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.

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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.1 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 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 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, \( \kappa \), 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

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1For a brief intellectual history on the debate about trade and inequality, see Goldberg (2015).
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 $\kappa$. 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 $\kappa$ around 1.5, which is in line with estimates of this Roy-Fréchet parameter in related contexts (e.g., Adao, Arkolakis and Esposito 2017, Burstein, Morales and Vogel 2015 and Hsieh, Hurst, Jones and Klenow 2013).

Armed with our estimate of $\kappa$, we calibrate the China shock following a strategy similar to that in Caliendo, Dvorkin and Parro (2015) 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).\(^2\) 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

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\(^2\)Recent papers that pursue a similar strategy in the trade context are Antras, de Gortari and Itskhoki (2016) and Carrère, Grujovic and Robert-Nicoud (2015). 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.
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increase is only slightly below than the welfare gains without inequality aversion.

Moving beyond the China shock, we also use our model to compute the group-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, which are 1.6%.

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). At the same time, by assuming competitive labor markets with a perfectly inelastic labor supply, all welfare effects operate through changes in real factor prices. As a result, we are unable to capture the effects of trade on employment, and the large associated costs to individuals inside groups. As discussed in detail towards the end of the paper, this is a challenging but important question for future research.

Our paper is related to several research areas in international trade. 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). 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 (2016), 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 ef-

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3Other empirical papers exploring the effects of trade shocks on local labor markets are Dauth, Findel-}

fects 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. 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. (2015), Lee (2016), and Adao et al. (2017) 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. (2015) emphasize the dynamics of adjustment after an unexpected trade shock, Lee (2016) focuses on the implications for the skill premium, and Adao et al. (2017) 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. 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 $\kappa$ 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 $\kappa$ that is needed to compute the group-level welfare effects of trade.

Finally, our paper is also related to Hsieh and Ossa (2011), 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 (2017), both of which estimate the effect of the China shock on the U.S. consumer price index.

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. Section 7 presents extensions of the baseline model and a discussion of employment effects. Section 8 concludes.

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 \( \sigma_s \), 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 \( \beta_is \). There are iceberg trade costs \( \tau_{ijs} \geq 1 \) to export goods in sector \( s \) from country \( i \) to country \( j \), with \( \tau_{iis} = 1 \).

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 \( L_{ig} \). This implies that labor supply is inelastic – workers simply choose the sector to which they supply their entire labor endowment. In Section 7 we discuss extensions that allow for endogenous labor supply arising from mobility of workers across groups or the possibility of home production.

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

\(^6\)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
is in autarky and collapses to the Roy model in Lagakos and Waugh (2013) (see also Hsieh et al. (2013)).

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. 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 $\lambda_{ijs}$ are sectoral trade shares given by

$$
\lambda_{ijs} = \frac{T_{is} (\tau_{ijs} w_{is})^{-\theta_s}}{\sum_i T_{is} (\tau_{ijs} w_{is})^{-\theta_s}}.
$$

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

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

where $\gamma_s \equiv \Gamma(1 - \sigma_s^{-1})^{1/(1-\sigma_s)}$.

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7There 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.

8As 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
Labor supply is determined by workers’ choices regarding which sector to work in. Let \( z = (z_1, z_2, \ldots, z_S) \) and let \( \Omega_{is} \equiv \{ z \text{ s.t. } w_{is}Z_s \geq w_{ik}Z_k \text{ for all } k \} \). A worker with productivity vector \( z \) in country \( i \) will choose sector \( s \) iff \( z \in \Omega_{is} \). Let \( F_{ig}(z) \) be the joint probability distribution of \( z \) 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 choose to work in sector \( s \) is:

\[
\pi_{igs} \equiv \int_{\Omega_{is}} dF_{ig}(z) = \frac{A_{igs}w_{is}^{\kappa_{ig}}}{\Phi_{ig}^{\kappa_{ig}}},
\]

where \( \Phi_{ig}^{\kappa_{ig}} = \sum_k A_{igk}w_{ik}^{\kappa_{ig}} \). In turn, the supply of efficiency units by this group to sector \( s \) is given by

\[
E_{igs} \equiv L_{ig} \int_{\Omega_{is}} z_s dF_{ig}(z) = \eta_{ig} \frac{\Phi_{ig}}{w_{is}} \pi_{igs} L_{ig},
\]

where \( \eta_{ig} \equiv \Gamma(1 - 1/\kappa_{ig}) \). One implication of this result is that income levels per worker are equalized across sectors. That is, for group \( ig \), we have

\[
\frac{w_{is}E_{igs}}{\pi_{igs}L_{ig}} = \eta_{ig} \Phi_{ig}.
\]

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., \( w_{is}E_{igs}/\sum w_{ik}E_{igk} \)) is also given by \( \pi_{igs} \). Note also that total income of group \( ig \) is \( Y_{ig} \equiv \sum_s w_{is}E_{igs} = \eta_{ig}L_{ig}\Phi_{ig} \), while total 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

\[
X_j = Y_j + D_j,
\]

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

\[
ELD_{is} \equiv \frac{1}{w_{is}} \sum_j \lambda_{ij} s / \beta_{js} X_j - \sum_{g \in G_i} E_{igs}.
\]

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\(^9\)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 \( \kappa_{ig} \) is replaced by \( \kappa_{ig}/(1 - \rho_{ig}) \), where \( \rho_{ig} \) measures the correlation parameter of ability draws across sectors for each worker.

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\(^9\)Costinot and Rodríguez-Clare (2014) and Kucheryavyy, Lyn and Rodríguez-Clare (2018).
Since $\lambda_{ijs}, Y_j$ and $E_{igs}$ are functions of the whole matrix of wages $w \equiv \{w_{is}\}$, the system $ELD_{is} = 0$ for all $i$ and $s$ is a system of equations in $w$ whose solution gives the equilibrium wages for 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 $w'_{is}E'_{igs} = \hat{\pi}_{igs}\hat{Y}_{ig}\hat{\pi}_{igs}\hat{Y}_{ig}$, equation $ELD'_{is} = 0$ can be written as

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

with

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

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

and

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

Given values for parameters $\theta_s$ and $\kappa_{ig}$, data on income levels, $Y_{ig}$, trade imbalances, $D_j$, trade shares, $\lambda_{ijs}$, expenditure shares, $\beta_{is}$, labor allocation shares $\pi_{igs}$, 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, $W_{ig} \equiv \frac{Y_{ig}/L_{ig}}{P_i}$. 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 prefer-
ences imply that
\[ \hat{W}_{ig} = \hat{Y}_{ig} \prod_s \hat{P}_{is}^{-\beta_{is}}. \quad (11) \]

From (2) and (9) and given \( \hat{T}_{is} = 1 \) for all \( s \) in domestic country \( i \), we have \( \hat{P}_{is} = \hat{w}_{is} \lambda_{is}^{1/\theta_s} \) while from (8) and (10) we have \( \hat{Y}_{ig} = \hat{w}_{ig} \pi_{igs}^{-1/\kappa_{ig}} \). 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 percentage change in the real wage of group \( g \) in country \( i \) is given by

\[ \hat{W}_{ig} = \prod_s \lambda_{is}^{-\beta_{is}/\theta_s} \cdot \prod_s \pi_{igs}^{-\beta_{is}/\kappa_{ig}}. \quad (12) \]

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

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

\[ D_{KL}(\pi_{ig} \parallel \beta_i) \equiv \sum_s \beta_{is} \ln(\beta_{is}/\pi_{igs}). \]

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,

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

We can then proceed as in ACR to substitute for \( d \ln w_{js} \) and \( d \ln (w_{is} \tau_{ij}s) \) in this expression. From the trade side of the model we have \( \frac{d \ln (\lambda_{ij}s)}{d \ln (w_{is} \tau_{ij}s)} = -\theta_s \), while from the labor side we have \( \frac{d \ln (\pi_{jgs})}{d \ln (w_{js}/w_{ik})} = -\kappa_{ig} \). Solving for \( d \ln (w_{is} \tau_{ij}s) \) and \( d \ln w_{js} \) from these two equations, respectively, and then plugging back into the expression for \( d \ln W_{jg} \) above yields \( d \ln W_{jg} = -\sum_s \beta_{js} \left[ \frac{d \ln \pi_{jgs}}{\kappa_{ijg}} + \frac{d \ln \lambda_{ij}s}{\theta_s} \right] \). Integration leads to the result in (12).
Note that if group \( ig \) was in full group-level autarky (i.e., not trading with any other group or country) then \( \pi_{ig} = \beta_i \). Thus, \( D_{KL}(\pi_{ig} \parallel \beta_i) \) is a measure of the degree of specialization as reflected in the divergence of the actual distribution \( \pi_{ig} \) relative to \( \beta_i \).

We can now write

\[
\prod_s \pi_{igs}^{-\beta_{is}/\kappa_{ig}} = \exp \left( \frac{1}{\kappa_{ig}} \left[ D_{KL}(\pi_{ig}^{\prime} \parallel \beta_i) - D_{KL}(\pi_{ig} \parallel \beta_i) \right] \right).
\]

This implies that, apart from the common term \( \prod_s \lambda_{iis}^{-\beta_{is}/\theta_{is}} \), 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 from trade (compared to other groups) 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.

