(\hat{A}_{gF}^{1/\mu} \hat{A}_{gNM}^{1/\kappa}\right). \tag{35}$$

Equation (35) is analogous to Equation (21), with the difference that now the dependent variable is the log of $\hat{y}_g \hat{\pi}_{gF}^{1/\mu}$ rather than the log of $\hat{y}_g$. The reason for the difference is that now we need to take into account that workers can mitigate the effect of a shock through changes in labor force participation as captured by $\hat{\pi}_{gF}^{1/\mu}$. Equation (34) is also quite similar: all else equal, a higher $\hat{\pi}_{gHP}$ leads to a lower expected income $(\hat{e}_g \hat{y}_g)$ with elasticity $1/\mu$. Finally, Equation (33) comes from the fact that an increase in the real income of employed workers goes along with an increase in the employment rate with elasticity $\alpha/(1-\alpha)$.

We use Equations (33)-(35) to estimate α, μ and κ using a standard GMM approach,

[60] One could imagine that frictional unemployment matters for the transmission of trade shocks to welfare because of the inefficiency in vacancy posting whenever the Hosios condition (i.e., $1 - \nu = \alpha$, see Hosios (1990)) is not satisfied. This is not the case, however, as revealed by the fact that the amplification above is not dependent on the difference between $1 - \nu$ and α. The reason that this inefficiency is irrelevant for the comparative statics of welfare is that the shock does not affect the share of final output that is used for vacancy posting, which is fixed at $1 - \nu$ given the zero-profit condition.

exploiting the cross-equation restriction on $1/\mu$ in equations (34) and (35).[61] We employ our standard instrumental variables Z_g (different types of CZ-group-level China shocks or the Bartik instrument). As a natural extension of the identifying assumption in our baseline estimation, we assume that Z_g is uncorrelated to the vector of error terms ϵ_g (i.e. $\mathbb{E}(Z_g' \epsilon_g) = 0$). Intuitively, this means that our instruments are uncorrelated with any group-level shocks that could affect earnings or employment (i.e. unobserved productivity and labor supply/demand shocks).

We estimate this model using an extended version of our baseline data, which includes group-level employment and labor force participation rates. For this exercise, individuals are classified under home production when they are not in the labor force. The results from our estimation are shown in Table 6, with each column representing a separate estimation based on our four instruments. Our estimates for κ are slightly lower than those from the baseline model, while those for α range between 0.2 and 0.5, which is consistent with estimates reviewed in Petrongolo and Pissarides (2001). In the following subsection, we show how these new estimates translate into aggregate and distributional welfare effects.

8.3 Quantitative Implications

Based on the estimation results in the previous subsection, we now explore the quantitative implications of the model with $\kappa = 1.5$ and home production and unemployment with $\alpha = 1/3$ and $\mu = 2.5$. We proceed as in the previous sections by calibrating the China shock and then using the model to quantify its effects across commuting zones in the U.S.

As expected from the theory discussion and the estimation results, commuting zones more exposed to the China shock experience declines in employment both due to an

[61] Specifically, we estimate the following system of equations

$$\begin{pmatrix} \ln \hat{y}_g \\ \ln (\hat{e}_g \hat{y}_g) \\ \ln \hat{y}_g \end{pmatrix} = \underbrace{\begin{pmatrix} x_g & 0 & 0 \\ 0 & x_g & 0 \\ 0 & 0 & x_g \end{pmatrix}}_{\equiv X_g} \Gamma + \underbrace{\begin{pmatrix} \ln \hat{e}_g & 0 & 0 \\ 0 & \ln \hat{\pi}_{gHP} & 0 \\ 0 & \ln \hat{\pi}_{gF} & \ln \hat{\pi}_{gNM} \end{pmatrix}}_{\equiv W_g} \beta + \underbrace{\begin{pmatrix} \epsilon_g^M \\ \epsilon_g^{HP} \\ \epsilon_g^{NM} \end{pmatrix}}_{\equiv \epsilon_g},$$

where $\beta = (\frac{1-\alpha}{\alpha}, -1/\mu, -1/\kappa)'$, X_g is the set of ADH controls from our baseline estimation (including intercepts that are not constrained by any cross-equation restriction), and the vector ϵ_g of error terms (which differ from $\left(\ln \left(\hat{A}_g^M\right)^\alpha, \ln \hat{A}_{gHP}, \ln \left(\hat{A}_{gF}^{1/\mu} \hat{A}_{gNM}^{1/\kappa}\right)\right)$ due to the inclusion on the ADH controls).

Table 6: GMM Estimation of the Model with Unemployment and Labor Force Participation

	(1)	(2)	(3)	(4)
$\ln \hat{E}$	0.985*	2.398*	4.389	1.002**
	(0.563)	(1.456)	(3.199)	(0.408)
$\ln \hat{\pi}_{HP}$	-0.312**	-0.519	-0.760	-0.362***
	(0.122)	(0.369)	(0.708)	(0.104)
$\ln \hat{\pi}_{NM}$	-0.633**	-0.972**	-1.001**	-0.834**
	(0.291)	(0.409)	(0.409)	(0.258)
Implied α	0.504	0.294	0.186	0.499
Implied μ	3.209	1.927	1.316	2.759
Implied κ	1.579	1.029	0.999	1.199
Observations	1444	1444	1444	1444
Import Penetration	Other (lagged)	Other (no lag)	US (no lag)	US Bartik

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the state level, and we weight by 1990 commuting zone populations. All log changes for the 2000–2007 period are multiplied by (10/7) to obtain decade-equivalent changes. Home production defined as not in the labor force (NiLF).

increase in unemployment and a decline in labor force participation (see Online Appendix Table I.5). Interestingly however, overall employment increases because the China shock leads to an increase in the average real wage across US commuting zones. This again shows how the reduced-form results in ADH are indicative of relative effects across communting zones differentially exposed to the China shock, but cannot tell us about the average effect, which here is generated via simulation from the calibrated general equilibrium model.

Turning to welfare, there are three ways in which search and matching and home production affect the welfare effects of trade shocks. First, search and matching leads to amplification, roughly by increasing welfare effects by 50 percent. Second, once we introduce home production, we change the notion of welfare, where the part of welfare that comes from home production is not affected by trade, which dampens welfare changes roughly by the share of employment in home production. Finally, allowing for movement in and out of home production leads to more favorable welfare effects since people can go into home production if real wages decrease (dampening the effect of the shock) and come out of home production if real wages increase (amplifying the positive effect of the shock).[62]

We see these effects play out as expected in Table 7. The first row shows the baseline, the second row adds endogenous unemployment via search and matching, the third row adds home production but with $\mu = 1$, and finally the last row shows the results for the full model with the calibrated value of μ. As we move from $\mu = 1$ to $\mu = 2.5$, the effect of the China shock becomes slightly more positive and there is less dispersion in the welfare effects. We also see that the gains from trade slightly fall with μ, which is because the effect of the return to autarky is less negative. Overall however, the welfare results in the full model with endogenous unemployment and labor-force participation are not significantly different from those in the baseline model.

Table 7: Welfare effects with and without frictional unemployment and home production

	The rise of China			**Gains from trade**		
	$\widehat{W}_{US}$	Mean	CV	$\widehat{W}_{US}$	Mean	CV
no SAM, no HP	0.215	0.270	1.160	1.557	1.586	0.579
with SAM, no HP	0.324	0.407	1.145	2.325	2.367	0.567
with SAM & HP, $\mu = 1$	0.211	0.263	1.167	1.533	1.556	0.585
with SAM & HP, $\mu = 2.5$	0.212	0.264	1.151	1.524	1.545	0.575

The first three columns display the welfare effects for the counterfactual rise of China, while the final three columns show the gains from trade. Columns 1 and 4 displays, for the relevant worker type, the aggregate welfare effect in percentage terms $100(\widehat{W}_{US} - 1)$, and columns 2 and 5 show the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g} - 1)$. The third column shows the coefficient of variation (CV). For the gains from trade, we simulate the return to autarky, and for that simulation report the negative of the above statistics. Full results are available in Online Appendix Tables I.5 and I.6. We compute standard errors for these counterfactual exercises in Appendix Table I.7.

[62]There may be a negative feedback effect here since a more elastic labor supply may also soften the effect of the shock on equilibrium real wages, but one would expect that such negative feedback effects would not overturn the mechanism described here for how $\mu > 0$ affects welfare in the counterfactual analysis.

This version of the model generates predictions for the impact of the China shock on income, unemployment and employment sectoral shares. As an analysis of model fit, we regress actual changes in the data for the period 2000-2007 on simulated changes for the employment rate, $\hat{e}_g$ and the share of employment in home production, $\hat{\pi}_{gHP}$. We find that, for both these variables, there is a positive and strongly significant relation between the simulated and the actual changes (see Appendix Table A.2, columns 1 and 2). Hence, qualitatively our model matches the patterns in the data.[63] [64]

Quantitatively, the model does well for the share of employment in home production, with an estimated coefficient of 1.13 – insignificantly different from unity. The model underpredicts the changes in the employment rate, with a coefficient of 2.68, but this underprediction almost entirely disappears when we increase the employment rate elasticity α from 1/3 to 1/2, which is consistent with our estimation results in Table 6.[65]

9 Conclusion

We think of this paper as establishing a bridge between two separate literatures. On the one hand, a recent wave of empirical work exemplified most prominently by Autor et al. (2013) has shown that trade shocks have important distributional implications, but without deriving welfare effects. On the other hand, research surveyed in Costinot and Rodríguez-Clare (2014) shows how to quantify the welfare effects of trade for a wide class of gravity models, but with so far little to say about distributional implications.[66] In this paper we extend the multi-sector gravity model of trade to allow for heterogeneous labor as in Roy (1951) and Lagakos and Waugh (2013) and with multiple groups

[63] Our model predictions also qualitatively match the patterns in the data for changes in income and the employment share in manufacturing. However, our one factor model does not account for changes in the labor share of revenue, which matters for the quantitative fit (Galle and Lorentzen 2021).

[64] As a sanity check, we also regress the model's predicted changes in employment and income per worker on ADH's China shock IV (see Appendix Table A.3). As expected, the China shock is positively associated with the predicted changes in home production shares, and negatively with changes in the employment rate and income per worker. All these correlations are strongly significant.

[65] When we change this elasticity from 1/3 to 1/2, the coefficient drops to 1.44, which is then also insignificantly different from unity (see column 3). In the quantification, we conservatively set $\alpha = 1/3$ to stay closely in line with the values in the literature.

[66] The only mention of distributional implications in Costinot and Rodríguez-Clare (2014) is in regards to Burstein and Vogel (2017), which is limited to quantifying welfare effects among low and high skilled workers.

of ex-ante identical workers as in Burstein et al. (2019), and use the resulting framework to derive a simple approach to computing group-level and aggregate welfare effects of trade shocks. We borrow the identification strategy proposed by Autor et al. (2013), but we use it here to estimate the model's key parameter governing the degree of labor heterogeneity and the distributional implications of trade shocks.

We use the model to quantify the welfare effects of the China shocks on groups in the United States defined as commuting zones. We find that the average effect is positive, that some groups experience losses more than six times as high as the average gain, and that those groups tend to be concentrated in the Midwest and the inland Eastern region of the US. At the same time, the burden of adjustment to the China shock is spread relatively equally across poor and rich groups. As a consequence, adjusting the welfare calculation for plausible levels of inequality aversion leads to only mild deviations from the standard aggregate effect. Extending our baseline model to allow for intermediate goods, within-country trade costs, heterogeneity within commuting zones, and endogenous employment does not substantially change these conclusions.

The question addressed in this paper is complex and our approach has obvious limitations. Most importantly, our analysis is silent on the effect of shocks on individuals within each group. We deal with this partially by considering finer groups – for example differentiating within a commuting zone by gender, age and education – but even then our approach fails to take into account the large costs of trade-induced layoffs to individual households in the absence of a proper safety net (see for example Autor et al. (2014) and Pierce and Schott (2020)). Our approach also leaves out the role of nominal wage frictions and endogenous trade imbalances, both of which can affect the path of unemployment after a trade shock as shown in Rodríguez-Clare et al. (2019) and Dix-Carneiro, Pessoa, Reyes-Heroles and Traiberman (2021). Understanding the relative importance of all these features in affecting the aggregate and distributional effects of trade shocks is an important challenge for future research.

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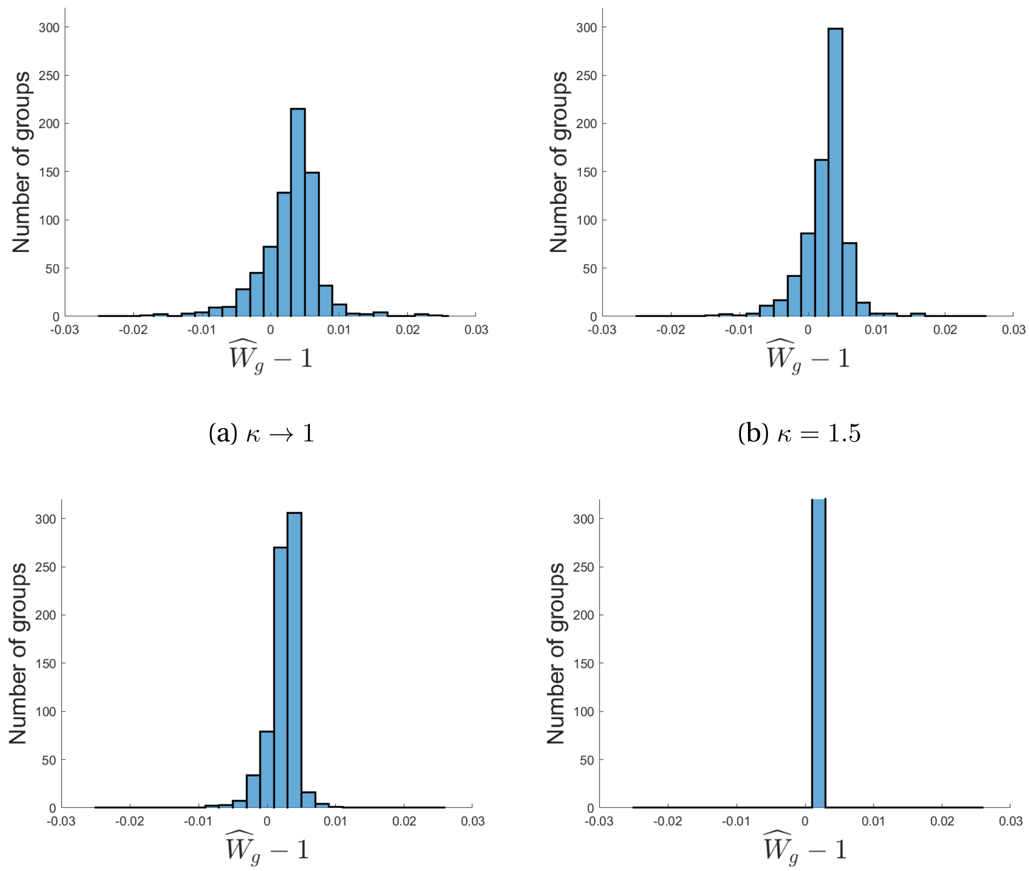
Appendix A Supplementary Tables and Figures for the Counterfactuals

Figure A.1: Distribution of the welfare effects for the rise of China



(a) $\kappa \to 1$

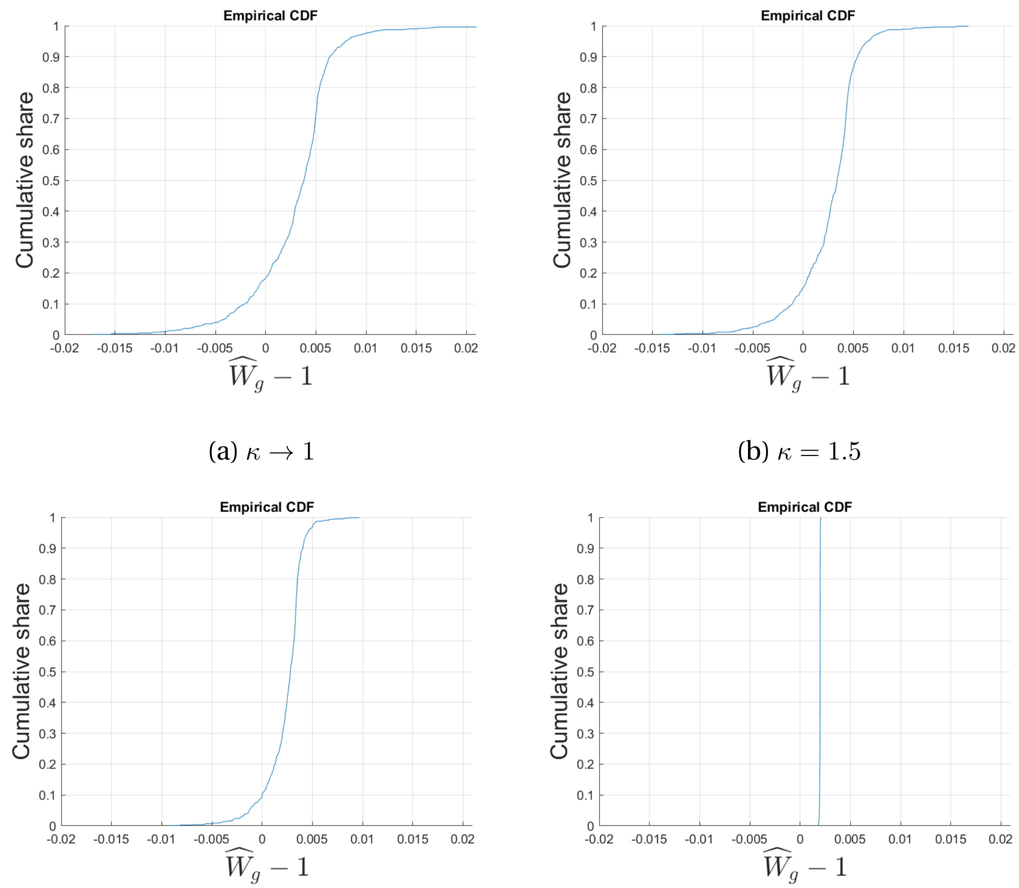
(b) $\kappa = 1.5$

(c) $\kappa = 3$

(d) $\kappa \to \infty$

This figure plots the distribution of $\hat{W}_g - 1$, where $\hat{W}_g$ are the welfare effects for all US groups from the counterfactual rise of China. The different panels show the welfare results for different values of κ, indicated at the bottom of each panel. The vertical axis counts the number of groups in each bin, and the total number of groups is 1444. For visual reasons, the scale of the vertical axis is censored at 300.

Figure A.2: Distribution of the welfare effects for the rise of China



(a) $\kappa \rightarrow 1$

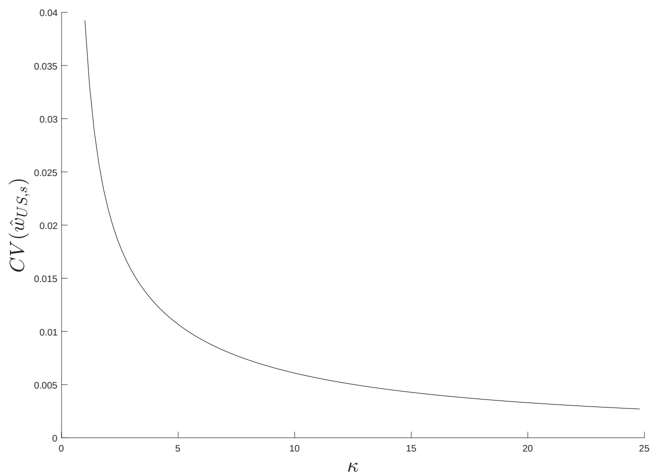
(b) $\kappa = 1.5$

(c) $\kappa = 3$

(d) $\kappa \rightarrow \infty$

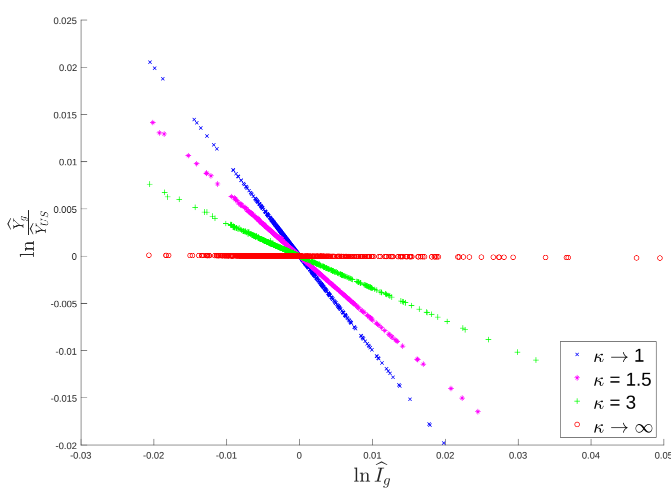
This figure plots the cumulative density functon of $\hat{W}_g - 1$, where $\hat{W}_g$ are the welfare effects for all US groups from the counterfactual rise of China. The different panels show the welfare results for different values of κ, indicated at the bottom of each panel.

Figure A.3: Equilibrium impact of κ on wage changes



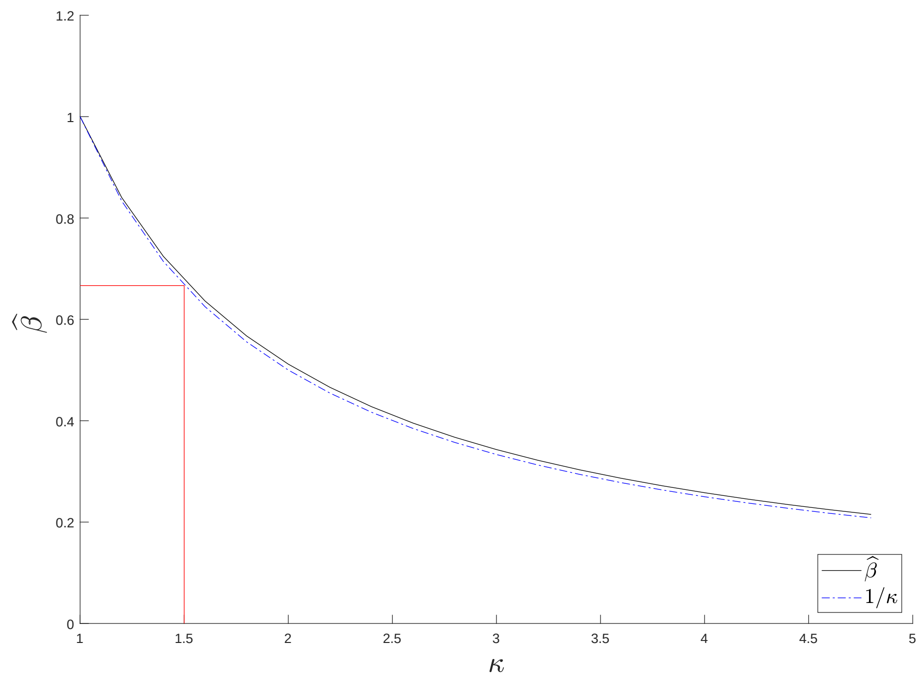
The figure plots the coefficient of variation for wage changes in the United States ($\hat{w}_{US,s}$) for a given China shock, as a function of κ.

Figure A.4: Changes in import competition and groups' relative income for the China shock



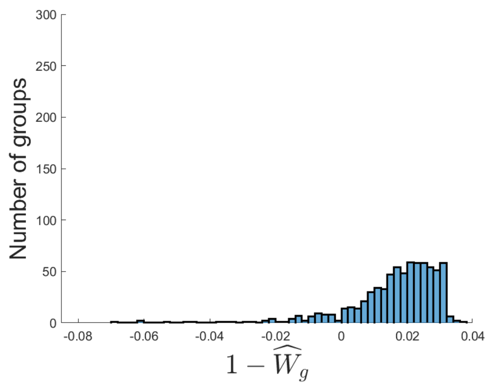
The figure plots the value for $\ln \frac{\hat{Y}_g}{\hat{Y}_{US}}$ in relation to $\ln \hat{I}_g = -\ln \sum_s \pi_{gs} \hat{r}_s$, our Bartik measure for the change in groups' import-competition. Each scatter represents the simulation results for a different value of κ, for values of $\hat{T}_{China,s}$ calibrated for $\kappa = 1.5$.

Figure A.5: A Bartik approximation of income changes

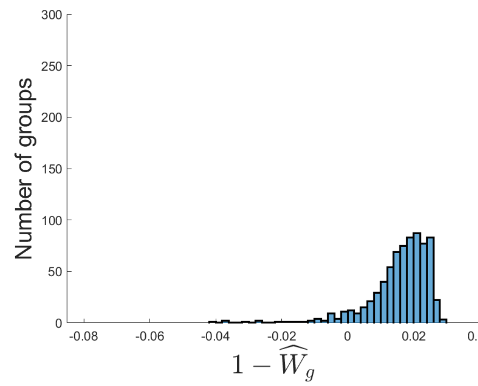


The coefficient $\hat{\beta}$, on the vertical axis, is estimated in the following regression: $\ln \hat{y}_g = \alpha + \beta \ln \sum_s \pi_{gs} \hat{r}_s + \varepsilon_g$, which is run separately for different sets of simulation outcomes for $\hat{y}_g$ and $\hat{r}_s$. Each set of simulation outcomes is obtained for a different value of κ (horizontal axis). The vertical line represents the preferred value for κ from the structural estimation in Section 4, and the solid horizontal line represents the associated value for β. Also note that Appendix Figure A.4 shows that the relation between the model-implied values for $\ln(\hat{Y}_g/\hat{Y})$ and $\ln \sum_s \pi_{gs} \hat{r}_s$ across groups in the United States for the impact of the calibrated China shock is (almost) exactly linear.

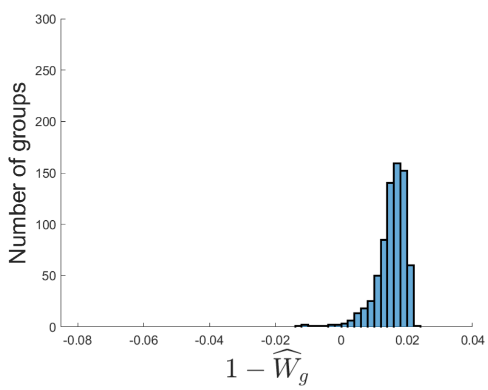
Figure A.6: Distribution of the Gains from Trade



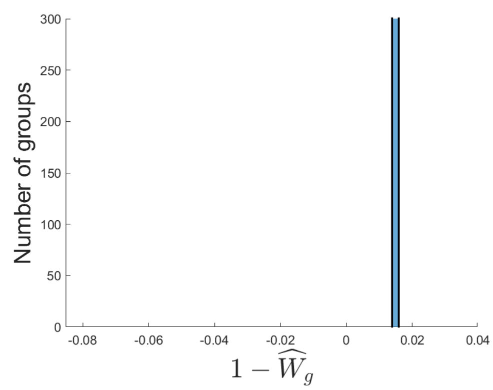
(a) $\kappa \to 1$



(b) $\kappa = 1.5$



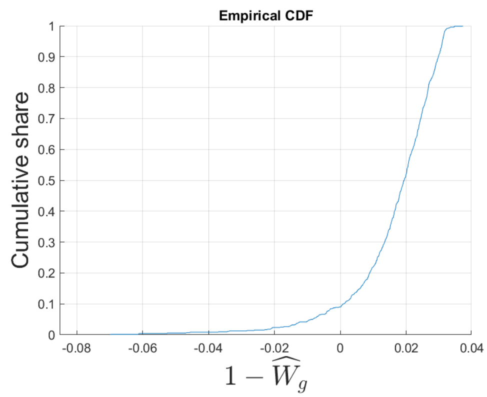
(c) $\kappa = 3$



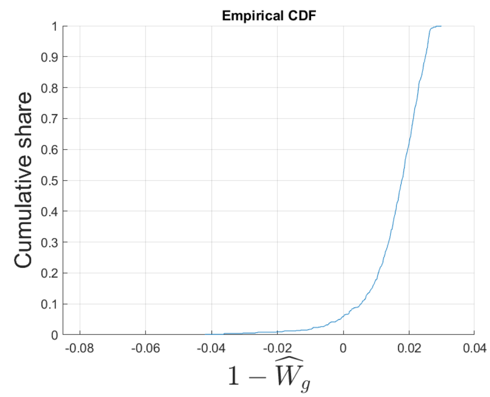
(d) $\kappa \to \infty$

This figure plots the distribution of $1-\hat{W}_g$, where $\hat{W}_g$ are the welfare effects for all US groups from a return to autarky. The different panels show the welfare results for different values of κ, indicated at the bottom of each panel. The vertical axis counts the number of groups in each bin, and the total number of groups is 1444. For visual reasons, the scale of the vertical axis is censored at 300.