As a parenthesis, 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 terms of trade are 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

The aggregate welfare effect can be obtained from Proposition 1 as \( \hat{W}_i \equiv \hat{Y}_i/\hat{P}_i = \sum_{g \in G_i} (Y_{ig}/Y_i) \hat{W}_{ig} \). Using (12), this can be written explicitly as

\[
\hat{W}_i = \prod_s \lambda_{iis}^{-\beta_{is}/\theta_{is}} \cdot \sum_{g \in G_i} \left( \frac{Y_{ig}}{Y_i} \right) \prod_s \pi_{igs}^{-\beta_{is}/\kappa_{ig}}.
\]

(13)
The aggregate welfare effect of a trade shock is no longer given by the multi-sector ACR term (i.e., \( \hat{W}_i \neq \prod_s \hat{\lambda}_{iss}^{\beta_{is}/\theta_{ss}} \)). This is because a trade shock will in general affect 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 \( \hat{\tau}_{ij} = \infty \) for all \( s \) and all \( i \neq j \) and \( \hat{D}_i = 0 \). Conveniently, solving for changes in wages in country \( i \) (i.e., solving for \( \hat{w}_{is} \) for \( s = 1, \ldots, S \)) from Equation (7) only requires knowing the values of employment shares, income levels and expenditure shares for country \( i \), namely \( \beta_{is} \) for all \( s \) and \( \pi_{igs} \) and \( Y_{ig} \) for all \( g, s \). This can be seen by letting \( \hat{\tau}_{ij} \to \infty \) in Equation (7), which yields

\[
\beta_{is} \sum_{g \in G_i} \hat{Y}_{ig} Y_{ig} = \sum_{g \in G_i} \hat{\pi}_{igs} \hat{Y}_{ig} \pi_{igs} Y_{ig}.
\]

(14)

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 \( \kappa_i \to \infty \).

Appendix C 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 autarky would imply

\[
\hat{W}_i^A = \prod_s \hat{\lambda}_{iss}^{\beta_{is}/\theta_{ss}} \cdot \exp\left[ -\frac{1}{\kappa_i} D_{KL}(r_i || \beta_i) \right].
\]

If there is inter-industry trade then \( D_{KL}(r_i || \beta_i) > 0 \) so (given \( r_i \)) a finite \( \kappa_i \) implies a lower \( \hat{W}_i^A \) than in the multi-sector ACR formula. Intuitively, a finite \( \kappa_i \) 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

$$GT_{ig} = 1 - \prod_s \lambda_{is}^{\beta_{is}/\theta_s} \cdot \exp \left( \frac{1}{\kappa_{ig}} \left[ D_{KL}(\pi_{ig}^A \parallel \beta_{is}) - D_{KL}(\pi_{ig} \parallel \beta_i) \right] \right).$$

The term $D_{KL}(\pi_{ig}^A \parallel \beta_{is}) - D_{KL}(\pi_{ig} \parallel \beta_i)$ 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

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

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:

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

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 $\left( \frac{\hat{Y}_{ig}}{\hat{Y}_i} \right)^{1-\kappa_i}$ is an adjustment to take into account how $(\hat{Y}_{ig}/\hat{Y}_i)^{\kappa_i}$ 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 $\kappa$ 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 $\hat{r}_{ik} \approx (\hat{w}_{is}/\hat{Y}_i)^{\kappa_i}$, implying that

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

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:

$$
\frac{\hat{Y}_{ig}}{\hat{Y}_i} \approx \left( \sum_s \pi_{igs} \frac{\beta_{is}}{r_{is}} \right)^{1/\kappa_i}.
$$

(16)

We can think of $\beta_{is}/r_{is}$ 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 $1/\kappa_i$. Note also that, since a foreign shock does not affect the autarky equilibrium, we can use the result in (16) to rewrite the approximation in (15) for any foreign shock in terms of the change in the index of import competition, $\hat{Y}_{ig}/\hat{Y}_i \approx \hat{I}_{ig}^{-1/\kappa_i}$.

### 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 Frechet with scale parameter $A_{igs}$ and shape parameter $\kappa_{ig}$, then income $\max_s w_{is} z_s$ for workers in group $ig$ is distributed Frechet with scale parameter $\Phi_{ig}^{\kappa_{ig}}$ and...
shape parameter $\kappa_{ig}$. Social welfare in country $i$ is then:

$$U_i = \left( \sum_{g \in G_i} \frac{\Gamma \left( 1 - \frac{1-\rho}{\kappa_{ig}} \right)}{\eta_{ig}} l_{ig} W_{ig}^{1-\rho} \right)^{\frac{1}{1-\rho}},$$

where $l_{ig} \equiv L_{ig}/L_i$.\textsuperscript{11}

In the quantitative section below we will focus on the case $\kappa_{ig} = \kappa_i$, which implies that

$$U_i = \tilde{\eta}_i \left( \sum_{g} l_{ig} W_{ig}^{1-\rho} \right)^{\frac{1}{1-\rho}},$$

where $\tilde{\eta}_i \equiv \frac{\Gamma \left( 1 - \frac{1}{\kappa_i} \right)}{\Gamma \left( 1 - \frac{1-\rho}{\kappa_i} \right)}$. 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 $GT_i \equiv 1 - \hat{W}_i^A$.\textsuperscript{12}

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 with different income levels. Then simple algebra reveals that

$$\tilde{U}_i = \left( \sum_{g} \omega_{ig} W_{ig}^{1-\rho} \right)^{\frac{1}{1-\rho}}. \quad (18)$$

### 2.8 Extensions of the baseline model

We have demonstrated how the combination of a stylized Roy 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. We also explained how the distributional effects are closely approximated by Bartik-style

\textsuperscript{11}This result is derived by integrating $U_i = \frac{1}{\Gamma(1-\rho)} \left( \sum_{g \in G_i} \int_0^\infty y^{1-\rho} L_{ig} dH_{ig}(y) \right)^{\frac{1}{1-\rho}}$, with $H_{ig}(y) = \exp \left(-\Phi_{ig}^{\kappa_{ig}} y^{-\kappa_{ig}} \right)$.

\textsuperscript{12}A Rawlsian approach to social welfare entails $\rho \to \infty$ and $\hat{U}_i = \min_{g} W_{ig}^{\prime}/\min_{g} W_{ig}$. If $\arg \min_{g} W_{ig}^{\prime} = \arg \min_{g} W_{ig} = h$ then $\hat{U}_i = \hat{W}_{ih}$, but of course this need not be the case. We discuss plausible values for $\rho$ in Section 5.
changes in import competition and how to integrate the full distribution of group-level effects 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 income changes, 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 sum, our stylized model is a flexible framework that delivers a rich set of results with only a few degrees of freedom. At the same time, we recognize that the model is highly stylized. In Section 7 we will relax some simplifying assumptions of the baseline model. In particular, we will introduce intermediate goods and a non-tradable sector, studying for each case the associated qualitative and quantitative implications.

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. 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 same data sources and definitions. These include labor income from the American Community Survey (ACS) and decennial censuses, employment shares across industries for each commuting zone from the County Business Patterns database, and trade flows from the UN Comtrade database. As in ADH, we focus our analysis on the periods 1990-2000 and 2000-2007. 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) is motivated by the availability of trade data from 1991 to 2000, and we multiply trade growth with the factor 10/9. Since trade figures are only available from 1991 for the time period 1991 to 2000, we multiplied trade growth with the factor 10/9.

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13Our 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.

14In 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.

15As 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.
2007) resulted from the data requirement on bilateral trade flows from the World Input-Output Database (WIOD), which are only available starting 1995.\textsuperscript{16} 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.

Since we require consistency between the trade and labor data, we focus on \( \pi_{igs} \) as shares of earnings, \( \pi_{igs} = \frac{Y_{igs}}{\sum_k Y_{igk}} \).\footnote{The World Input-Output Database (WIOD) is discussed in Timmer, Dietzenbacher, Los, Stehrer and Vries (2015).} For US groups we also set \( Y_{igs} = \frac{Y_{ACS}^{igs}}{\sum_h Y_{ih}^{ACS}} Y_{WIOD}^{ks} \), where the superscript denotes the data source.

Appendix B 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.

4 Estimation

The \( \kappa \) 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 estimation strategy for this parameter that builds on the seminal work of ADH.