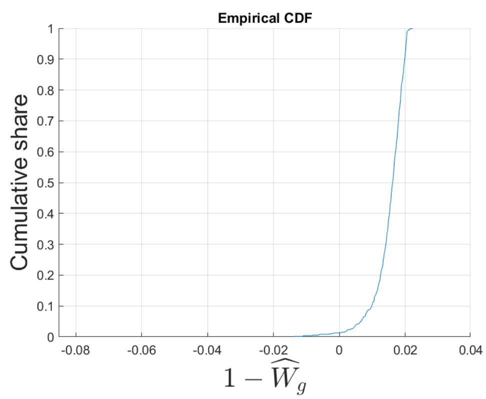
Figure A.7: Cumulative Density Functions for the Gains from Trade



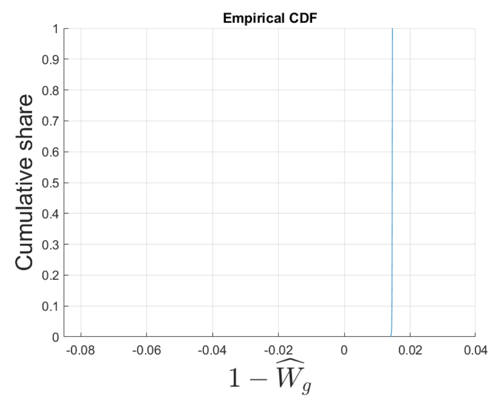
(a) $\kappa \to 1$



(b) $\kappa = 1.5$



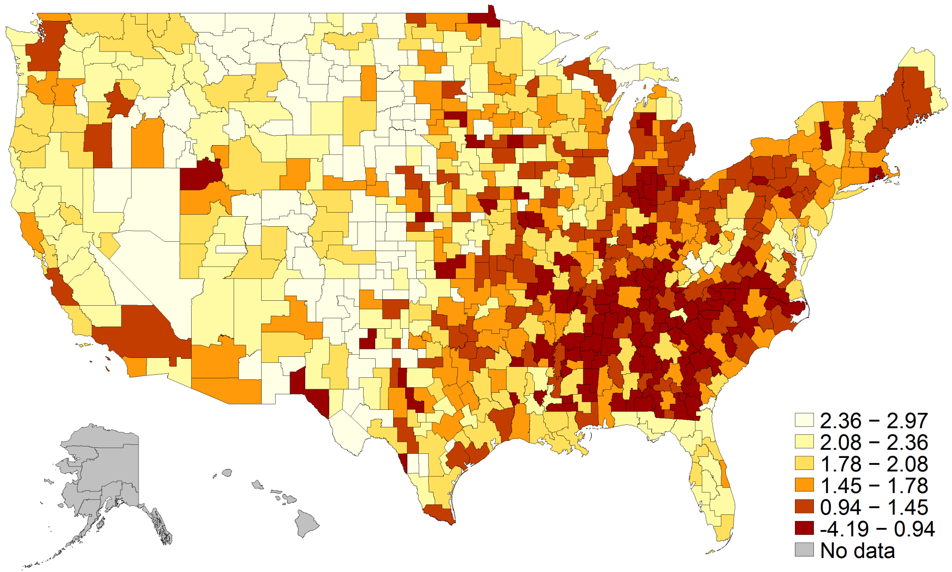
(c) $\kappa = 3$



(d) $\kappa \to \infty$

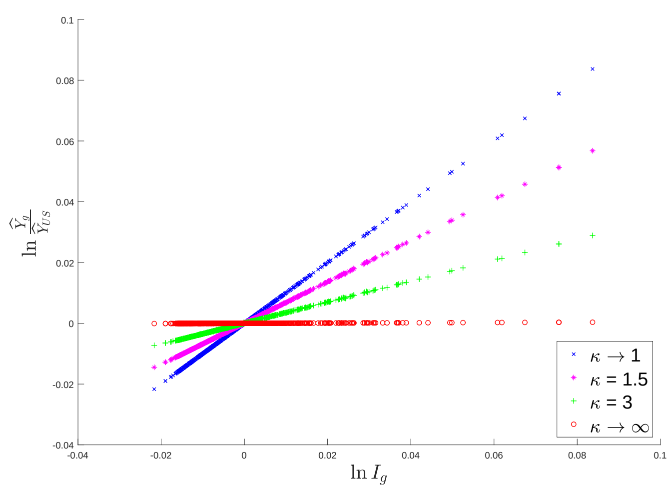
This figure plots the cumulative density functon of $1 - \hat{W}_g$, where $\hat{W}_g$ are the welfare effects for all US groups from a return to autarky. The different panels show the welfare results for different values of κ, indicated at the bottom of each panel.

Figure A.8: Geographical Distribution of the Gains from Trade



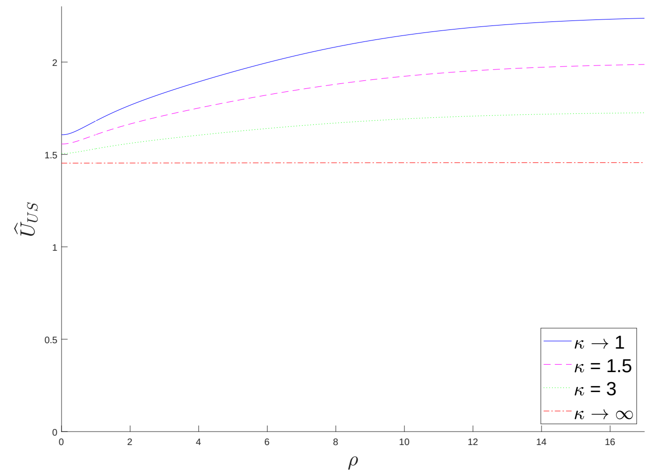
This figure plots the geographic distribution of $100(1-\hat{W}_g)$, where $\hat{W}_g$ are the welfare effects for group g in the US from a return to autarky for our preferred value of $\kappa = 1.5$.

Figure A.9: Import competition and groups' relative gains from return to autarky



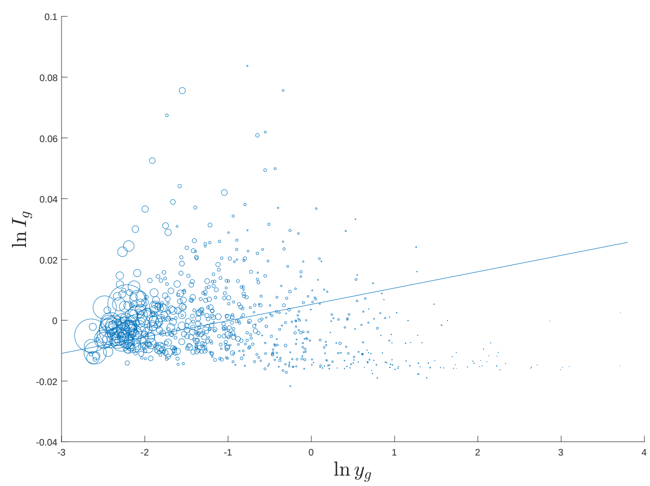
The figure plots the value for $\ln \frac{\hat{Y}_g}{\hat{Y}_{US}}$ in relation to $\ln I_g = \sum_s \pi_{igs} \frac{\beta_{is}}{r_{is}}$, our Bartik measure for groups' import-competition. Each scatter represents the simulation results for the return to autarky for a different value of κ.

Figure A.10: Inequality-adjusted Gains from Trade



The figure plots the relationship between the inequality-adjusted gains from trade $\hat{U}_{US} \equiv \left(\sum_g \omega_g \hat{W}_g^{1-\rho}\right)^{\frac{1}{1-\rho}}$ and ρ. Here, ρ is the coefficient of relative risk aversion for the agent behind the veil of ignorance and $\omega_g \equiv \frac{l_g (Y_g/L_g)^{1-\rho}}{\sum_h l_h (Y_h/L_h)^{1-\rho}}$ a modified weight for group g. The vertical axis displays $100(1-\hat{U}_{US})$.

Figure A.11: Group-level Import Competition and Income



The figure plots the relationship between $\ln I_g \equiv \ln \sum_s \pi_{igs} \frac{\beta_{is}}{r_{is}}$, our measure for regional import-competition, and the logarithm of group-level average income per worker. The solid line displays the linear fit of this relationship, with each commuting zone weighted by its population size. The size of a circle indicates the population size of that commuting zone.

Table A.1: List of Sectors

Sector Nr.	Sector description	β_s	r_s	β_s/r_s	$\lambda_{US,US,s}$
15-16	Food, Beverages and Tobacco	0.03	0.03	0.98	0.95
17-19	Textiles and Textile or Leather Products	0.01	0.01	1.52	0.57
20	Wood and Products of Wood and Cork	0.01	0.01	1.09	0.86
21-22	Pulp, Paper, Printing and Publishing	0.02	0.02	0.98	0.94
23	Coke, Refined Petroleum and Nuclear Fuel	0.01	0.01	1.03	0.91
24	Chemicals and Chemical Products	0.02	0.02	1.01	0.82
25	Rubber and Plastics	0.01	0.01	1.01	0.89
26	Other Non-Metallic Mineral	0.01	0.01	1.06	0.85
27-28	Basic Metals and Fabricated Metal	0.03	0.02	1.06	0.86
29	Machinery, Nec	0.02	0.02	0.95	0.75
30-33	Electrical and Optical Equipment	0.04	0.04	1.07	0.62
34-35	Transport Equipment	0.04	0.03	1.06	0.73
36-37	Manufacturing, Nec; Recycling	0.01	0.01	1.26	0.67
	Non-manufacturing	0.75	0.76	0.98	0.98

This table lists the 14 sectors used in our analysis. The first column has the ISIC Rev.3 sectors for each of the manufacturing subsectors, and the second column has the sector description. The next three columns show the Cobb-Douglas expenditure share, the earnings share r_s and the sectoral import-competition index β_s/r_s for the US. The final column has the domestic expenditure share for the US, $\lambda_{US,US,s}$.

Table A.2: Fit of China shock counterfactuals to the data

	(1)	(2)	(3)	(4)
	Actual $\ln \widehat{e}_g$	Actual $\ln \widehat{\pi}_{gHP}$	Actual $\ln \widehat{e}_g$	Actual $\ln \widehat{\pi}_{gHP}$
Model-predicted $\ln \widehat{e}_g$ $(\alpha = 1/3)$	2.680***			
	(0.736)			
Model-predicted $\ln \widehat{\pi}_{gHP}$ $(\alpha = 1/3)$		1.128**		
		(0.522)		
Model-predicted $\ln \widehat{e}_g$ $(\alpha = 1/2)$			1.443***	
			(0.410)	
Model-predicted $\ln \widehat{\pi}_{gHP}$ $(\alpha = 1/2)$				0.947**
				(0.438)
Constant	-0.00590***	-0.0535***	-0.00582***	-0.0535***
	(0.00196)	(0.00697)	(0.00198)	(0.00700)
Observations	722	722	722	722
R^2	0.021	0.011	0.019	0.011

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors, in parentheses, are clustered at the state level. The table regresses values in the actual data for the period 2000-2007 on simulated values for the counterfactual China shock. Columns 1 and 2 set $\alpha = 1/3$ in the simulations, while columns 3 and 4 set $\alpha = 1/2$.