ADH find that, at the level of US commuting zones (which we chose as the empirical counterpart of our groups), the China shock leads to a significant contraction in manufacturing employment and a decline in earnings. To connect these findings to our model, we start by setting \( \kappa_g = \kappa \) and using \( \hat{y}_g = \hat{\Phi}_g \) together with equations (8) and (10) to get that \( \hat{y}_g = \hat{A}_g^{1/\kappa} \hat{\pi}_g^{1/\kappa} \) for any \( s \) (where \( y_g \equiv Y_g / L_g \)). Specializing this for the non-manufacturing sector, \( s = NM \), adding a \( t \) subscript to denote time periods, and taking logs yields

\[
\ln \hat{y}_{gt} = \alpha_t + \beta \ln \hat{\pi}_{gNMt} + \varepsilon_{gt},
\]

where \( \alpha_t \equiv \hat{w}_{NMt} \), \( \beta \equiv -1/\kappa \) and \( \varepsilon_{gt} \equiv \ln \hat{A}_g^{1/\kappa} \). We can use this equation to estimate
\( \kappa \) from a cross-group regression of \( \ln \hat{y}_{gt} \) on \( \ln \hat{\pi}_{gNMt} \) (pooling across periods).\(^{18}\) However, since the model implies that productivity shocks lead to employment reallocation across sectors then \( \mathbb{E}[\ln \hat{\pi}_{gNMt} \cdot \varepsilon_{gt}] \neq 0 \), and so instead of running a simple OLS regression we pursue an instrumental-variable strategy to find a consistent estimate of \( \kappa \). In particular, we use the China shock variable constructed by ADH, namely

\[
Z_{gt} \equiv \sum_{s \in M} \pi_{gst-10} \Delta IP_{st}^{China-Other}, \tag{20}
\]

as an instrument for \( \ln \hat{\pi}_{gNMt} \). Here \( M \) refers to the subset of manufacturing sub-industries and

\[
\Delta IP_{st}^{China-Other} \equiv \frac{\Delta Imports_{st}^{China-Other}}{l_{st-10}^{US}},
\]

where \( l_{st-10}^{US} \) denotes US employment in sector \( s \) in year \( t - 10 \), \( Imports_{st}^{China-Other} \) are imports from China by a group of countries similar to the US, and \( \Delta \) refers to the change over period \( t \).\(^{19}\) We focus on the two time periods used in ADH, namely 1990-2000 and 2000-2007.

ADH argue for the need to control for commuting-zone characteristics that may be correlated with the China shock. Such controls can be accommodated in our model by assuming that the unobserved productivity shock \( \ln A_{gNMt} \) is correlated with a vector of group-level variables \( X_{gt} \). Formally, we assume that \( \varepsilon_{gt} = X'_{gt} \Theta + \epsilon_{gt} \), where \( \Theta \) is a vector of parameters and \( \epsilon_{gt} \) is an unobserved shock satisfying \( \mathbb{E}(\epsilon_{gt}|X_{gt}) = 0 \). The estimating equation is then

\[
\ln \hat{y}_{gt} = \alpha_t + \beta \ln \hat{\pi}_{gNMt} + X'_{gt} \Theta + \epsilon_{gt}. \tag{21}
\]

The estimation of \( \kappa \) as \( -1/\beta \) from an IV regression of (21) with instrument \( Z_{gt} \) for

---

\(^{18}\)We focus on the non-manufacturing sector in our estimation, which allows us to build on the primary finding in ADH, namely the contraction in manufacturing employment caused by the China shock. This way, we obtain a strong first stage in our IV estimation (explained below.) In principle, we could also apply estimation equation (19) to other sectors, but for these sectors the China shock is too weak an instrument for predicting \( \hat{\pi}_{gs} \), which inhibits the IV estimation of \( \kappa \). Since the ADH instrument is a shock at the level of aggregate manufacturing, it is unsurprising that its effect on employment in the individual manufacturing sectors is much weaker.

\(^{19}\)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.
\ln \hat{\pi}_{gNMt} \text{ is consistent if } \text{cov}(Z_{gt}, \ln \hat{\pi}_{gNMt}) \neq 0 \text{ and } \text{cov}(Z_{gt}, \epsilon_{gt}) = 0, \text{ where the covariances are taken with respect to } g \text{ for each } t.^{20} \text{ Taking our model in Equations (7) - (10) as the data-generating process for each period, the first condition, on instrument relevance, is satisfied if there are large technology shocks in China.}^{21} \text{ Such shocks should increase Chinese exports to other countries and to the US, leading to the contraction of the manufacturing sector in the most exposed groups and implying that } \text{cov}(Z_{gt}, \ln \hat{\pi}_{gNMt}) > 0, \text{ as found by ADH.}

Turning to the second condition, on instrument validity, note that

\[ \text{cov}(Z_{gt}, \epsilon_{gt}) = \sum_{s \in M} \Delta IP^{\text{China} \rightarrow \text{Other}}_{st} \text{E}[\pi_{gst}^{10} \text{E}[\epsilon_{gt}|\pi_{gst}^{10}]], \]

where \( \pi_{gt} \equiv (\pi_{g1t}, \ldots, \pi_{gSt}).^{22} \text{ It is then immediate that if } \epsilon_{gt} \text{ is mean independent (i.e., } \text{E}(\epsilon_{gt}|Z_{gt}, X_{gt}) = 0 \text{ for all } gt \text{) then } \text{cov}(Z_{gt}, \epsilon_{gt}) = 0, \text{ regardless of the distribution of the rest of the shocks. The condition would fail, for example, if non-manufacturing productivity tended to fall in groups specialized in sectors experiencing a strong increase in Chinese exports to other countries – according to the equation above, this would imply that } \text{cov}(Z_{gt}, \epsilon_{gt}) > 0. \text{ We interpret the controls introduced by ADH as helping to alleviate this concern, since now the condition that group-level non-manufacturing productivity shocks are mean independent is only conditional on those controls (i.e., we need } \text{E}(\epsilon_{gt}|Z_{gt}, X_{gt}) = 0 \text{ rather than } \text{E}(\epsilon_{gt}|Z_{gt}) = 0). \]

According to Goldsmith-Pinkham, Sorkin and Swift (2018), we can think of the Bartik-style IV approach above as relying on a number of instruments, one for each sector, with sector \( s \) instrument being the interaction variable \( Z_{gst} \equiv \pi_{gst}^{10} \Delta IP^{\text{China} \rightarrow \text{Other}}_{st}. \text{ Following the logic above, the condition for validity of this instrument is then simply } \text{E}[\pi_{gst}^{10} \text{E}[\epsilon_{gt}|\pi_{gst}^{10}]] = 0 \text{ for all } s, \text{ which again is guaranteed if } \epsilon_{gt} \text{ is mean indepen-

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20Formally, we run a two-stage least squares regression with dependent variable \( y_{gst} \), regressors (\( \ln \hat{\pi}_{gNMt}, X_{gst} \)) and instruments (\( Z_{gst}, X_{gst} \)).

21Formally, given initial data, parameters \( \{\theta_s\} \) and \( \kappa \), and a set of shocks (including \( \{\epsilon_s\} \) and \( \{\hat{T}_{\text{China},s}\} \)), the model in hat changes in Equations (7) - (10) generates \( \{\hat{y}_s\}, \{\pi_{gNMt}\} \) and \( \{\Delta IP^{\text{China} \rightarrow \text{Other}}_{st}\}. \text{ We think of our data as } \{\Delta IP^{\text{China} \rightarrow \text{Other}}_{st}\} \text{ and subsample } y_{gst} \text{ and } \pi_{gNMt} \text{ for } g = 1, \ldots, G < G, \text{ with } G \text{ large (we could formalize this as a continuum of groups) so that there is no aggregate randomness coming out of the } \epsilon_s \text{ shocks. This implies that } \{\Delta IP^{\text{China} \rightarrow \text{Other}}_{st}\} \text{ is determined independently of the group-level shocks } \{\epsilon_s\}, \text{ a property that we use to formalize the covariances considered below. Consistency is for the limit as } G \rightarrow \infty.

22To be more rigorous, note that the term \( \Delta IP^{\text{China} \rightarrow \text{Other}}_{st} \) is also random and so, to take it outside the expectation in \( \text{E}[\pi_{gst}^{10} \Delta IP^{\text{China} \rightarrow \text{Other}}_{st} \epsilon_{gt}] \), we should think of the covariances above as conditional on \( \{\Delta IP^{\text{China} \rightarrow \text{Other}}_{st}\}. \)
dent.

**Borusyak, Hull and Jaravel (2018)** provide a weaker condition for instrument validity by thinking of consistency in terms of the number of sectors rather than the number of groups. This condition is 

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

as the number of sectors in \( M \) goes to infinity. The sector shares \( \pi_{gst-10} \) are now allowed to be correlated with the error term \( \epsilon_{gt} \), as long as this correlation is orthogonal to the sector-specific China shocks.

Table 1 presents the results of the IV regression described above, with slight variations in the construction of the instrument. 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 displays 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.

Our range of estimated values for \( \kappa \) is consistent with estimates of sector/occupation employment elasticities obtained by Adao et al. (2017), for sectors, and Hsieh et al. (2013) and Burstein et al. (2015), for occupations. Despite different modeling and estimation approaches, these papers find parameters of sector/occupation productivity dispersion (analogous to our \( \kappa \)) between 1.1 and 2.2.

Our estimation strategy relies on assuming a Fréchet distribution, which restricts the mechanisms through which the China shock affects inequality. In particular, the Fréchet assumption implies that there will be no effect of the China shock on within-

---

23Following the analysis in Goldsmith-Pinkham et al. (2018), we calculate Rotemberg weights for each sector, as these weights clarify which sectors drive most of the variation in the instrument across commuting zones (see Appendix Table A.4). To alleviate concerns of one particular sector driving the results, we construct 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 \( \hat{\kappa} \) do not change significantly and all fall within the range of 1.17 to 3.12 (see Appendix Table A.5).

24In the first column, we use the instrument defined in equation (20), which is identical to the ADH instrument. The other columns serve as a robustness tests, informed by the analysis in Borusyak et al. (2018) and Goldsmith-Pinkham et al. (2018). In column 2, we define the instrument as \( Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{\text{China} \rightarrow \text{Other}} \). Hence, if the China shock is exogenous, then the instruments in both column 1 and 2 should be valid. Next, columns 3 and 4 define the instrument as \( Z_{gt} \equiv \sum_{s \in M} \pi_{gst} \Delta IP_{st}^{\text{China} \rightarrow \text{US}} \) and \( Z_{gt} \equiv \ln \sum_{s \in M} \pi_{gst} F_{st} \), respectively. Given these definitions, if the instrument in column 2 satisfies the exclusion restriction from Goldsmith-Pinkham et al. (2018), then the instruments in columns 3 and 4 satisfy it as well. 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).
Table 1: Estimation of $\kappa$

<table>
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<th>(1)</th>
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<tbody>
<tr>
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<td>ln $\hat{y}_g$</td>
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<td>ln $\hat{y}_g$</td>
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</tr>
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<td>$\ln \hat{\pi}_{NM}$</td>
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<td>-0.639**</td>
<td>-0.704**</td>
<td>-0.487***</td>
</tr>
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<td></td>
<td>(0.211)</td>
<td>(0.303)</td>
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<td>0.667</td>
<td>0.662</td>
<td>0.677</td>
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</table>

IV-estimation results for specification (21), where $y_g$ is average earnings per worker, and $\pi_{gNM}$ 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 $Z_{gt} = \sum s \in M \pi_{gst} - 10 \Delta IP_{China \rightarrow Other}$, column (2) uses $Z_{gt} = \sum s \in M \pi_{gst} \Delta IP_{China \rightarrow Other}$, column (3) uses $Z_{gt} = \sum s \in M \pi_{gst} \Delta IP_{China \rightarrow US}$, and column (4) uses our Bartik variable for the US: $Z_{gt} = \ln \sum s \pi_{gst} \hat{r}_{st}$.

Due to data constraints on $\pi_{gst-10}$, we have not constructed $Z_{gt} = \sum s \in M \pi_{gst-10} \Delta IP_{China \rightarrow US}$. 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 $\kappa$ estimates implied by the model and the fourth row displays the F-statistic from the first stage.

Due to data constraints on $\pi_{gst-10}$, we have not constructed $Z_{gt} = \sum s \in M \pi_{gst-10} \Delta IP_{China \rightarrow US}$. 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 $\kappa$ estimates implied by the model and the fourth row displays the F-statistic from the first stage.

The majority of our estimates yield no statistically significant evidence that the China shock increased within-group inequality. In Appendix Table A.7 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.

For the next section, where we will run simulations to analyze the quantitative role of $\kappa$ in our framework, we will set our preferred value at $\kappa = 1.5$. In addition, we will also show results for $\kappa \rightarrow 1$ (the theoretical lower bound for $\kappa$), 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.

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.\(^{26}\) 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 \( \hat{\lambda}_{China,Other,s} = \frac{\sum_{j \in Other} \lambda_{China,j,s}^{2007}}{\sum_{j \in Other} \lambda_{China,j,s}^{2000}} \). In a second step we calibrate \( \hat{T}_{China,s} \) so that the model-implied changes in the US expenditure share 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 \( \kappa \): 1, 1.5, 3 and \( \infty \), and for \( \theta_s = 5 \) for all \( s \).\(^{27}\) 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.

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

---

\(^{25}\)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 \( \kappa = 1.5 \).

\(^{26}\)This calibration is inspired by the procedure in Caliendo et al. (2015), who calibrate \( \hat{T}_{China,s} \) to match predicted changes in US imports from China. Instead of imports, we focus on the expenditure shares \( \hat{\lambda}_{China,US,s} \), and thereby avoid any complications arising from matching sectoral deflators for US imports across simulations and data.

\(^{27}\)To more clearly see the impact of \( \kappa \) on the welfare effects from the China shock, the results for different values of \( \kappa \) correspond to the shock \( \hat{T}_{China,s} \) as calibrated for \( \kappa = 1.5 \). Separately calibrating \( \hat{T}_{China,s} \) for each value of \( \kappa \) leads to broadly similar results – see Appendix Table A.2.
Table 2: The Welfare Effects of the China Shock on the US

<table>
<thead>
<tr>
<th>$\kappa$</th>
<th>Aggregate</th>
<th>Mean</th>
<th>CV</th>
<th>Min.</th>
<th>Max.</th>
<th>ACR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rightarrow 1$</td>
<td>0.24</td>
<td>0.30</td>
<td>1.40</td>
<td>-1.73</td>
<td>2.32</td>
<td>0.14</td>
</tr>
<tr>
<td>1.5</td>
<td>0.22</td>
<td>0.27</td>
<td>1.16</td>
<td>-1.42</td>
<td>1.64</td>
<td>0.15</td>
</tr>
<tr>
<td>3</td>
<td>0.20</td>
<td>0.24</td>
<td>0.80</td>
<td>-0.90</td>
<td>0.97</td>
<td>0.16</td>
</tr>
<tr>
<td>$\rightarrow \infty$</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
<td>0.20</td>
</tr>
</tbody>
</table>

The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms $100(\hat{W}_{US} - 1)$, and the second column shows the mean welfare effect: $100\left(\frac{1}{G} \sum_g \hat{W}_{US,g} - 1\right)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have $\text{Min.} \equiv \min_g 100(\hat{W}_{US,g} - 1)$ and $\text{Max.} \equiv \max_g 100(\hat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_s \hat{\lambda}_{US,s}^{-\beta_{US,s}/\theta_s} - 1\right)$. The values for $\hat{T}_{China,s}$ are calibrated for $\kappa = 1.5$.

The CV is 116%, and the range is $[-1.42\%, 1.64\%]$. While 18 groups lose more than 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).

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.\(^29\)

The distributional impact of the China shock depends on $\kappa$, as a lower $\kappa$ 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 the CV and the difference between maximal and minimal $\hat{W}_{US,g}$ tend to zero as $\kappa$ approaches infinity (see Table 2). For $\kappa \rightarrow 1$, the CV reaches a maximum at 140%, and the

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\(^{28}\)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.

\(^{29}\)Our quantitative analysis assumes that the effect of the China shock on prices are the same across groups. This is consistent with (Bai and Stumpner 2017), who find “no evidence for heterogeneous effects across consumer groups by income or region.”
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 \( \kappa = 1.5 \).

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.\(^{30,31}\)

5.3 Import competition and income

In Section 2.6, we showed we can approximate changes in relative income 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 using the model to compute the implied group-level income changes for different values of \( \kappa \) and then running the following regression on the simulated data:

\[
\ln \hat{y}_g = \alpha + \beta \ln \sum_s \pi_{gs} \hat{r}_s + \varepsilon_g. \tag{22}
\]

\(^{30}\)Appendix Figure A.1 visualizes how \( \kappa \) governs the distributional impact of the China shock by plotting the full distribution of \( \hat{W}_{US,g} \) for different values of \( \kappa \).

\(^{31}\)In the final column, we notice that \( \kappa \) indirectly also affects the multi-sector ACR term, even though \( \hat{T}_{China,s} \) is held constant. This is because \( \kappa \) affects wage changes in all countries and thereby also the changes in expenditure shares \( \hat{\lambda}_{j,s} \).
Figure 2 plots the resulting values of $\hat{\beta}$ for each $\kappa$. As expected, $\hat{\beta}$ decreases monotonically with $\kappa$, with a relationship very well approximated by $\hat{\beta} = 1/\kappa$.  

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 $\kappa$ (horizontal axis). The vertical line represents the preferred value for $\kappa$ from the structural estimation in Section 4, and the solid horizontal line represents the associated value for $\beta$.

The finding that $\ln \hat{y}_g \approx \ln \hat{y} + \frac{1}{\kappa} \ln \sum_s \pi_{gs} \hat{r}_s$ 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 $\pi_{gs}$.  

Second, we can also take this relationship to the data and test this empirical prediction of the model. We run specification (22) with the ADH shock as an instrument across groups in the United States for the impact of the calibrated China shock are (almost) exactly linear. 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.  

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$^{32}$Figure A.2 in the Appendix also shows that 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 are (almost) exactly linear.  