Table A.3: Regression of predicted changes in employment and income per worker on ADH's China shock

	(1)	(2)	(3)
	$\ln \widehat{\pi}_{gHP}$	$\ln \widehat{e}_g$	$\ln \widehat{y}_g$
$\sum_{s\in M} \pi_{gs} \Delta IP_{st}^{China\to USA}$	0.305***	-0.041***	-0.081***
	(0.087)	(0.012)	(0.023)
Mean and sd of depedent variable	-0.493	0.0657	0.131
	(0.596)	(0.0794)	(0.159)
First Stage Coeff.	0.528	0.528	0.528
First Stage F	29.30	29.30	29.30
Observations	722	722	722
Instrument	$China \to Other$	$China \to Other$	$China \to Other$

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors, in parentheses, are clustered at the state level. The table regresses model predicted changes in employment and income per worker on the actual ADH's China shock for the period 2000-2007. All dependent variables are based on Section 8's model and assume $\alpha = 1/3$ (for ease of exposition, all dependent variables are multiplied by 100. We also provide the means and standard deviations of the dependent variables in rows 3 and 4). The regressor of interest is the original ADH import exposure measure ($\sum_{s\in M} \pi_{gs} \Delta IP_{st}^{China\to USA}$), which is instrumented using the ADH instrumental variable: $\sum_{s\in M} \pi_{gst} \Delta IP_{st}^{China\to Other}$. All regressions include the same controls employed in ADH's preferred specification: lagged manufacturing shares, period fixed effects, Census division fixed effects, and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade

Online Appendix

Online Appendix B Proofs for the baseline model

B.1 Proof for Proposition 2

We want to show that the aggregate gains from trade are higher when $\kappa_{ig} = \kappa < \infty$ than when $\kappa_{ig} \to \infty$ for all $g \in G_i$. Given the definition of the gains from trade, and using Equation (14), we must show that $\sum_{g \in G_i} (Y_{ig}/Y_i) \prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa} < 1$, or using $y_{ig} \equiv Y_{ig}/Y$ and Equation (10),

$$\sum_g y_{ig} \prod_s \left(\hat{w}_{is} \left(\sum_k \pi_{igk} \hat{w}_k^{\kappa} \right)^{-1/\kappa} \right)^{-\beta_{is}} < 1.$$

Rewriting this equation as $\sum_{g \in G_i} y_{ig} \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa} < \prod_s \hat{w}_{is}^{\beta_{is}}$, we can write what we want to show as

$$\sum_{g \in G_i} y_{ig} x_{ig} < \prod_s \hat{w}_{is}^{\beta_{is}},$$

where $x_{ig} \equiv \left(\sum_s \pi_{igs} \hat{w}_{is}^{\kappa}\right)^{1/\kappa}$, and where, from Equation (15), $\hat{w}_{is}$ is given by the solution of

$$\beta_{is} \sum_{g \in G_i} x_{ig} y_{ig} = \sum_{g \in G_i} \hat{w}_{is}^{\kappa} x_{ig}^{1-\kappa} \pi_{igs} y_{ig} \text{ for } s = 1, ..., S. \tag{36}$$

Solving for $\hat{w}_{is}$ from this equation and plugging into the inequality above we see that we need to prove that

$$\left(\sum_g y_{ig} x_{ig} \right)^{\kappa} < \prod_s \left(\beta_{is} \frac{\sum_g y_{ig} x_{ig}}{\sum_g x_{ig}^{1-\kappa} \pi_{igs} y_{ig}} \right)^{\beta_{is}}.$$

This can be rewritten as

$$\prod_s \left(\sum_g \left(\frac{x_{ig}}{\sum_m y_{im} x_{im}} \right)^{1-\kappa} \pi_{igs} y_{ig} \right)^{\beta_{is}} < \prod_s \beta_{is}^{\beta_{is}},$$

where $y_{ig}, \beta_{is}, \pi_{igs}$ are all between zero and one, and

$$\sum_s \beta_{is} = \sum_s \pi_{igs} = \sum_g y_{ig} = 1.$$

To proceed, let $z_{is} \equiv \sum_g \left(\frac{x_{ig}}{\sum_m y_{im} x_{im}} \right)^{1-\kappa} \pi_{igs} y_{ig}$ and note that

$$\sum_s z_{is} = \sum_g \left(\frac{x_{ig}}{\sum_m y_{im} x_{im}} \right)^{1-\kappa} y_{ig} \leq 1,$$

where the inequality comes from the fact that κ is positive combined with the power mean inequality, which implies that

$$\left(\sum_g y_{ig} x_{ig}^{1-\kappa} \right)^{1/(1-\kappa)} \leq \sum_g y_{ig} x_{ig}.$$

To finish the proof, note that if $\sum_s z_{is} \leq 1$ and $z_{is} > 0$ for all s then we must have

$$\prod_s z_{is}^{\beta_{is}} \leq \prod_s \beta_{is}^{\beta_{is}},$$

with equality only if $z_{is} = \beta_{is}$ for all s. We now show that if $r_{is} \neq \beta_{is}$ for some s then we must have $z_{is} \neq \beta_{is}$ for some s. We do so by contradiction: imagine that $r_{is} \equiv \sum_g \pi_{igs} y_{ig} \neq \beta_{is}$ for some s and that $z_{is} = \beta_{is}$ for all s. Plugging from the definition of x_{ig} into Equation 36 and rearranging we see that $\hat{w}_{is}$ for $s = 1, ..., S$ is determined from the system of equations given by

$$\beta_{is} \sum_g \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa} \right)^{1/\kappa} y_{ig} = \sum_g \frac{\hat{w}_{is}^{\kappa}}{\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa}} \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa} \right)^{1/\kappa} \pi_{igs} y_{ig}$$

for $s = 1, ..., S$. For future purposes, note that $\hat{w}_{is} = 1$ for all s is not a solution given that, by assumption, $\sum_g \pi_{igs} y_{ig} \neq \beta_{is}$ for some s. Solving for β_s from this equation, we see that $z_s = \beta_s$ is equivalent to

$$\sum_g \left(\frac{\left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa}}{\sum_h \left(\sum_k \pi_{ihk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa} y_{ih}} \right)^{1-\kappa} \pi_{igs} y_{ig} = \sum_g \frac{\hat{w}_{is}^{\kappa}}{\sum_k \pi_{igk} \hat{w}_k^{\kappa}} \frac{\left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa}}{\sum_h \left(\sum_k \pi_{ihk} \hat{w}_{ik}^{\kappa}\right)^{1/\kappa} y_{ih}} \pi_{igs} y_{ig}.$$

Simplifying, this is equivalent to

$$\sum_g \left(\sum_k \pi_{igk} \hat{w}_{ik}^{\kappa} \right)^{1/\kappa} y_{ig} = \hat{w}_{is}.$$

The only solution to this system is $\hat{w}_{is} = 1$ for all s, but we know that this is not possible. This establishes a contradiction and shows that if $\sum_g \pi_{igs} y_{ig} \neq \beta_{is}$ for some s then $z_{is} \neq \beta_{is}$ for some s. This finishes the proof.

B.2 Proof for Bartik approximation

To prove the statement in footnote 15, we aim to show that

$$\sum_s \pi_{igs} \frac{r'_{is}}{r_{is}} = \frac{\sum_s \pi_{igs} \beta_{is} / r_{is}}{\sum_s \pi'_{igs} \beta_{is} / r'_{is}}$$

using

$$\pi_{igs} = L_{igs} w_{is} / Y_{ig},$$
$$r_{is} = \sum_g L_{igs} w_{is} / Y_i.$$

Since

$$I_{ig} \equiv \sum_s \pi_{igs} \beta_{is} / r_{is}$$

and using hat notation, this can also be written as

$$\sum_s \pi_{igs} \hat{r}_{is} = 1 / \hat{I}_{ig}.$$

Proof: Using the above equations for π_{igs} and r_{is} we see that

$$\sum_s \pi_{igs} \frac{r'_{is}}{r_{is}} = \frac{\sum_s \pi_{igs} \beta_{is} / r_{is}}{\sum_s \pi'_{igs} \beta_{is} / r'_{is}}$$

is equivalent to

$$\sum_s \left(L_{igs} w_{is}/Y_{ig}\right) \frac{\sum_g L_{igs} w'_{is}/Y'_i}{\sum_g L_{igs} w_{is}/Y_i} = \frac{\sum_s \left(L_{igs} w_{is}/Y_{ig}\right) \beta_{is}/ \left(\sum_g L_{igs} w_{is}/Y_i\right)}{\sum_s \left(L_{igs} w'_{is}/Y'_{ig}\right) \beta_{is}/ \left(\sum_g L_{igs} w'_{is}/Y'_i\right)}$$

But this is equivalent to

$$\sum_s \frac{L_{igs} w_{is}}{Y_{ig}} \frac{w'_{is} \sum_g L_{igs}}{w_{is} \sum_g L_{igs}} = \frac{Y'_{ig}}{Y_{ig}} \frac{\sum_s L_{igs} w_{is} \beta_{is}/w_{is} \sum_g L_{igs}}{\sum_s L_{igs} w'_{is} \beta_{is}/w'_{is} \sum_g L_{igs}}$$

or

$$\sum_s \frac{w'_{is} L_{igs}}{Y_{ig}} = \frac{Y'_{ig}}{Y_{ig}} \frac{\sum_s L_{igs} \beta_{is}/\sum_g L_{igs}}{\sum_s L_{igs} \beta_{is}/\sum_g L_{igs}}$$

or

$$\sum_s \frac{w'_{is} L_{igs}}{Y_{ig}} = \frac{Y'_{ig}}{Y_{ig}}$$

or

$$\sum_s w'_{is} L_{igs} = Y'_{ig}$$

which is true by definition.

Online Appendix C Data description

As in ADH, our group-level labor market data is obtained from the 1990 and 2000 Census and the American Community Survey (ACS).[67] Both datasets are downloaded from IPUMS using standardized variables. Our labor market data for the years 1990 and 2000 is derived from a 5% sample of the respective censuses. For the year 2007, labor market figures are based on ACS data. Group income is defined as the log of average wages at the commuting zone level. Following ADH, we restrict our sample to individuals who were between 16 and 64 years old and who were working in the year preceding the survey. Residents of institutional group quarters are dropped. Labor supply is measured by the product of weeks worked times usual number of hours per week. As in ADH, for workers with missing values, we impute the mean of workers in the same education-occupation cell, or, if the education-occupation cell is empty, the mean of workers in

[67] The ACS is designed to be comparable to the Census.

the same education cell. All calculations are weighted by the Census sampling weight multiplied with the labor supply weight. We exclude self-employed workers and individuals with missing wages, weeks or hours. Finally, as in ADH, wages are inflated to the year 2007 using the Personal Consumption Expenditure Index.[68]

Detailed group-sector employment shares at the 3-digit SIC level (required for the China shock instruments) are obtained from the County Business Pattern database.

For robustness tests, we also employ data from the NBER-CES Manufacturing Industry Database and the EU KLEMS Database (for the years 1990, 2000, and 2007) to construct the industry Bartik using manufacturing and non-manufacturing payroll. For the extension with heterogeneous workers (Sections 7.2 and 7.3), we compute all employment and income variables using ACS data. This is necessary because the CBP data does not include worker demographic characteristics necessary to split workers by education, age and gender. We employ ACS data to contruct group-level income and employment variables, with groups now defined by Commuting Zones, age (below and above 50 years), education (no college vs. at least some college, following ADH's definition), and gender (male vs. female). The drawback of using ACS data is that the level of industry aggregation employed in our shift-share instruments will be higher (due to data limitations). Instead of having group employment shares in each of th 395 manufacturing industries, we are restricted to group-employment shares in each of our 13 manufacturing subsectors. Thus, in this section our shift-share insruments are given by $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to Other}$, where s represents each of our 13 aggregated manufacturing sectors and g represents CZ by age, gender and education groups. We also employ contemporaneous shares (π_{gst}) instead of lagged shares due to data availability considerations. For the Section 8 extension with employment effects, we again rely on ACS data to obtain group level employment and home production shares. We define home production to include workers not in the labor force (NiLF). The employment share is given by the ratio of the number of employed workers and the number of individuals in the labor force.

[68]The Census and ACS Public Use Microdata Areas (PUMAs) are mapped into commuting zones using a crosswalk provided by David Dorn.

Online Appendix D Supplementary Estimation Results

Table D.1: Within-group Inequality and the China shock

	China Shock measure		
Dependent variable:	Other (lagged)	Other (no lag)	US (no lag)
$\ln \hat{\sigma}_{y_g}$	-0.560	-1.225*	-0.863**
	(0.482)	(0.691)	(0.417)
$\Delta SD(\ln y_g)$	0.293**	0.178	0.0881
	(0.0900)	(0.144)	(0.0948)
$\ln \frac{\hat{p90}}{\hat{p10}}$	0.886**	0.505	0.322
	(0.278)	(0.389)	(0.252)
$\ln \frac{\hat{p75}}{\hat{p25}}$	0.230	0.0262	0.0492
	(0.147)	(0.190)	(0.111)
$\ln \frac{\hat{y}_{gM}}{\hat{y}_{gNM}}$	0.422	0.406	0.324
	(0.297)	(0.416)	(0.272)
Observations	1444	1444	1444

Reduced form analysis of the impact on the China shock on measures of within-group inequality. Each row represents a different measure of within group inequality: log change in group-level standard deviation of weekly earnings, change in the standard deviation of log weekly earnings, log change in the 90/10 ratio in earnings, log change in the 75/25 ratio in earnings, and log change in the ratio of average manufacturing vs. non-manufacturing income (all measures are given in 10-year equivalents). Each column represents three different measures of the China shock. Column 1 reports the OLS point estimate in which lagged imports to other HI countries is used as as instrument, column (2) reports analogous estimates in which the China shock measure is not lagged, column (3) reports coefficients in the case in which US imports is used as an instrument (without any lag). Standard errors (in parentheses) are clustered at the state level, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. All specifications include the same set of controls employed in our baseline κ estimation (Table 1).

Table D.2: Rotemberg Weights (China to Other): Top 5 Industries

Industry	$-\widehat{(1/\kappa)}$	Weights	F-First Stage	Industry Code	Period
Electronic Computers	-1.707	0.246	3.92	3571	2000
Furnitures and Fixtures	-0.319	0.099	24.42	2599	2000
Semiconductors	-1.440	0.085	7.35	3674	2000
Blast Furnaces	0.120	0.049	10.56	3312	2000
Telephones	-0.927	0.0468	3.37	3661	2000

Rotemberg weights calculated for the shiftshare estimation where the "shares" are for the years 1990 and 2000, and the "shifts" are based on Chinese imports by Other countries, using the methodology from Goldsmith-Pinkham et al. (2018). The parameter β captures the second stage coefficient when the industry share is used as an instrument for $\ln \hat{\pi}_{NM}$, while the parameter α corresponds to the Rotemberg weight.

Table D.3: Estimation of κ - Excluding industries (China to Other instrument)

		Industry Excluded				
	Baseline	Electronic Computers	Furnitures and Fixtures	Semiconductors	Blast Furnaces	Telephones
$\ln \hat{\pi}_{NM}$	-0.639**	-0.316	-0.682**	-0.584*	-0.676**	-0.631**
	(0.303)	(0.290)	(0.328)	(0.303)	(0.312)	(0.296)
Implied κ	1.564	3.161	1.467	1.711	1.479	1.584
First Stage Coeff.	0.489	0.680	0.446	0.478	0.475	0.489
First Stage F	24.02	25.70	17.68	22.43	24.59	24.56
Observations	1444	1444	1444	1444	1444	1444
First Stage R^2	0.667	0.684	0.664	0.671	0.665	0.668
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Instrument	IP to Other	IP to Other	IP to Other	IP to Other	IP to Other	IP to Other

IV-estimation results for specification (23), corresponding to results of column 2, Table 1. Standard errors in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. Columns (2) through (6) exclude each of the top five industries from the construction of the shiftshare instrument, where the "shifts" are based on Chinese imports by Other countries.