$^{33}$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.
for \( \ln \sum_g \pi_g \hat{r}_s \).\(^{34}\) 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 A.8). Although high standard errors on the estimated coefficient prohibits us from making strong inferences for the associated values for \( \kappa \), the implied value for \( \kappa \) is not significantly 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 (17) (see Figure 3). The consensus in the literature is that plausible values for the coefficient of inequality aversion \( \rho \) are between 1 and 3.\(^{35}\) 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 4. For higher degrees of inequality aversion, i.e. when \( \rho > 3 \), \( \hat{U}_{US} \) increases monotonically with \( \rho \).\(^{36}\)

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 4. This explains why \( \hat{U}_{US} \) is larger than the standard welfare effect for very high values of \( \rho \). Importantly, regardless of the exact value of \( \rho \), \( \hat{U}_{US} \) is always positive. Hence, for any degree of inequality aversion, social welfare increases due to the rise of China.

---

\(^{34}\) We employ the same specification we used for our baseline \( \kappa \) estimation (Table 1), except that now the RHS variable is \( \ln \sum_g \pi_g \hat{r}_s \) rather than \( \ln \hat{\pi}_{NMg} \).

\(^{35}\) 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 \( \rho \) 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).

\(^{36}\) The theory does not predict how \( \hat{U}_{US} \) changes as function of \( \rho \). Based on the result in equation 18, 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 \( \omega_g \) are themselves dependent on the power \( 1 - \rho \).
Figure 3: Inequality-Adjusted welfare-effects from the China shock

The figure plots the relationship between the inequality-adjusted welfare effects of the rise of China $\hat{U}_{US} \equiv \left( \sum_g \omega_g W_g^{1-\rho} \right)^{\frac{1}{1-\rho}}$ and $\rho$. Here, $\rho$ is the coefficient of relative risk aversion for the agent behind the veil of ignorance and $\omega_g \equiv \frac{i_g(y_g/L_g)^{1-\rho}}{\sum_h i_h(y_h/L_h)^{1-\rho}}$ a modified weight for group $g$. The vertical axis displays $100(\hat{U}_{US} - 1)$.

Figure 4: Initial group-level income and our Bartik measure of import competition

The figure plots the relationship between $\ln \hat{f}_g = \ln(\sum_{i,s} \pi_{i,g,s} \hat{r}_{i,s})^{-1}$, 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. The size of a circle indicates the population size for that commuting zone.
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 $\kappa$, 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 $\kappa$ 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 Figure A.3).

<table>
<thead>
<tr>
<th>$\kappa$</th>
<th>Aggregate</th>
<th>Mean</th>
<th>CV</th>
<th>Min.</th>
<th>Max.</th>
<th>ACR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\to 1$</td>
<td>1.61</td>
<td>1.65</td>
<td>0.82</td>
<td>-6.98</td>
<td>3.72</td>
<td>1.45</td>
</tr>
<tr>
<td>1.5</td>
<td>1.56</td>
<td>1.59</td>
<td>0.58</td>
<td>-4.19</td>
<td>2.97</td>
<td>1.45</td>
</tr>
<tr>
<td>3</td>
<td>1.51</td>
<td>1.52</td>
<td>0.31</td>
<td>-1.38</td>
<td>2.22</td>
<td>1.45</td>
</tr>
<tr>
<td>$\to \infty$</td>
<td>1.45</td>
<td>1.45</td>
<td>0</td>
<td>1.45</td>
<td>1.45</td>
<td>1.45</td>
</tr>
</tbody>
</table>

The first column displays the aggregate gains from trade for the US, in percentage terms ($100(1 - \hat{W}_{US})$) and the second column shows the mean welfare effect: $100(\frac{1}{\sum_g 1 - \hat{W}_{US,g}})$. Here, $\hat{W}_{US}$ and $\hat{W}_{US,g}$ 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. = $\min_g 100(1 - \hat{W}_{US,g})$ and Max. = $\max_g 100(1 - \hat{W}_{US,g})$, respectively. The final column displays the multi-sector ACR term $100 \left( 1 - \prod_s \hat{\lambda}_{US,US,s} \right)$.

As implied by the analysis above (Sections 2.6 and 5.3), our Bartik measure of import competition $I_g \equiv \sum \pi_{gs} \hat{\beta}_s$ perfectly ranks groups in terms of winners and losers from trade for all values of $\kappa$ (see Appendix Figure A.4). The textile industry faces the highest degree of import competition (with $\hat{\beta}_s = 1.52$; 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 and Southern Appalachia regions (see Figure 5).

**Figure 5: 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 6 shows that for $\rho > 0$, the inequality-adjusted gains from trade are higher than the standard gains, $IGT > GT$, and that $IGT$ increases with $\rho$. This is a reflection of the fact that, as illustrated in Figure 7, the large majority of low-income groups experiences negative degrees of import-competition under free trade ($\ln I_g < 0$).
Figure 6: Inequality-adjusted Gains from Trade

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

Figure 7: Group-level Import Competition and Income

The figure plots the relationship between $\ln I_g \equiv \ln \sum_s \pi_{igs} \frac{\beta_{its}}{\beta_{its}}$, 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. The size of a circle indicates the population size of that commuting zone.
7 Extensions and Discussion

In this section we discuss extensions to allow for an input-output structure and a non-tradable sector. We also discuss the link between our model and the empirical literature on the employment effects of the China shock.

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 Equations (3) and (4)). On the trade side, the model is identical to Caliendo 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

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

with

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

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

$$\hat{W}_{ig} = \prod_{s,k} \lambda_{ik}^{-\beta_{is}\tilde{a}_{isk}/\theta_s} \cdot \prod_{s,k} \pi_{igk}^{-\beta_{is}\tilde{a}_{isk}(1-\alpha_{ik})/\kappa_{ig}}$$

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

For this extended model, for $\kappa = 1.5$ we find a gain from the China shock of 0.28%
and gains from trade of 3.03% (see Table 4). 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 A.5). Hence, the ranking of groups in terms of relative welfare effects is robust to allowing for intermediate goods.

### 7.2 A non-tradable sector

We have so far assumed that all employment is in tradable sectors. We now relax this assumption by introducing a sector for which the output is not tradable even between groups within a country. An important implication is that price indices now vary across groups.

The labor supply remains exactly as in the baseline model (see Equations (3) and (4)). On the trade side, any tradable sector \( s \in TR \) is also modeled identically as in the baseline setting (see Equations (1) and (2)). The difference is that now there is a non-tradable sector, \( s = NT \), and for this sector the excess demand for labor for group \( ig \) is

\[
ELD_{igNT} = \frac{1}{w_{igNT}} \beta_{igNT} Y_{ig} - E_{igNT}.
\]

The expression for a group's welfare change is identical to the one in the baseline model, except that the expenditure shares \( \beta_{ig} \) and the price index \( P_{ig} \) are now group-specific:

\[
\hat{W}_{ig} = \frac{\hat{Y}_{ig}}{\hat{P}_{ig}} = \prod_s \lambda_{iis}^{-\beta_{igs}/\theta_s} \cdot \prod_s \pi_{igs}^{-\beta_{igs}/\kappa_{ig}}.
\]

Our estimation strategy for \( \kappa \) remains the same except for the need to update sector definitions in the data. Once we redefine sector-level employment shares with respect

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37Since the labor supply side of the model is unaltered compared to the baseline model, the \( \kappa \) estimation from Section 4 remains valid. This explains why we continue to use the same values for \( \kappa \) in the quantification of this model.
Table 4: Counterfactual analysis for the model with intermediates

(a) The rise of China

| $\kappa$ | Aggregate Mean CV Min. Max. ACR |
|---------|-------------------|--------|---------|------|------|
| $\rightarrow 1$ | 0.32 | 0.37 | 0.96 | -1.72 | 2.24 | 0.21 |
| 1.5 | 0.28 | 0.33 | 0.80 | -1.30 | 1.63 | 0.22 |
| 3.0 | 0.26 | 0.29 | 0.53 | -0.71 | 0.99 | 0.22 |
| $\rightarrow \infty$ | 0.24 | 0.24 | 0 | 0.24 | 0.24 | 0.24 |

(b) Gains from trade

| $\kappa$ | Aggregate Mean CV Min. Max. ACR |
|---------|-------------------|--------|---------|------|------|
| $\rightarrow 1$ | 3.10 | 3.10 | 0.46 | -4.55 | 4.87 | 2.89 |
| 1.5 | 3.03 | 3.03 | 0.32 | -2.08 | 4.23 | 2.89 |
| 3 | 2.96 | 2.96 | 0.17 | 0.40 | 3.57 | 2.89 |
| $\rightarrow \infty$ | 2.89 | 2.89 | 0 | 2.89 | 2.89 | 2.89 |

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 $T_{\text{China, s}}$ 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 gains from trade for the US, in percentage terms $100(1 - \tilde{W}_{US})$ and the second column shows the mean welfare effect: $100\left(\frac{1}{G} \sum_{g} 1 - \tilde{W}_{US,g}\right)$. Here, $\tilde{W}_{US}$ and $\tilde{W}_{US,g}$ 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 $\text{Min.} = \min_{g} 100(1 - \tilde{W}_{US,g})$ and $\text{Max.} = \max_{g} 100(1 - \tilde{W}_{US,g})$, respectively. The final column displays the multi-sector ACR term $100 \left(1 - \prod_{s,k} \tilde{\lambda}_{US,US,k}^{\tilde{\theta}_{US,s} \tilde{a}_{US,s,k}/\theta_{s}}\right)$.

To total employment in tradable sectors, the model again leads to Equation (19) and so we can just run the same regression associated with Equation (21) with the updated employment shares. This leads to values for $\kappa$ between 3.7 and 7.6 – see Appendix Table A.9 for the full estimation results. The reason for the change in the estimate of $\kappa$ is that the updated non-manufacturing sector employment shares are more volatile as

\[38\] We assume that the primary sector, transportation, post and telecommunication, wholesale trade and financial intermediation are tradable while construction, retail trade and hotels and restaurants are non-tradable.
they are now defined relative to a smaller total employment. This leads to a lower $\hat{\beta}$ in Equation (21) and hence a higher $\hat{\kappa}$.

The quantitative results for the China shock and the gains from trade with a non-tradable sector, the updated employment shares, and the new estimates of $\kappa$ are presented in Table 5. For $\kappa = 3.7$, the China shock leads to an average group-level welfare gain of 0.19%, with a CV of 73%. As expected given the role of $\kappa$ explained in Section 5, these numbers are lower than those for the baseline model with $\kappa = 1.5$, where the average gain was 0.27% and the CV was 116%. Most importantly however, the correlation between the group-level welfare effects with non-tradables and the baseline model is strong at 92% (see Appendix Figure A.6).\(^{39}\)

\(^{39}\)For the autarky results, the average gain and the CV are again lower in the model with non-tradables, with a 54% correlation between group’s welfare gains across the two models. The reason for this lower correlation is that an important source of gains from trade disappears for many groups due to a large share of the non-manufacturing sector now being non-tradable.
Table 5: Counterfactual analysis with a non-tradable sector

(a) The rise of China

<table>
<thead>
<tr>
<th>κ</th>
<th>Mean</th>
<th>CV</th>
<th>Min.</th>
<th>Max.</th>
<th>ACR</th>
</tr>
</thead>
<tbody>
<tr>
<td>→ 1</td>
<td>0.25</td>
<td>1.50</td>
<td>-1.57</td>
<td>2.49</td>
<td>0.14</td>
</tr>
<tr>
<td>3.7</td>
<td>0.19</td>
<td>0.73</td>
<td>-0.49</td>
<td>0.88</td>
<td>0.16</td>
</tr>
<tr>
<td>7.6</td>
<td>0.17</td>
<td>0.47</td>
<td>-0.22</td>
<td>0.57</td>
<td>0.16</td>
</tr>
<tr>
<td>→∞</td>
<td>0.15</td>
<td>0.23</td>
<td>0.04</td>
<td>0.28</td>
<td>0.17</td>
</tr>
</tbody>
</table>

(b) Gains from trade

<table>
<thead>
<tr>
<th>κ</th>
<th>Mean</th>
<th>CV</th>
<th>Min.</th>
<th>Max.</th>
<th>ACR</th>
</tr>
</thead>
<tbody>
<tr>
<td>→ 1</td>
<td>1.43</td>
<td>0.86</td>
<td>-6.17</td>
<td>4.86</td>
<td>1.47</td>
</tr>
<tr>
<td>3.7</td>
<td>1.34</td>
<td>0.30</td>
<td>-0.77</td>
<td>2.84</td>
<td>1.47</td>
</tr>
<tr>
<td>7.6</td>
<td>1.32</td>
<td>0.22</td>
<td>0.31</td>
<td>2.57</td>
<td>1.47</td>
</tr>
<tr>
<td>→∞</td>
<td>1.31</td>
<td>0.23</td>
<td>0.32</td>
<td>2.31</td>
<td>1.47</td>
</tr>
</tbody>
</table>

The tables show summary statistics for welfare effects of US groups for the model where one sector is non-tradable. Panel (a) shows results for the counterfactual rise of China, where the values for $T_{China,s}$ are calibrated for $κ = 3.6$. Panel (b) shows results for group-level gains from trade. The first column shows the mean welfare effect: $100\left(\frac{1}{G} \sum g \tilde{W}_{ng} - 1\right)$ for all groups in the US. The second column shows the coefficient of variation (CV), and for the third and fourth column we have Min. $\equiv \min_g 100(\tilde{W}_{US,g} - 1)$ and Max. $\equiv \max_g 100(\tilde{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100 \left(\prod_s \hat{\lambda}_{US,US,s}^{\tilde{\beta}_{US,s}/\theta_s} - 1\right)$ in panel (a) and $100 \left(1 - \prod_s \hat{\lambda}_{US,US,s}^{\tilde{\beta}_{US,s}/\theta_s}\right)$ in panel (b). Note that we are unable to calculate aggregate welfare changes across all groups in the US without knowledge of the initial value of the price index $P_g$ for each group.

7.3 Employment Effects

We have built a model with perfectly inelastic labor supply - as is standard in the literature on gains from trade - and with no mobility across groups (or regions). One obvious implication is that our model cannot generate changes in employment in response to trade shocks. Since such employment changes are one of the key empirical results in ADH, we now discuss whether allowing for mobility, commuting or a positive labor supply elasticity could make our model consistent with those results.
At a theoretical level, the assumption that there is no mobility across regions can trivially be relaxed with no change in our results. Since groups differ only in the parameters of the distribution from which individuals draw their productivities (the $A_{igs}$ parameters), the fact that sector-level wages $w_{is}$ are national implies that there is no incentive for an individual with some given productivity vector to switch to another region. But an alternative interpretation of the model is that $A_{igs}$ is the labor productivity of group $ig$ in sector $s$, and that individuals in all groups draw their productivity vector from the same distribution. According to this interpretation, individuals would have incentives to move across regions since wages would be $w_{is}A_{igs}$. In Appendix Section E, we show how one can use data on mobility across regions to extend our counterfactual analysis to this alternative model. 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.\footnote{Caliendo et al. (2015) and Adao et al. (2017) 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. Their results also point to weak effects of trade shocks on mobility across regions.}

Employment could also adjust through changes in commuting patterns, as in Monte, Redding and Rossi-Hansberg (2015). 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 be a significant margin of adjustment.

A final possible adjustment in employment to the trade shock arises from changes in the employment to population ratio. This margin is central to the empirical analysis in ADH. As is well known, it is challenging to explain a large response of employment to labor-demand shocks by allowing for a choice between labor and leisure given standard preferences. This is because the values of the elasticity of marginal utility with respect to consumption that are commonly used in the literature are equal to or higher than one, and this implies that the income effect is weakly stronger than the substitution effect, leading to a perfectly inelastic or downward sloping labor supply curve.\footnote{With preferences $u(c, l) = \frac{c^{1-\sigma}}{1-\sigma} - \frac{l^{1+1/\psi}}{1+1/\psi}$, the labor supply elasticity is $\epsilon = \frac{\psi(1-\sigma)}{1+\psi\sigma}$. Standard estimates}
Assuming that income effects are nonexistent (as in so called GHH preferences, Greenwood, Hercowitz and Huffman (1988)) would lead to an upward sloping labor supply curve, but this may be more appropriate to model business cycle fluctuations than the medium to long-run adjustment to a trade shock. Alternatively, one could assume that there is compensation for trade shocks, in which case income effects would be weaker, leading potentially to a positively sloped labor supply curve. Any of these explanations would imply weaker distributional implications from the China shock, either because agents have an extra margin of adjustment or because of compensation. To us, this suggests the need to entertain some kind of labor market friction that can generate involuntary unemployment in response to a negative trade shock.

8 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. 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 of ex-ante identical workers as in Burstein et al. (2015), 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 (e.g., Hall 2009) have $\sigma \geq 1$ and hence $\epsilon \leq 0$ – a downward sloping labor-supply curve. We obtained our own values of $\epsilon$ by running regressions estimating the effect of the China shock ($Z_g$'s of Table 1) on the log change in group level income and employment rate (in all regressions we included the controls employed in the estimations of Table 1). The coefficients for $Z_g$ in the income regressions tended to be smaller than those obtained in the employment rate regressions, implying labor-supply elasticities above 1.

42 The only mention of distributional implications in Costinot and Rodríguez-Clare (2014) is in regards to Burstein and Vogel (2016), which is limited to quantifying welfare effects among low and high skilled workers.
the United States defined as commuting zones. We find that the average effect is positive, that some groups experience losses more than five 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.

The question addressed in this paper is complex and our approach has obvious limitations. Most importantly, our analysis adheres to the tradition in the trade literature and uses a static model with a competitive labor market and a perfectly inelastic labor supply. Thus, we do not address some of the features that have been highlighted in the empirical literature, most importantly the effects on employment. As mentioned earlier, it seems useful to explore how allowing for some kind of labor-market friction could generate involuntary unemployment in response to a trade shock, as in Carrère et al. (2015) or Coşar et al. (2016). More research on this topic is clearly needed.