Table D.4: Rotemberg Weights (China to US): Top 5 Industries

Industry	$-\widehat{(1/\kappa)}$	Weights	F-First Stage	Industry Code	Period
Electronic Computers	-1.707	0.297	0.874	3571	2000
Furnitures and Fixtures	-0.319	0.220	14.756	2599	2000
Motor Vehicle Parts	-1.330	0.059	5.001	3714	2000
House Furnishings	-1.052	0.059	4.107	2392	2000
Electronic Components	-0.762	0.049	1.637	3679	2000

Rotemberg weights calculated for the shiftshare estimation where the "shares" are for the years 1990 and 2000, and the "shifts" are based on US imports from China, using the methodology from Goldsmith-Pinkham et al. (2018) . The parameter β captures the second stage coefficient when the industry share is used as an instrument for $\ln \hat{\pi}_{NM}$, while the parameter α corresponds to the Rotemberg weight.

Table D.5: Estimation of κ - Excluding industries (China to US instrument)

		Industry Excluded				
	Baseline	Electronic Computers	Furnitures and Fixtures	Motor Vehicle Parts	House Furnishing	Electronic Components
$\ln \hat{\pi}_{NM}$	-0.704**	-0.352	-0.852**	-0.672**	-0.692**	-0.773**
	(0.295)	(0.344)	(0.360)	(0.312)	(0.311)	(0.313)
Implied κ	1.420	2.844	1.174	1.488	1.445	1.294
First Stage Coeff.	0.287	0.337	0.237	0.270	0.275	0.285
First Stage F	29.52	16.44	17.72	26.97	26.42	27.47
Observations	1444	1444	1444	1444	1444	1444
First Stage R^2	0.662	0.683	0.648	0.665	0.663	0.656
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Instrument	IP to US	IP to US	IP to US	IP to US	IP to US	IP to US

IV-estimation results for specification (23), corresponding to results of column 3, Table 1. Standard errors in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. Columns (2) through (6) exclude each of the top five industries from the construction of the shiftshare instrument, where the "shifts" are based on US imports from China.

Table D.6: [BHJ] Industry-level Estimation of κ

	(1)	(2)	(3)	(4)
Panel A: Other (lag)				
$\ln \hat{\pi}_{NM}$	-0.358*	-0.270	0.575	0.750
	(0.209)	(0.295)	(0.803)	(0.979)
	[0.302]	[0.395]	[0.935]	[1.187]
Implied κ	2.791	3.699	-1.739	-1.334
First-stage F-stat.	30.447	26.552	9.158	4.450
Panel B: Other (no lag)				
$\ln \hat{\pi}_{NM}$	-0.639**	-0.639**	-0.366	-0.252
	(0.261)	(0.302)	(0.549)	(0.623)
Implied κ	1.564	1.564	2.732	3.968
First-stage F-stat.	11.913	12.997	11.470	7.144
Panel C: US (no lag)				
$\ln \hat{\pi}_{NM}$	-0.704**	-0.704**	-0.412	0.009
	(0.254)	(0.305)	(0.642)	(0.861)
Implied κ	1.420	1.420	2.430	-108.0
First-stage F-stat.	8.708	9.493	6.058	2.361
Panel D: US Bartik (in level)				
$\ln \hat{\pi}_{NM}$	-0.559*	-0.354	-0.306	-0.748**
	(0.317)	(0.273)	(0.285)	(0.367)
Implied κ	1.788	2.829	3.264	1.337
First-stage F-stat.	41.68	52.17	51.59	19.81
CZ Controls				
ADH	X	X	X	X
Beginning-of-period mfg. share	X			
IV mfg. share		X	X	X
IV mfg. share $\times t$			X	X
Sectoral IV mfg. shares $\times t$				X
Industry Controls				
Period Indicators			X	X
Sector-by-period Indicators				X
Observations	796	794	794	794

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. This table performs industry-level estimation and various specification tests proposed by BHJ (Borusyak et al. 2018) -Table 1. The results in this table correspond to the shift-share IV coefficients from our main estimation model (equation (23), Table 1). Column (1) replicates our main estimation approach (including all the original ADH regressors and beginning-of-period manufacturing shares controls). Column (2) replaces the beginning-of-period manufacturing shares control with manufacturing shares for the time-period that underlies the instrument (we refer to these as "IV mfg. shares"). Column 3 interacts the aforementioned shares with period indicators. Column (4) adds regional shares of 10 manufacturing sub-sectors (based on Acemoglu et al. (2016) definitions), all interacted with period indicators. The last row reflects the number of observations in the equivalent industry-level regressions, with the non-manufacturing industry aggregate included in column 1 (with a shock of zero), but not in columns (2)-(4). Significance stars reflect the standard errors in parentheses, which are clustered at the level of 3-digit SIC codes following the procedure in BHJ. Standard errors in square brackets are obtained from *location-level* regressions and clustered at the industry level using 3-digit SIC codes, following Adão et al. (2019). We do not obtain these standard errors for the China shocks with no lag since our industry-employment share matrix for the year 2000 is not full rank. For "Other (lag)", these shares are lagged by 10 years, whereas for "Other (no lag)" and "US (no lag)", these shares are from the beginning of the period.

Table D.7: [BHJ] Overidentification Tests for κ

	(1)	(2)	(3)
$\ln \hat{\pi}_{NM}$	-0.294	-0.294	-0.266*
	(0.180)	(0.209)	(0.152)
Estimator	2SLS	LIML	GMM
Implied κ	3.397	3.403	3.760
First-stage F-stat.	12.68	12.68	12.68
Hansen J Stat.	6.303	6.296	6.303
Hansen J d.f.	7	7	7
Hansen J p-value	0.505	0.506	0.505
Observations	796	796	796

This table presents overidentified estimates analogous to BHJ (Borusyak et al. 2018) (Table 4), applied to our baseline estimation model (equation (23)). Column 1 reports an overidentified estimate of the coefficient corresponding to column 1 of Table 1 (using the "Other (no lag)" version of our instrument), obtained via a two-stage least squares regression of industry-level average earnings growth residuals on industry-level average manufacturing employment growth residuals, instrumenting by growth of imports (per U.S. worker) in eight non-U.S. countries separately (Australia, Switzerland, Germand, Denmark, Spain, Finland, Japan, New Zealand), controlling for period fixed effects, and weighting by average industry exposure. Column 2 reports the corresponding limited information maximum likelihood estimate, while column 3 reports a two-step optimal GMM estimate. Standard errors, the optimal GMM weight matrix, first-stage F-statistics, and the Hansen χ^2 test of overidentifying restrictions all allow for clustering of shocks at the SIC3 industry group level.

Table D.8: The rise of China and the Bartik measure for import competition

	(1)	(2)	(3)
	$\ln \hat{y}_g$	$\ln \hat{y}_g$	$\ln \hat{y}_g$
$\ln \sum_s \pi_{gs} \hat{r}_s$	1.230*	1.735**	1.845**
	(0.727)	(0.824)	(0.787)
Implied κ	0.810	0.576	0.542
F First Stage	42.66	18.80	16.35
Observations	1444	1444	1444
R^2	0.677	0.664	0.660
Instrument	IP to other (lagged)	IP to other (no lag)	IP to the US

Estimation results when regressing changes in CZs' average income per worker on $\ln \sum_s \pi_{gs} \hat{r}_s$, instrumented by the ADH shock. Labor shares π_{gs} are measured as the share of workers using the CBP data in 1990 and 2000. We aggregate the shares at the 2 digit-ISIC industry level. Column (1) reports the second stage coefficient in which imports to other high income countries and lagged employment shares are used when constructing the instrument, column (2) is analogous to column (1) but does not employ lagged shares. Column (3) reports the second stage coefficient in the case in which US imports is used as an instrument (without lagged employment shares). Standard errors (in parentheses) are clustered at the state level, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. All specifications include the same set of controls employed in our baseline κ estimation (Table 1).

Online Appendix E Supplementary counterfactual results for the baseline model

Table E.1: Welfare effects for separately calibrated China shocks

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.25	0.33	1.43	-2.20	2.46	0.15
1.5	0.22	0.27	1.16	-1.42	1.64	0.15
	(0.02)	*(0.03)*	*(0.25)*	*(0.35)*	*(0.58)*	*(0.01)*
3.0	0.18	0.21	0.74	-0.63	0.84	0.15
$\to \infty$	0.14	0.14	0	0.14	0.14	0.14

Compared to Table 2, here the values for $\hat{T}_{China,s}$ are separately calibrated for each value of κ. The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms $(100(\widehat{W}_{US}-1)$, and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g}-1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$\equiv \min_g 100(\widehat{W}_{US,g}-1)$ and Max.$\equiv \max_g 100(\widehat{W}_{US,g}-1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s}-1\right)$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta}=1/\hat{\kappa}$, for each statistic when $\kappa=1.5$.

Table E.2: Welfare effects of the China shock for alternative θ_s values

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.18	0.25	1.84	-2.05	1.58	0.07
1.5	0.17	0.24	1.62	-1.81	1.35	0.08
	(0.01)	*(0.02)*	*(0.24)*	*(0.29)*	*(0.25)*	*(0.01)*
3.0	0.15	0.21	1.25	-1.34	1.00	0.10
$\to \infty$	0.17	0.17	0	0.16	0.16	0.16

Compared to Table 2, here the values for the trade elasticities take on the median value of prominent estimates of θ_s in the literature (see Table B.3, column 5 of Bartelme et al. (2019)). The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms $(100(\widehat{W}_{US} - 1)$, and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g} - 1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$\equiv$ $\min_g 100(\widehat{W}_{US,g} - 1)$ and Max.$\equiv$ $\max_g 100(\widehat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s} - 1\right)$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, for each statistic when $\kappa = 1.5$.

Table E.3: Gains from trade for alternative θ_s values

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	1.36	1.40	0.97	-7.26	3.47	1.20
1.5	1.31	1.33	0.69	-4.46	2.72	1.20
	(0.05)	*(0.06)*	*(0.27)*	*(2.55)*	*(0.68)*	*(0)*
3.0	1.25	1.27	0.37	-1.64	1.97	1.20
$\to \infty$	1.20	1.20	0.01	1.16	1.21	1.20

Compared to Table 3, here the values for the trade elasticities take on the median value of prominent estimates of θ_s in the literature (see Table B.3, column 5 of Bartelme et al. (2019)). The first column displays the aggregate gains from trade for the US, in percentage terms $(100(1 - \widehat{W}_{US}))$ and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g 1 - \widehat{W}_{US,g})$. Here, $\widehat{W}_{US}$ and $\widehat{W}_{US,g}$ are the aggregate and group-level welfare change from a return to autarky for the US. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.= $\min_g 100(1 - \widehat{W}_{US,g})$ and Max.=$\max_g 100(1 - \widehat{W}_{US,g})$, respectively. The final column displays the multi-sector ACR term $100\left(1 - \prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s}\right)$. The third row has standard errors in parentheses, computed using the delta method and numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, for each statistic when $\kappa = 1.5$.

Online Appendix F Extension with intermediate goods

F.1 Theory for the extension with intermediates

Here we provide the theoretical background for the extended model in Section 7.1, and prove Proposition 3.

Recall that the labor supply in this model is exactly as in the baseline model (see equations (3) and (4)), and trade shares and the price indices are given as in equations (1) and (2), except that instead of w_{is} we now have c_{is}, where c_{is} is given by

$$c_{is} = w_{is}^{1-\gamma_{is}} \prod_k P_{ik}^{\gamma_{iks}}, \tag{37}$$

with

$$P_{js} = \zeta_s^{-1} \left(\sum_i T_{is} \left(\tau_{ijs} c_{is}\right)^{-\theta_s} \right)^{-1/\theta_s}. \tag{38}$$

The terms γ_{iks} are Cobb-Douglas input shares: a share γ_{iks} of the output of industry s in country i is used buying inputs from industry k, and $1-\gamma_{is}$ is the share spent on labor, with $\gamma_{is} = \sum_k \gamma_{iks}$.

Combining equations (37) and (38) yields

$$P_{js} = \zeta_s^{-1} \left(\sum_i T_{is} \left(\tau_{ijs} w_{is}^{(1-\gamma_{is})} \prod_k P_{ik}^{\gamma_{iks}} \right)^{-\theta_s} \right)^{-1/\theta_s}.$$

Given wages, this equation represents a system of $N \times S$ equations in P_{js} for all j and s, which can be used to solve for P_{js} and hence c_{is} and λ_{ijs} given wages. This implies that trade shares are an implicit function of wages. Letting X_{js} and R_{js} be total expenditure and total revenues for country j on sector s, then $R_{is} = \sum_{j=1}^{n} \lambda_{ijs} X_{js}$, while Cobb-Douglas preferences and technologies imply that $X_{js} = \beta_{js}(Y_j + D_j) + \sum_{k=1}^{S} \gamma_{jsk} R_{jk}$, where D_j are trade imbalances satisfying $\sum_j D_j = 0$. These equations constitute a system of linear equations that we can use to solve for revenues given income levels and trade shares,

$$R_{is} = \sum_j \lambda_{ijs} \left(\beta_{js} Y_j (1 + d_j) + \sum_{k=1}^{S} \alpha_{jsk} R_{jk} \right),$$

where $d_j \equiv D_j/Y_j$. Since trade shares and income levels themselves are a function of wages, this implies that revenues are a function of wages. The excess demand for efficiency units in sector s of country i is now

$$ELD_{is} \equiv \frac{(1-\gamma_{is})}{w_{is}} R_{is} - \sum_{g \in G_i} \mathcal{Z}_{igs}.$$

As in the baseline model, the system $ELD_{is} = 0$ for all i and s is a system of equations that we can use to solve for wages. In turn, given wages we can solve for all the other variables of the model.