References


—, Eduardo Morales, and Jonathan Vogel, 2015, “Accounting for changes in between-group inequality,” *unpublished manuscript, UCLA, Princeton and NYU.*


Faber, Benjamin, 2014, “Trade Liberalization, the Price of Quality, and Inequality: Evidence from Mexican Store Prices,” *working paper*.


Appendix A  Background Tables and Figures

Figure A.1: Distribution of the welfare gains from the rise of China

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 \( \kappa \), 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: 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 $\ln \hat{I}_g = -\ln \sum_s \pi_g r_s$, our Bartik measure for the change in groups’ import-competition. Each scatter represents the simulation results for a different value of $\kappa$, for values of $\hat{T}_{China,s}$ calibrated for $\kappa = 1.5$. 
Figure A.3: Distribution of the Gains from Trade

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 $\kappa$, 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.4: Import competition and groups’ relative gains from return to autarky

The figure plots the value for $\ln \frac{\hat{Y}_g}{Y_{US}}$ in relation to $\ln I_g$, our Bartik measure for groups’ import-competition. Each scatter represents the simulation results for the return to autarky for a different value of $\kappa$. 
Figure A.5: Comparison of the baseline model and the model with intermediate goods

This figure compares the welfare changes for the two models, showing $\hat{W}_y - 1$ for the rise of China, and $1 - \hat{W}_y$ for the return to autarky, each time for $\kappa = 1.5$. 
Figure A.6: Comparison of baseline model with the model with non-tradables

This figure compares the welfare changes for the two models, showing $\hat{W}_g - 1$ for the rise of China, and $1 - \hat{W}_g$ for the return to autarky. For the model with non-tradables we use the simulation results for $\kappa = 3.7$, while for the baseline model we use the results for $\kappa = 1.5$. 
Table A.1: List of Sectors

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

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 $\beta_s/r_s$ for the US. The final column has the domestic expenditure share for the US, $\lambda_{US,US,s}$. 
Table A.2: The Welfare Effects of the China Shock on the US

<table>
<thead>
<tr>
<th>$\kappa$</th>
<th>Aggregate</th>
<th>Mean</th>
<th>CV</th>
<th>Min.</th>
<th>Max.</th>
<th>ACR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rightarrow 1$</td>
<td>0.25</td>
<td>0.33</td>
<td>1.43</td>
<td>-2.20</td>
<td>2.46</td>
<td>0.15</td>
</tr>
<tr>
<td>1.5</td>
<td>0.22</td>
<td>0.27</td>
<td>1.16</td>
<td>-1.42</td>
<td>1.64</td>
<td>0.15</td>
</tr>
<tr>
<td>3</td>
<td>0.18</td>
<td>0.21</td>
<td>0.74</td>
<td>-0.63</td>
<td>0.84</td>
<td>0.15</td>
</tr>
<tr>
<td>$\rightarrow \infty$</td>
<td>0.14</td>
<td>0.14</td>
<td>0</td>
<td>0.14</td>
<td>0.14</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Compared to Table 2, here the values for $\hat{T}_{China,s}$ are separately calibrated for each value of $\kappa$. The first column displays the aggregate welfare effect of the China shock for the US, in percentage terms $(100(\hat{W}_{US} - 1))$, and the second column shows the mean welfare effect: $100\left(1 - \frac{\sum_g \hat{W}_{US,g}}{G}\right)$. The third column shows the coefficient of variation (CV), and for the fourth and fifth column we have Min.$\equiv\min_g 100(\hat{W}_{US,g} - 1)$ and Max.$\equiv\max_g 100(\hat{W}_{US,g} - 1)$, respectively. The final column displays the multi-sector ACR term $100\left(\prod_s \hat{\lambda}_{US,s} - \beta_{US,s} - 1\right)$.

Table A.3: Estimation of $\kappa$ - full set of results

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln \hat{y}_g$</td>
<td>-2.465***</td>
<td>-0.639**</td>
<td>-2.280***</td>
<td>-0.704**</td>
<td>-207.6</td>
<td>-0.487**</td>
</tr>
<tr>
<td>$\ln \hat{\pi}_{NM}$</td>
<td>(0.270)</td>
<td>(0.303)</td>
<td>(0.377)</td>
<td>(0.295)</td>
<td>(1233.7)</td>
<td>(0.183)</td>
</tr>
<tr>
<td>Implied $\kappa$</td>
<td>0.41</td>
<td>1.56</td>
<td>0.44</td>
<td>1.42</td>
<td>0.005</td>
<td>2.05</td>
</tr>
<tr>
<td>F-First Stage</td>
<td>84.43</td>
<td>24.02</td>
<td>75.94</td>
<td>29.52</td>
<td>0.03</td>
<td>67.87</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.</td>
<td>0.668</td>
<td>.</td>
<td>0.662</td>
<td>.</td>
<td>0.677</td>
</tr>
</tbody>
</table>

IV-estimation results for specification (21), where $\hat{y}_g$ is average earnings per worker, and $\pi_{g,NM}$ is the labor share employed in non-manufacturing. Labor shares $\pi_{gs}$ are measured as the share of workers using the CBP data. Columns (1) and (2) use as an instrument the Chinese import penetration to other countries, columns (3) and (4) the Chinese import penetration to the US, while columns (5) and (6) use as an instrument the industry Bartik with the shares of 1990 and 2000. 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 $\kappa$ estimates implied by the model and the fourth row displays the F-statistic from the first stage.
Table A.4: Rotemberg Weights (China to Other): Top 5 Industries

<table>
<thead>
<tr>
<th>Industry</th>
<th>$\beta$</th>
<th>$\alpha$</th>
<th>F-First Stage</th>
<th>Industry code</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronic Computers</td>
<td>-1.707</td>
<td>0.246</td>
<td>3.92</td>
<td>3571</td>
<td>2000</td>
</tr>
<tr>
<td>Furniture and Fixtures</td>
<td>-0.319</td>
<td>0.099</td>
<td>24.42</td>
<td>2599</td>
<td>2000</td>
</tr>
<tr>
<td>Semiconductors</td>
<td>-1.440</td>
<td>0.085</td>
<td>7.35</td>
<td>3674</td>
<td>2000</td>
</tr>
<tr>
<td>Blast Furnaces</td>
<td>0.120</td>
<td>0.049</td>
<td>10.56</td>
<td>3312</td>
<td>2000</td>
</tr>
<tr>
<td>Telephones</td>
<td>-0.927</td>
<td>0.047</td>
<td>3.37</td>
<td>3661</td>
<td>2000</td>
</tr>
</tbody>
</table>

Rotemberg weights calculated for the shares of 1990 and 2000 using the methodology from Goldsmith-Pinkham et al. (2018) and Imports to Other countries. The parameter $\beta$ captures the second stage coefficient when the industry share is used as an instrument for $\ln \hat{\pi}_{NM}$, while the parameter $\alpha$ corresponds to the Rotemberg weight.

Table A.5: Estimation of $\kappa$ - Excluding industries (China to Other instrument)

<table>
<thead>
<tr>
<th>Industry Excluded</th>
<th>Baseline</th>
<th>Electronic Computers</th>
<th>Furniture and fixtures</th>
<th>Semiconductors</th>
<th>Blast Furnaces</th>
<th>Telephones</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln \hat{\pi}_{NM}$</td>
<td>-0.639**</td>
<td>-0.321</td>
<td>-0.682**</td>
<td>-0.587*</td>
<td>-0.677**</td>
<td>-0.633**</td>
</tr>
<tr>
<td></td>
<td>(0.303)</td>
<td>(0.292)</td>
<td>(0.328)</td>
<td>(0.307)</td>
<td>(0.312)</td>
<td>(0.297)</td>
</tr>
<tr>
<td>Implied $\kappa$</td>
<td>1.56</td>
<td>3.12</td>
<td>1.47</td>
<td>1.70</td>
<td>1.48</td>
<td>1.58</td>
</tr>
<tr>
<td>F-First Stage</td>
<td>24.02</td>
<td>25.59</td>
<td>17.66</td>
<td>22.17</td>
<td>24.67</td>
<td>24.59</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.667</td>
<td>0.684</td>
<td>0.664</td>
<td>0.671</td>
<td>0.664</td>
<td>0.668</td>
</tr>
</tbody>
</table>

IV-estimation results for specification (21), 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 instrument.
Table A.6: Estimation of $\kappa$ - Excluding industries (China to US instrument)