The next step is to write the hat algebra system. From $ELD'_{is} = 0$ we get

$$\sum_{g \in G_i} \hat{\pi}_{igs} \hat{\Phi}_{ig} \pi_{igs} Y_{ig} = (1-\gamma_{is}) \sum_{j=1}^{n} \lambda_{ijs} \hat{\lambda}_{ijs} \left(\beta_{js} \left(\sum_{g \in G_j} \hat{\Phi}_{jg} Y_{jg} (1 + \hat{d}_j d_j) \right) + \sum_{k=1}^{S} \gamma_{jsk} \hat{R}_{jk} R_{jk} \right),$$

where $\hat{\Phi}_{ig}$ is as in (8) and

$$\hat{\lambda}_{ijs} = \frac{\hat{T}_{is} \left(\hat{\tau}_{ijs} \hat{w}_{is}^{1-\gamma_{is}} \prod_k \hat{P}_{ik}^{\gamma_{iks}} \right)^{-\theta_s}}{\hat{P}_{js}^{-\theta_s}},$$

$$\hat{P}_{js}^{-\theta_s} = \sum_i \lambda_{ijs} \hat{T}_{is} \left(\hat{\tau}_{ijs} \hat{w}_{is}^{(1-\gamma_{is})} \prod_k \hat{P}_{ik}^{\gamma_{iks}} \right)^{-\theta_s},$$

and

$$\hat{R}_{is} R_{is} = \sum_j \lambda_{ijs} \hat{\lambda}_{ijs} \left(\beta_{js} \left(\sum_{g \in G_j} \hat{\Phi}_{jg} Y_{jg} (1 + \hat{d}_j d_j) \right) + \sum_{k=1}^{S} \gamma_{jsk} \hat{R}_{jk} R_{jk} \right).$$

For welfare analysis, it is useful to fully solve for $\{P_{js}\}$ in terms of trade shares. We start with $\lambda_{jjs} = T_{js} c_{js}^{-\theta_s} / (\zeta_s P_{js})^{-\theta_s}$, which implies that

$$\ln P_{is} = \ln \left(\zeta_s^{-1} \left(T_{is}/\lambda_{iis} \right)^{-1/\theta_s} w_{is}^{1-\gamma_{i,s}} \right) + \sum_k \gamma_{iks} \ln P_{ik}.$$

Letting $\Upsilon_i \equiv \{\gamma_{iks}\}_{k,s=1,\ldots,S}$ (an $S \times S$ matrix), $B_i \equiv \left\{ \ln \left(\zeta_s^{-1} \left(T_{is}/\lambda_{iis} \right)^{-1/\theta_s} w_{is}^{1-\gamma_{is}} \right) \right\}_{s=1,\ldots,S}$

(an $S \times 1$ matrix) and $X_i \equiv \{\ln P_{is}\}_{s=1,\ldots,S}$ (an $S \times 1$ matrix), then we have

$$X_i = \left(I - \Upsilon_i^T\right)^{-1} B_i,$$

where I is the $S \times S$ identity matrix. Letting $\widetilde{a}_{isk}$ be the typical element of $\left(I - \Upsilon_i^T\right)^{-1}$, then we see that

$$P_{is} = \prod_k \left(\zeta_s^{-1} \left(T_{ik}/\lambda_{iik}\right)^{-1/\theta_k} w_{ik}^{1-\gamma_{ik}}\right)^{\widetilde{a}_{isk}}.$$

This implies that welfare changes for group ig are given by

$$\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{\hat{\Phi}_{ig}^{1/\kappa_{ig}}}{\prod_{s,k}\left(\hat{\lambda}_{iik}^{1/\theta_k} \hat{w}_{ik}^{1-\gamma_{ik}}\right)^{\beta_{is}\widetilde{a}_{isk}}}.$$

In general, we can check that $\sum_k \left(1-\gamma_{i,k}\right) \widetilde{a}_{i,sk} = 1$, and hence $\sum_{s,k} \left(1-\gamma_{i,k}\right) \beta_{is}\widetilde{a}_{i,sk} = 1$, so we can rewrite the above result as

$$\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{1}{\prod_{s,k}\left(\hat{\lambda}_{iik}^{1/\theta_k} \hat{\Phi}_{ig}^{-(1-\gamma_{ik})/\kappa_{ig}} \hat{w}_{ik}^{1-\gamma_{ik}}\right)^{\beta_{is}\widetilde{a}_{isk}}}$$

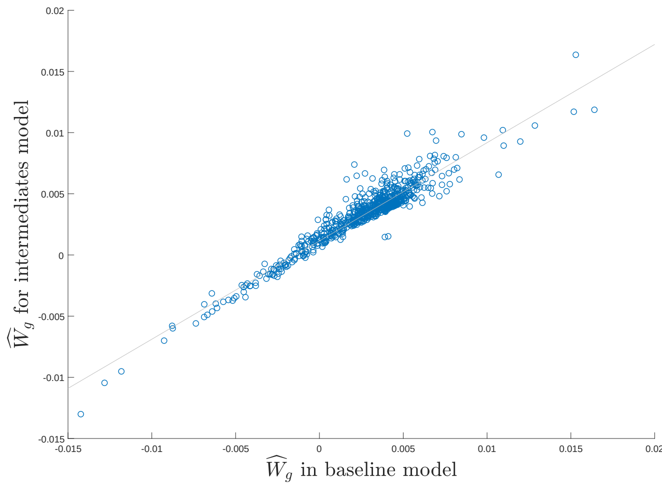
But then, using $\hat{w}_{is}\hat{\Phi}_{ig}^{-1/\kappa_{ig}} = \hat{\pi}_{igs}^{1/\kappa_{ig}}$, we get

$$\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{1}{\prod_{s,k}\left(\hat{\lambda}_{iik}^{1/\theta_k} \hat{\pi}_{igk}^{(1-\gamma_{ik})/\kappa_{ig}}\right)^{\beta_{is}\widetilde{a}_{isk}}}.$$

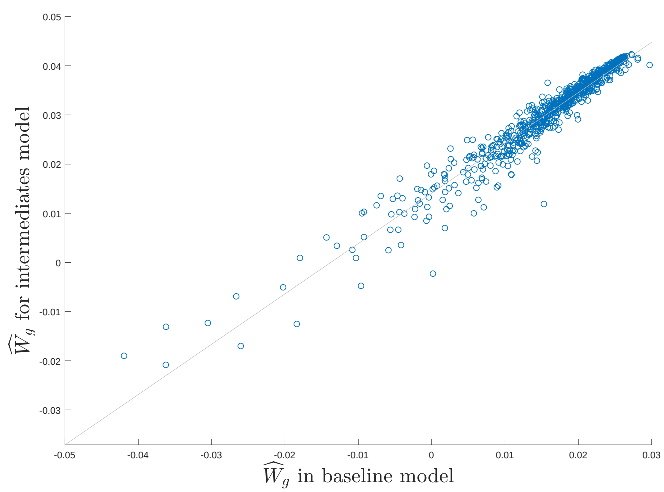
This establishes the result in Proposition 3.

F.2 Counterfactual results for the extension with intermediates

Figure F.1: Comparison of the baseline model and the model with intermediate goods



(a) The rise of China



(b) Gains from trade

This figure compares the welfare changes for the two models, showing $\widehat{W}_g - 1$ for the rise of China, and $1 - \widehat{W}_g$ for the return to autarky, each time for $\kappa = 1.5$.

Table F.1: Counterfactual analysis for the model with intermediates

(a) The rise of China

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.39	0.47	0.71	-1.43	1.73	0.28
1.5	0.37	0.43	0.58	-1.07	1.27	0.29
	(0.02)	*(0.03)*	*(0.14)*	*(0.39)*	*(0.41)*	*(0.01)*
3.0	0.35	0.39	0.37	-0.53	0.83	0.31
$\to \infty$	0.34	0.34	0	0.34	0.34	0.34

(b) Gains from trade

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	2.91	3.06	0.37	-3.36	4.71	2.74
1.5	2.86	2.95	0.26	-1.34	4.06	2.74
	(0.05)	*(0.09)*	*(0.11)*	*(1.84)*	*(0.59)*	*(0)*
3.0	2.80	2.85	0.14	0.69	3.40	2.74
$\to \infty$	2.74	2.74	0	2.74	2.74	2.74

The tables show summary statistics for welfare effects of US groups for the model with an input-output structure. Panel (a) shows results for the counterfactual rise of China, where the values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$, under the model with intermediates. Panel (b) shows results for group-level gains from trade. The first column displays the aggregate welfare effect for the US, in percentage terms $100(\widehat{W}_{US} - 1)$ and the second column shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,g} - 1)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$=\min_g 100(\widehat{W}_{US,g} - 1)$ and Max.=$\max_g 100(\widehat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_{s,k} \hat{\lambda}_{US,US,k}^{-\beta_{US,s}\tilde{a}_{US,sk}/\theta_s} - 1\right)$. For the gains from trade we simulate the return to autarky and report the negative of the above statistics for the obtained counterfactual results. The third row has standard errors, computed using the delta method, in parentheses.

Online Appendix G Additional results for the extension with imperfect substitutes

Table G.1: Estimates for κ_m by education level

	(1)	(2)	(3)
$\ln \hat{\pi}_{NM}$	-0.688**	-0.818***	-0.639**
	(0.218)	(0.216)	(0.267)
Implied κ	1.454	1.223	1.565
First Stage Coeff.	2.071	1.527	2.391
First Stage F	123.1	58.68	94.07
College educated	Pooled	Yes	No
Observations	2888	1444	1444

IV-estimation results for specification (23), where y_g is average earnings per worker, and π_{gNM} is the employment share in non-manufacturing for group g. Groups are now defined by commuting zones and worker type m (non-college vs. college). We first estimate a pooled model with all groups in column (1). We then estimate the model separately for each worker type τ: column (2) presents estimates for college workers, column (3) for non-college workers. The shift-share insruments are constructed using contemporaneous group-specific employment shares at the 13-sector level obtained from ACS data (this is the only available level of disaggregation available that contains worker demographic data). Our instruments are $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to Other}$, where s represents each of our 13 aggregated manufacturing sectors and g represents CZ by age and education groups. Standard errors are clustered at the state level and reported in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. The first row shows the second-stage results, while the third row has the corresponding κ estimates implied by the model and the fourth row displays the F-statistic from the first stage. All regressions include state by period fixed effects in addition to the controls employed in ADH's preferred specification: lagged manufacturing shares and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

Table G.2: The rise of China for college and non-college workers as imperfect substitutes.

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	ACR	Roy gains	$\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}$
				Non-College Workers				
$\to 1$	0.24	0.32	0.99	-1.06	1.48	0.14	0.10	0.00
1.5	0.23	0.30	0.75	-0.57	1.05	0.15	0.08	0.00
	(0.29)	*(2.04)*	*(24.47)*	*(29.95)*	*(36.05)*	*(0.83)*	*(1.93)*	*(0.85)*
3.0	0.24	0.28	0.44	-0.29	0.66	0.16	0.05	0.02
$\to \infty$	0.27	0.27	0.00	0.27	0.27	0.20	0.00	0.07
				College Workers				
$\to 1$	0.23	0.40	1.00	-1.63	2.35	0.14	0.09	0.00
1.5	0.19	0.33	0.85	-1.37	1.60	0.15	0.04	-0.01
	(0.04)	*(0.07)*	*(0.14)*	*(0.31)*	*(0.67)*	*(0.01)*	*(0.04)*	*(0.01)*
3.0	0.14	0.24	0.66	-0.90	0.87	0.16	0.01	-0.03
$\to \infty$	0.09	0.09	0.00	0.09	0.10	0.20	0.00	-0.10

Results for the rise of China for the model in Section 7.2, where college and non-college workers are imperfect substitutes. The first column displays the aggregate welfare effect of the China shock for the US for education type m, in percentage terms $100(\widehat{W}_{US,m} - 1)$, and the second column shows the mean welfare effect for that education type: $100(\frac{1}{G_{US,m}} \sum_g \widehat{W}_{US,mg} - 1)$. The third column shows the coefficient of variation, and for the fourth and fifth column we have Min.$\equiv \min_g 100(\widehat{W}_{US,mg} - 1)$ and Max.$\equiv \max_g 100(\widehat{W}_{US,mg} - 1)$, respectively. The sixth column displays the multi-sector ACR term $100\left(\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s} - 1\right)$, the seventh column the aggregate Roy term for education type m, $100(\sum_{g\in G_m}\left(\frac{Y_{img}}{Y_{im}}\right)\prod_s \hat{\pi}_{imgs}^{-\beta_{is}/\kappa} - 1)$, and the eight column $100(\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)} - 1$. The values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$. Standard errors for the benchmark results in the second row, computed using the delta method and the numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, in parentheses.

Table G.3: Gains from trade for college and non-college workers as imperfect substitutes.

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	ACR	Roy gains	$\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}$
				Non-College workers				
$\to 1$	1.41	1.52	0.81	-7.23	3.03	1.45	-0.03	0.00
1.5	1.39	1.46	0.57	-4.38	2.47	1.45	-0.02	-0.04
	(0.03)	*(0.06)*	*(0.23)*	*(2.59)*	*(0.51)*	*(0)*	*(0.01)*	*(0.04)*
3.0	1.36	1.39	0.30	-1.53	1.90	1.45	-0.01	-0.08
$\to \infty$	1.33	1.33	0.00	1.33	1.33	1.45	0.00	-0.12
				College workers				
$\to 1$	1.89	1.96	0.40	-4.18	2.96	1.45	0.45	0.00
1.5	1.80	1.85	0.29	-2.24	2.53	1.45	0.30	0.06
	(0.08)	*(0.1)*	*(0.11)*	*(1.77)*	*(0.4)*	*(0)*	*(0.13)*	*(0.05)*
3.0	1.72	1.74	0.15	-0.29	2.09	1.45	0.15	0.12
$\to \infty$	1.63	1.63	0.00	1.63	1.63	1.45	0.00	0.18

Results for the gains from trade for the model in Section 7.2, where college and non-college workers are imperfect substitutes. The first column displays the aggregate welfare effect of the China shock for the US for education type m, in percentage terms $100(1-\widehat{W}_{US,m})$, and the second column shows the mean welfare effect for that education type: $100(1-\frac{1}{G_{US,m}}\sum_g \widehat{W}_{US,mg})$. The third column shows the coefficient of variation, and for the fourth and fifth column we have Min.$\equiv \min_g 100(1-\widehat{W}_{US,mg})$ and Max.$\equiv \max_g 100(1-\widehat{W}_{US,mg})$, respectively. The sixth column displays the multi-sector ACR term $100\left(1-\prod_s \widehat{\lambda}_{US,US,s}^{-\beta_{US,s}/\theta_s}\right)$, the seventh column the aggregate Roy term for education type m, $100(\sum_{g\in G_m}\left(1-\frac{Y_{img}}{Y_{im}}\right)\prod_s \hat{\pi}_{imgs}^{-\beta_{is}/\kappa})$, and the eight column $100(1-\prod_s \hat{\chi}_{ims}^{-\beta_{is}/(\eta-1)}$. The values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$. Standard errors for the benchmark results in the second row, computed using the delta method and the numerical derivatives with respect to $\hat{\beta} = 1/\hat{\kappa}$, in parentheses.

Table G.4: Differences in κ for college and non-college workers

(a) The rise of China

		$\widehat{W}_{US}$	Mean	CV	Roy gains	College premium
$\kappa \to \infty$	$\eta = 1.6$	0.15	0.15	0.15	0.00	-0.03
$\kappa = 1.5$	$\eta = 1.6$	0.22	0.32	0.81	0.07	-0.01
$\kappa_{NC} = 1.56; \kappa_{CO} = 1.22$	$\eta = 1.6$	0.23	0.33	0.86	0.08	0.01
$\kappa = 1.5$	$\eta \to \infty$	0.22	0.32	0.77	0.07	0.00

(b) Gains from trade

		$\widehat{W}_{US}$	Mean	CV	Roy gains	College premium
$\kappa \to \infty$	$\eta = 1.6$	1.45	1.48	0.14	0.00	1.00
$\kappa = 1.5$	$\eta = 1.6$	1.56	1.66	0.44	0.11	0.10
$\kappa_{NC} = 1.56; \kappa_{CO} = 1.22$	$\eta = 1.6$	1.57	1.68	0.49	0.10	0.11
$\kappa = 1.5$	$\eta \to \infty$	1.56	1.55	0.55	0.11	0.00

The table presents the welfare effects for trade shocks for the model with college and non-college workers as potentially imperfect substitutes. Panel (a) shows results for the rise of China and panel (b) for the gains from trade. The first two columns provide the parameter values for the simulation results in that row, where $\eta \to \infty$ implies that all labor is perfectly substitutable. Column 3 display the aggregate welfare effect for all workers in the US, in percentage terms $100(\widehat{W}_{US,m} - 1)$, column 4 shows the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,mg} - 1)$, and column 5 the coefficient of variation (CV). The sixth column shows the aggregate Roy gains $100(\sum_{mg}\left(\frac{Y_{img}}{Y_i}\right)\prod_s \hat{\pi}_{imgs}^{-\beta_{is}/\kappa} - 1)$, and the final column the change in the college premium $100(\prod_s (\hat{\chi}_{iCs}/\hat{\chi}_{iNCs})^{-\beta_{is}/(\rho-1)} - 1)$. The China shock is separately calibrated for the parameter values in each row. For the gains from trade, we simulate the return to autarky, and for that simulation report the negative of the aggregate and mean welfare effect.

Online Appendix H Heterogeneity within commuting zones and trade costs

H.1 Heterogeneity by age and education

As mentioned in Section 7.3, we can easily extend the baseline model to allow for heterogeneous effects of trade shocks by age and education level. To this end, we simply split each commuting zone by worker type, where the four types are defined by workers' age (younger versus older than 50 years) and level of education (non-college versus college educated[69]), so that now we have 2888 groups. In addition, we allow for trade costs between U.S. states (in addition to trade costs across countries), while retaining the assumption of frictionless trade across groups within states. Conceptually, the model is identical to the baseline from Section 2, except that U.S. states now play a role identical to the role of countries in the baseline model, and each worker type has a potentially different value for κ_m. In particular, if group img belongs to state n then

$$\hat{W}_{img} = \prod_s \hat{\lambda}_{nns}^{-\beta_{ns}/\theta_s} \cdot \prod_s \hat{\pi}_{igs}^{-\beta_{ns}/\kappa_{im}}. \tag{39}$$

Updating the starting point for estimating κ_m to our new setting, we have that $\hat{y}_{nmg} = \hat{A}_{nmgs}^{1/\kappa_m} \hat{w}_{ns} \hat{\pi}_{nmgs}^{1-/\kappa_m}$, where κ_m is specific to a worker type, and wages $\hat{w}_{ns}$ vary by U.S. state. In practice, we account for these changes by estimating Equation (23) separately by worker type and by adding state by period fixed effects to absorb differences in wage changes across states in each period. The resulting point estimates for κ_m vary from 1.4 for young college workers to 2.9 for older non-college workers (see Table H.1).

Armed with our different κ_m estimates, we use this framework to analyze how the quantitative results change when we have various worker types within a CZ and allow for within-US trade costs. We borrow the necessary data from Rodríguez-Clare et al. (2019), who construct a dataset using data from the Import and Export Merchandise Trade Statistics (from the U.S. Census Bureau), the Commodity Flow Survey and the Regional Economic Accounts of BEA Commodity Flow Service.

When we simulate the welfare impact of the China shock, we find only modest dif-

[69] Following ADH, we include workers with at least one year of college in the college educated group.

ferences across worker groups (see Table H.2, Panel a).[70] Old college workers experience the highest average gains, while old non-college workers the lowest, at 0.25% and 0.18% respectively. These differences persist when we impose an identical κ for all types, so the variation in κ_m is not driving these differences. Notably, the type with the lowest gains – old non-college workers – have the highest average employment shares in the three sectors that contract the most, namely electrical and optical equipment, textiles and "manufacturing NEC & Recycling." In contrast, old college workers have higher employment shares in the sectors that expand the most, namely the chemicals industry and the coke, petroleum and nuclear fuel industry. For the overall gains from trade, Panel (b) shows that college workers (young or old) have higher gains than non-college workers, which is mainly driven by their higher average employment shares in the non-manufacturing sector (78% versus 72%). This non-manufacturing sector is one of the few net exporting sectors, which therefore expands when the economy opens up to trade.

A simple variance decomposition shows that 85.2 percent of the variance in welfare changes across groups is explained by the commuting zone to which they belong, while their type explains 0.3 percent of the overall variance.[71] This implies that the baseline model already captures most of the action regarding the distributional welfare effects of the China shock.

H.2 Heterogeneity by gender and education

We have also considered the case with worker types defined by gender and education level. The main difference is that the female non-college workers have an imprecisely estimated $\kappa_m = 26.7$, whereas κ_m is between 1.3 and 1.65 for the other worker types (See Table H.3). These female non-college workers gain the least from the China shock, and this is true both with the estimated κ_m for each group and setting $\kappa_m = 1.5$ for all groups. Appendix Table H.4 has the full results. As in the case with groups defined by age and education, when we define groups by gender and education most of the

[70] In this and all other simulations of the China shock, we recalibrate the shock following the same procedure as that in Section 5.1.

[71] We run the regression $\ln \hat{y}_g = \delta_m + \delta_{CZ} + \epsilon_g$, where δ_m and δ_{CZ} are fixed effects for worker type and CZ, respectively, and then use $\frac{cov(\ln \hat{y}_g, \delta_{CZ})}{var(\ln \hat{y}_g)}$ as the share of the variance explained by the commuting zone, and similarly for the share of the variance explained by the group's type.

variance in the welfare changes comes from commuting zone fixed effects, which explain 86.6% of the variance, while worker-type fixed effects explain only 1.96% of the variance.

Table H.1: Estimates for κ_m by age and education level

	(1)	(2)	(3)	(4)	(5)
$\ln \hat{\pi}_{NM}$	-0.558**	-0.346	-0.648**	-0.551**	-0.707**
	(0.203)	(0.363)	(0.304)	(0.203)	(0.231)
Implied κ	1.791	2.889	1.544	1.814	1.414
First Stage Coeff.	2.180	2.047	2.744	1.738	1.664
First Stage F	132.4	38.99	90.09	31.25	64.26
College educated	Pooled	No	No	Yes	Yes
Age 50 or older	Pooled	Yes	No	Yes	No
Observations	5776	1444	1444	1444	1444

IV-estimation results for specification (23), where y_g is average earnings per worker, and π_{gNM} is the employment share in non-manufacturing for group g. Groups are now defined by commuting zones and worker type m (non-college vs. college, and below age 50 vs. age 50 and above). We first estimate a pooled model with all groups in column (1). We then estimate the model separately for each worker type τ: column (2) presents estimates for older non-college workers, column (3) for young non-college workers, while columns (4) and (5) present results for college workers who are older and young, respectively. The shift-share insruments are constructed using contemporaneous group-specific employment shares at the 13-sector level obtained from ACS data (this is the only available level of disaggregation available that contains worker demographic data). Our instruments are $Z_{gt} \equiv \sum_{s\in M} \pi_{gst} \Delta IP_{st}^{China\to Other}$, where s represents each of our 13 aggregated manufacturing sectors and g represents CZ by age and education groups. Standard errors are clustered at the state level and reported in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. The first row shows the second-stage results, while the third row has the corresponding κ estimates implied by the model and the fourth row displays the F-statistic from the first stage. All regressions include state by period fixed effects in addition to the controls employed in ADH's preferred specification: lagged manufacturing shares and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

Table H.2: Heterogeneity in Welfare Effects by Age and Education

	Mean	CV	Mean	CV
All	0.23	1.21	1.41	0.77
	(0.008)	*(0.106)*	*(0.02)*	*(0.122)*
Young, Non-college	0.24	1.06	1.28	0.87
	(0.008)	*(0.089)*	*(0.111)*	*(0.251)*
Old, Non-college	0.21	1.31	1.10	1.07
	(0.018)	*(0.222)*	*(0.138)*	*(0.263)*
Young, College	0.23	1.21	1.63	0.60
	(0.009)	*(0.08)*	*(0.048)*	*(0.044)*
Old, College	0.26	1.24	1.63	0.61
	(0.014)	*(0.078)*	*(0.046)*	*(0.062)*

The first two columns display the welfare effects for the counterfactual rise of China, while the final two columns show the gains from trade. Columns 1 and 3 display, for the relevant worker type, the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,mg}-1)$. The second and third column show the coefficient of variation (CV). For the gains from trade, we simulate the return to autarky, and for that simulation report the negative of the mean welfare gain. Standard errors, computed using the delta method and numerical derivatives for each of the statistics, in parentheses.

Table H.3: Estimates for κ_m by gender and education level

	(1)	(2)	(3)	(4)	(5)
$\ln \hat{\pi}_{NM}$	-0.466**	-0.749**	-0.037	-0.770**	-0.605**
	(0.156)	(0.289)	(0.293)	(0.316)	(0.237)
Implied κ	2.146	1.336	26.75	1.299	1.652
First Stage Coeff.	2.286	2.523	2.934	1.423	1.632
First Stage F	134.7	58.43	119.9	20.82	85.39
College educated	Pooled	No	No	Yes	Yes
Male	Pooled	Yes	No	Yes	No
Observations	5776	1444	1444	1444	1444

IV-estimation results for specification (23), where y_g is average earnings per worker, and π_{gNM} is the employment share in non-manufacturing for group g. Groups are now defined by commuting zones and worker type m (non-college vs. college, and below male vs. female). We first estimate a pooled model with all groups in column (1). We then estimate the model separately for each worker type τ: column (2) presents estimates for male non-college workers, column (3) for female non-college workers, while columns (4) and (5) present results for male and female college workers, respectively. The shift-share insruments are constructed using contemporaneous group-specific employment shares at the 13-sector level obtained from ACS data (this is the only available level of disaggregation available that contains worker demographic data). Our instruments are $Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{China \to Other}$, where s represents each of our 13 aggregated manufacturing sectors and g represents CZ by age and education groups. Standard errors are clustered at the state level and reported in parentheses, with * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. The first row shows the second-stage results, while the third row has the corresponding κ estimates implied by the model and the fourth row displays the F-statistic from the first stage. All regressions include state by period fixed effects in addition to the controls employed in ADH's preferred specification: lagged manufacturing shares and beginning-of-period conditions (% college educated, % foreign-born, % employment among women, % employment in routine occupations, and the average offshorability index).

Table H.4: Heterogeneity in Welfare Effects by Gender and Education

	Mean	CV	Mean	CV
All	0.18	1.00	1.43	0.53
	(0.033)	*(1.388)*	*(0.002)*	*(0.41)*
Female, Non-college	0.14	1.16	1.30	0.58
	(0.233)	*(3.717)*	*(0.517)*	*(0.897)*
Male, Non-college	0.21	0.80	1.43	0.50
	(0.214)	*(0.291)*	*(0.299)*	*(0.398)*
Female, College	0.17	0.92	1.53	0.51
	(0.044)	*(0.666)*	*(0.727)*	*(0.1)*
Male, College	0.18	1.13	1.47	0.52
	(0.106)	*(1.346)*	*(0.084)*	*(0.215)*

The first three columns display the welfare effects for the counterfactual rise of China, while the final three columns show the gains from trade. Columns 1 and 4 displays, for the relevant worker type, the aggregate welfare effect for that worker type in the US, in percentage terms $100(\widehat{W}_{US,m} - 1)$, and columns 2 and 5 show the mean welfare effect: $100(\frac{1}{G}\sum_g \widehat{W}_{US,mg} - 1)$. The third column shows the coefficient of variation (CV). For the gains from trade, we simulate the return to autarky, and for that simulation report the negative of all the above statistics. Standard errors, computed using the delta method and numerical derivatives for each of the statistics, in parentheses.

Online Appendix I Model with voluntary and involuntary unemployment

I.1 Equilibrium system for model with employment effects

For the model in Section 8, the equilibrium system to solve for wages $\{w_{is}\}$ is still given by Equation (6):

$$ELD_{is} \equiv \frac{1}{w_{is}} \sum_j \lambda_{ijs} \beta_{js} X_j - \sum_{g \in G_i} \mathcal{Z}_{igs}.$$

The difference is that now we have $\mathcal{Z}_{igs} = \frac{\pi_{igs} \pi_{igF} W_{ig} L_{ig}}{\nu \omega_{is}}$, where $\omega_{is} = w_{is}/P_i$ is the real wage,

$$\pi_{igs} = \frac{A_{igs} \omega_{is}^{\kappa}}{\sum_{k \in F} A_{igk} \omega_{ik}^{\kappa}},$$

and π_{igF} and W_{ig} are given by Equations (28) and (29) respectively , where the latter depends on the employment rate e_{ig}, given by Equation (30).

I.2 Additional counterfactual results for the model with unemployment

Table I.5: Impact of the rise of China with voluntary and involuntary unemployment

(a) Changes in real income

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\to 1$	0.23	0.29	1.37	-1.87	2.37	0.14
1.5	0.21	0.26	1.15	-1.54	1.72	0.15
3.0	0.20	0.23	0.81	-0.98	1.03	0.16
$\kappa \to \infty$	0.20	0.20	0.11	0.11	0.25	0.20

(b) Changes in home production share

κ	$\widehat{\pi}_{US,HP}$	Mean	CV	Min.	Max.
$\to 1$	-0.56	-0.72	-1.38	-5.70	4.82
1.5	-0.54	-0.65	-1.16	-4.18	3.96
3.0	-0.52	-0.58	-0.81	-2.54	2.49
$\kappa \to \infty$	-0.49	-0.49	-0.11	-0.61	-0.27

(c) Changes in employment rate

κ	$\widehat{e}_{US}$	Mean	CV	Min.	Max.
$\to 1$	0.08	0.10	1.37	-0.63	0.79
1.5	0.08	0.09	1.15	-0.52	0.57
3.0	0.07	0.08	0.81	-0.33	0.34
$\kappa \to \infty$	0.07	0.07	0.11	0.04	0.08

The tables show summary statistics for the effect of the China shock for the model with frictional unemployment and home production, with $\mu = 2.5$. Panel (a) documents the aggregate real income gains for the US as $100(\widehat{W}_{US}-1)$ (column 1) and the mean gains as $100\frac{1}{G}(\sum_g \widehat{W}_{US,g}-1)$ (column 2). Panel (b) shows the aggregate and mean change in π_{gHP} as $100(\widehat{\pi}_{US,HP}-1)$ (column 1) and $100\frac{1}{G}(\sum_g \widehat{\pi}_{USg,HP}-1)$ (column 2). Finally, Panel (c) shows the change in the employment rate $100(\widehat{e}_{US}-1)$ (column 1) and $100(\widehat{e}_{USg,HP}-1)$. In each panel, the third column shows the coefficient of variation (CV), and the fourth and fifth column show the minimum and maximum change Min.$\equiv$ $\min_g 100(\widehat{x}_{US,g}-1)$ and Max.$\equiv$ $\max_g 100(\widehat{x}_{US,g}-1)$, where x is the relevant variable for that panel. The final column in Panel (a) shows the aggregate ACR gains for the US, in percentage terms.

Table I.6: Impact of trade with home production and frictional unemployment

(a) Real income gains from trade

κ	$\widehat{W}_{US}$	Mean	CV	Min.	Max.	$\prod_s \widehat{\lambda}_s^{-\beta_s/\theta_s}$
$\rightarrow 1$	1.57	1.61	0.80	-6.28	3.91	1.45
1.5	1.52	1.54	0.58	-3.77	3.15	1.45
3.0	1.47	1.48	0.33	-1.23	2.36	1.45
$\rightarrow \infty$	1.42	1.41	0.11	0.78	1.76	1.45

(b) Changes in home production share

κ	$\widehat{\pi}_{US,HP}$	Mean	CV	Min.	Max.
$\rightarrow 1$	-3.16	-4.20	-0.77	-10.50	14.11
1.5	-3.28	-4.00	-0.57	-8.32	8.83
3.0	-3.43	-3.81	-0.33	-6.16	3.02
$\rightarrow \infty$	-3.60	-3.62	-0.11	-4.54	-1.98

(c) Changes in employment rate

κ	$\widehat{e}_{US}$	Mean	CV	Min.	Max.
$\rightarrow 1$	0.43	0.54	0.79	-2.05	1.32
1.5	0.44	0.52	0.57	-1.24	1.06
3.0	0.46	0.50	0.33	-0.41	0.79
$\rightarrow \infty$	0.48	0.47	0.11	0.26	0.59

The tables show summary statistics for opening up to trade for the model with frictional unemployment and home production, based on a simulation of the return to autarky. Panel (a) documents the aggregate gains from trade for the US as $100(1 - \widehat{W}_{US})$ (column 1) and the mean gains as $100\frac{1}{G}(\sum_g 1 - \widehat{W}_{US,g})$ (column 2). Panel (b) shows the aggregate and mean change in π_{gHP} as $100(1 - \widehat{\pi}_{US,HP})$ (column 1) and $100\frac{1}{G}(\sum_g 1 - \widehat{\pi}_{USg,HP})$ (column 2). Finally, Panel (c) shows the change in the employment rate $100(1 - \widehat{e}_{US})$ (column 1) and $100(1 - \widehat{e}_{USg,HP})$. In each panel, the third column shows the coefficient of variation (CV), and the fourth and fifth column show the minimum and maximum change Min.$\equiv \min_g 100(1 - \widehat{x}_{US,g})$ and Max.$\equiv \max_g 100(1 - \widehat{x}_{US,g})$, where x is the relevant variable for that panel. The final column in Panel (a) shows the aggregate ACR gains for the US, in percentage terms.

Table I.7: Standard errors for results with home production and unemployment

(a) The rise of China

	Aggregate	Mean	CV	Min.	Max.
$\widehat{W}_g$	0.27	0.33	1.26	-2.08	2.42
	(0.03)	*(0.03)*	*(0.17)*	*(0.25)*	*(0.47)*
$\widehat{\pi}_{gHP}$	-0.72	-0.90	-1.28	-6.38	5.99
	(0.19)	*(0.27)*	*(0.17)*	*(2.51)*	*(2.15)*
$\widehat{e}_g$	0.14	0.17	1.26	-1.05	1.20
	(0.04)	*(0.05)*	*(0.17)*	*(0.28)*	*(0.31)*

(b) Gains from trade

	Aggregate	Mean	CV	Min.	Max.
$\widehat{W}_g$	1.84	1.87	0.68	-5.90	4.23
	(0.19)	*(0.18)*	*(0.17)*	*(1.99)*	*(0.57)*
$\widehat{\pi}_{gHP}$	-4.29	-5.45	-0.67	-12.69	14.65
	(1.17)	*(1.52)*	*(0.15)*	*(5.03)*	*(7.81)*
$\widehat{e}_g$	0.78	0.94	0.68	-2.91	2.14
	(0.24)	*(0.28)*	*(0.17)*	*(0.91)*	*(0.55)*

The tables show summary statistics for the variables listed in the first column for US groups for the model with home production and frictional unemployment. Panel (a) shows results for the counterfactual rise of China, and Panel (b) shows results for opening up to trade, starting from autarky. The first column of results shows the aggregate effect, and the second column the average effect. The third column displays the coefficient of variation (CV), and for the fourth and fifth column we show the minimum and maximum change. All results are in terms of percentage changes. Standard errors are computed using the delta method and shown in parentheses. Throughout, we use the estimation results specification 4 from Table 6, where $\alpha = 0.499$, $\mu = 2.762$ and $\kappa = 1.199$, since these coefficients are the most precisely estimated. We use the variance-covariance matrix obtained for this specification when computing the standard errors using the delta method.

Online Appendix J Mobility across Groups

Here we consider an extension of the benchmark model where workers can move across regions but not across countries. Assume that each worker gets a draw in each sector and each region. Workers also have an "origin region." We say that a worker with origin region g is "from region g." Each worker gets a draw z in each region-sector combination (h, s) from a Fréchet distribution with parameters κ and A_{ihs}. Workers are fully described by a matrix $\boldsymbol{z} = \{z_{hs}\}$ and an origin region g. A worker from region g in country i that wants to work in region h of country i suffers a proportional adjustment to income determined by ξ_{igh}, with $\xi_{igg} = 1$ and $\xi_{igh} \leq 1$ for all i, g, h. Thus, a worker from g that works in region h in sector s has income of $w_{is}\xi_{igh}z_{hs}$.

We now let

$$\Omega_{igfs} \equiv \{\boldsymbol{z} \text{ s.t. } w_{is}\xi_{igf}z_{fs} \geq w_{ik}\xi_{igh}z_{hk} \text{ for all } h, k\}.$$

A worker with productivity matrix $\boldsymbol{z}$ from region g in country i will choose region-sector (f, s) iff $\boldsymbol{z} \in \Omega_{igfs}$. The share of workers in group g in country i that choose to work in (f, s) is then

$$\pi_{igfs} \equiv \int_{\Omega_{gfs}} dF(\boldsymbol{z}) = \frac{A_{fs}\left(\xi_{igf}w_{is}\right)^{\kappa}}{\Phi_{ig}^{\kappa}},$$

where $\Phi_{ig}^{\kappa} \equiv \sum_{h,k} A_{ihk}\left(\xi_{igh}w_{ik}\right)^{\kappa}$.

The efficiency units supplied by this group in sector (f, s) are given by

$$\mathcal{Z}_{igfs} \equiv L_{ig}\int_{\Omega_{gfs}} z_{fs}dF_i(z) = \pi_{igfs}\eta L_{ig}\frac{\Phi_{ig}}{w_{is}\xi_{igf}}.$$

Total income of group g in country i is $Y_{ig} \equiv \sum_{f,s} w_{is}\xi_{gf}E_{igfs} = \eta L_{ig}\Phi_{ig}$. Moreover, the share of income obtained by workers in group g in country i in region-sector (f, s) is also given by π_{igfs}, while (ex-ante) per capita income for workers of group g in country i is $Y_{ig}/L_{ig} = \eta\Phi_{ig}$.

Let $\mu_{igh} \equiv \sum_s \pi_{ighs}$ be the share of workers from g that work in h. It is easy to verify that $\pi_{ighs}/\mu_{igh} = \pi_{ihhs}/\mu_{ihh}$ for all i, g, h, s. Thus, conditional on locating in region h, all workers irrespective of their origin have sector employment shares given by $\pi_{ihs} \equiv \pi_{ighs}/\mu_{igh}$. The shares π_{ihs} and μ_{igh} will be enough to characterize the equilibrium below.

The labor demand side of the model is exactly as in the case with no labor mobility across regions. Putting the supply and demand sides of the economy together, we see that excess demand for efficiency units in sector s of country i is

$$ELD_{is} \equiv \frac{1}{w_{is}} \sum_{j} \lambda_{ijs} \beta_{js} Y_j - \sum_{g,h} E_{ighs}.$$

Noting that λ_{ijs}, Y_j and E_{ighs} are functions of the whole matrix of wages $\boldsymbol{w} \equiv \{w_{is}\}$, the system $ELD_{is} = 0$ for all i, s is a system of equations in $\boldsymbol{w}$ whose solution gives the equilibrium wages for a given choice of numeraire.

Turning to comparative statics, the implications of a trade shock can be characterized in similar fashion as before. Changes in wages can be obtained as the solution to the system of equations given by

$$\sum_{g,h} \hat{\pi}_{ihs} \hat{\Phi}_{ig} \mu_{igh} \pi_{ihs} Y_{ig} = \sum_{j} \lambda_{ijs} \hat{\lambda}_{ijs} \beta_{is} \sum_{g} \hat{\Phi}_{jg} Y_{jg} \tag{40}$$

with $\hat{\Phi}^{\kappa}_{ig} = \sum_{h,s} \mu_{igh} \pi_{ihs} \hat{w}^{\kappa}_{is}$, (9) and $\hat{\pi}_{ihs} = \hat{\pi}_{ighs}/\hat{\mu}_{igh}$, $\hat{\pi}_{ighs} = \hat{w}^{\kappa}_{is}/\hat{\Phi}^{\kappa}_{ig}$, and $\hat{\mu}_{igh} = \sum_s \pi_{ihs} \hat{\pi}_{ighs}$. Equation (40) can be solved for $\hat{w}_{is}$ given data on income levels, Y_{ig}, trade shares, λ_{ijs}, migration shares μ_{igh}, employment shares π_{ihs}, and the shocks, $\hat{\tau}_{ijs}$ and $\hat{T}_{js}$. In turn, given $\hat{w}_{is}$, changes in trade shares can be obtained from (9), while changes in migration and employment shares can be obtained from the expressions for $\hat{\pi}_{ihs}$ and $\hat{\mu}_{igh}$ above.

Given $\hat{w}_{ik}$, the following proposition analogous to Proposition 1 characterizes the impact of a trade shock on ex-ante real wages for different groups of workers.

Proposition 6. *Given some trade shock, the ex-ante percentage change in the real wage of group g in country i is given by* $\hat{W}_{ig} = \prod_{s} \hat{\lambda}_{iis}^{-\beta_{is}/\theta} \cdot \prod_{s} \left(\hat{\mu}_{igg} \hat{\pi}_{igs}\right)^{-\beta_{is}/\kappa}$.

For the limit case $\kappa \to 1$ we again have $\lim_{\kappa \to 1} \hat{Y}_{ig}/\hat{Y}_i = 1/\hat{I}_{ig}$, except that now $I_g \equiv \sum_s v_{igs} \frac{\beta_{is}}{r_{is}}$, where $\nu_{igs} \equiv \sum_h \mu_{igh} \pi_{ihs}$ is the share of workers from region g that work in sector s.