<table>
<thead>
<tr>
<th>Industry Excluded</th>
<th>Baseline</th>
<th>Electronic Computers</th>
<th>Furniture and fixtures</th>
<th>Semiconductors</th>
<th>Blast Furnaces</th>
<th>Telephones</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln \hat{\pi}_{NM}$</td>
<td>-0.704**</td>
<td>-0.361</td>
<td>-0.852**</td>
<td>-0.709**</td>
<td>-0.735**</td>
<td>-0.723**</td>
</tr>
<tr>
<td>(0.295)</td>
<td>(0.345)</td>
<td>(0.360)</td>
<td>(0.293)</td>
<td>(0.306)</td>
<td>(0.289)</td>
<td></td>
</tr>
<tr>
<td>Implied $\kappa$</td>
<td>1.42</td>
<td>2.77</td>
<td>1.17</td>
<td>1.41</td>
<td>1.36</td>
<td>1.38</td>
</tr>
<tr>
<td>F-First Stage</td>
<td>29.52</td>
<td>16.38</td>
<td>17.72</td>
<td>29.23</td>
<td>27.34</td>
<td>29.91</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.662</td>
<td>0.683</td>
<td>0.648</td>
<td>0.662</td>
<td>0.659</td>
<td>0.661</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Instrument</td>
<td>IP to US</td>
<td>IP to US</td>
<td>IP to US</td>
<td>IP to US</td>
<td>IP to US</td>
<td>IP to US</td>
</tr>
</tbody>
</table>

IV-estimation results for specification (21), 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 instrument.
### Table A.7: Within-group Inequality and the China shock

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Other (lagged)</th>
<th>Other (no lag)</th>
<th>US (no lag)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln \hat{\sigma}_{y_g}^{-0.560}$</td>
<td>-0.560</td>
<td>-1.225*</td>
<td>-0.863**</td>
</tr>
<tr>
<td>(0.482)</td>
<td>(0.691)</td>
<td>(0.417)</td>
<td></td>
</tr>
<tr>
<td>$\Delta SD(\ln y_g)$</td>
<td>0.293**</td>
<td>0.178</td>
<td>0.0881</td>
</tr>
<tr>
<td>(0.0900)</td>
<td>(0.144)</td>
<td>(0.0948)</td>
<td></td>
</tr>
<tr>
<td>$\ln \hat{p}<em>{90}^{p</em>{10}}$</td>
<td>0.886**</td>
<td>0.505</td>
<td>0.322</td>
</tr>
<tr>
<td>(0.278)</td>
<td>(0.389)</td>
<td>(0.252)</td>
<td></td>
</tr>
<tr>
<td>$\ln \hat{p}<em>{25}^{p</em>{75}}$</td>
<td>0.230</td>
<td>0.0262</td>
<td>0.0492</td>
</tr>
<tr>
<td>(0.147)</td>
<td>(0.190)</td>
<td>(0.111)</td>
<td></td>
</tr>
<tr>
<td>$\ln \frac{\hat{y}<em>{gM}}{\hat{y}</em>{gNM}}$</td>
<td>0.422</td>
<td>0.406</td>
<td>0.324</td>
</tr>
<tr>
<td>(0.297)</td>
<td>(0.416)</td>
<td>(0.272)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
</tbody>
</table>

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 $\kappa$ estimation (Table 1).
Table A.8: The rise of China and the Bartik measure for import competition

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln \hat{y}_g )</td>
<td>1.230*</td>
<td>1.735**</td>
<td>1.845**</td>
</tr>
<tr>
<td></td>
<td>(0.727)</td>
<td>(0.824)</td>
<td>(0.787)</td>
</tr>
<tr>
<td>( \ln \sum_s \pi_{gs} \hat{r}_s )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Implied ( \kappa )</td>
<td>0.810</td>
<td>0.576</td>
<td>0.542</td>
</tr>
<tr>
<td>F First Stage</td>
<td>42.66</td>
<td>18.80</td>
<td>16.35</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.677</td>
<td>0.664</td>
<td>0.660</td>
</tr>
</tbody>
</table>

IV-estimation results for specification (22), where \( y_g \) is measured as average earnings per worker. Labor shares \( \pi_{gs} \) 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 HI 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 \( \kappa \) estimation (Table 1).
Table A.9: Estimation of $\kappa$ when one sector is non-tradable

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln \hat{\pi}_{NM}$</td>
<td>-0.132*</td>
<td>-0.233**</td>
<td>-0.268**</td>
<td>-0.221**</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.110)</td>
<td>(0.111)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Implied $\kappa$</td>
<td>7.58</td>
<td>4.29</td>
<td>3.73</td>
<td>4.53</td>
</tr>
<tr>
<td>F-First Stage</td>
<td>57.48</td>
<td>24.21</td>
<td>24.38</td>
<td>58.94</td>
</tr>
<tr>
<td>Observations</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
<td>1444</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.683</td>
<td>0.668</td>
<td>0.660</td>
<td>0.670</td>
</tr>
</tbody>
</table>

IV-estimation results for specification (21) with adjustment for non-tradables, where $y_g$ is average earnings per worker, and $\pi_{g, NM}$ is the labor share employed in non-manufacturing. Labor shares $\pi_g$, are measured as the share of workers using the CBP data. Column (1) uses imports from China to other high income countries, column (2) the imports from China to the US, while column (3) uses as an instrument the industry Bartik. The first row shows the second-stage results, while the third row has the corresponding $\kappa$ estimates implied by the model and the fourth row displays the F-statistic from the first stage.
Appendix B  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). 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. We also follow ADH and 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 the same education cell and 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.

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 the NBER-CES Manufacturing Industry Database and EU/KLEMS, etc. for the years 1990, 2000, and 2007 to construct the industry Bartik using payroll. The EU/KLEMS data is used to construct the change in non-manufacturing payroll.

Appendix C  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 (13), we must show that $\sum_{g \in G_i} \left( \frac{Y_{ig}}{Y_i} \right) \prod_s \frac{\pi_{igs}^{1-\beta_s}}{\kappa} < 1$, or using $y_{ig} \equiv \frac{Y_{ig}}{Y}$.

\[43\] The ACS is designed to be comparable to the Census.

\[44\] The Census and ACS Public Use Microdata Areas (PUMAs) are mapped into commuting zones using a crosswalk provided by David Dorn.
and Equation (10),

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

Rewriting this equation as $\sum_{g \in G_i} y_{ig} \left( \sum_k \pi_{igm} \hat{w}_k^\kappa \right)^{1/\kappa} < \prod_s \hat{w}_is^\beta_{is}$, 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 (14), $\hat{w}_is$ is given by the solution of

$$\beta_{is} \sum_{g \in G_i} x_{ig} y_{ig} = \sum_{g \in G_i} \hat{w}_is^{\kappa} x_{ig}^{1-\kappa} \pi_{igs} y_{ig} \text{ for } s = 1, \ldots, S. \quad (26)$$

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 $\kappa$ 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 26 and rearranging we see that $\hat{w}_{is}$ for $s = 1, \ldots, S$ is determined from the system of equations given by

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

for $s = 1, \ldots, S$. 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 $\beta_s$ from this equation, we see that $z_{is} = \beta_s$ is equivalent to

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

Simplifying, this is equivalent to

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

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.
Appendix D  Intermediate Goods

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

Combining equations (23) and (24) yields

\[ P_{js} = \gamma_s^{-1} \left( \sum_i T_{is} \left( \tau_{ijs} u_{is}^{(1-\alpha_{is})} \prod_k P_{\alpha_{iks}}^{\alpha_{iks}} \right) \right)^{-1/\theta_s}. \]

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 \( \lambda_{ijs} \) 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

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

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

\[ ELD_{is} \equiv \left( \frac{1 - \alpha_{is}}{w_{is}} \right) R_{is} - \sum_{g \in G_i} E_{igs}. \]

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

\[ \sum_{g \in G_i} \tilde{\pi}_{i} g \hat{\Phi}_{ig} \pi_{i} g Y_{ig} = (1 - \alpha_{is}) \sum_{j=1}^{n} \lambda_{ijs} \hat{\lambda}_{ijs} \left( \beta_{js} \left( \sum_{g \in G_j} \hat{\Phi}_{jg} Y_{jg} (1 + \hat{d}_j d_j) \right) + \sum_{k=1}^{S} \alpha_{jsk} \hat{R}_{jk} R_{jk} \right), \]
where \( \Phi_{ig} \) is as in (8) and

\[
\hat{\lambda}_{ij} = \frac{\hat{T}_{is} \left( \frac{\hat{\tau}_{ij} \hat{w}_{is}^{-1-\alpha_{is}} \prod_k \hat{\rho}_{ik}^{1-\alpha_{is}}} {\hat{\rho}_{js}^{-\theta_s}} \right)^{-\theta_s}} {\hat{P}_{js}^{-\theta_s}},
\]

\[
\hat{P}_{js}^{-\theta_s} = \sum_i \lambda_{ij} \hat{T}_{is} \left( \frac{\hat{\tau}_{ij} \hat{w}_{is}^{1-\alpha_{is}} \prod_k \hat{\rho}_{ik}^{1-\alpha_{is}}} {\hat{\rho}_{js}^{-\theta_s}} \right)^{-\theta_s},
\]

and

\[
\hat{R}_{is} R_{is} = \sum_j \lambda_{ij} \hat{\lambda}_{ij} \left( \beta_{js} \left( \sum_{g \in G_j} \phi_{jg} y_{jg} (1 + \hat{d}_j) \right) + \sum_{k=1}^S \alpha_{jsk} \hat{R}_{jk} R_{jk} \right).
\]

For welfare analysis, it is useful to fully solve for \( \{ P_{js} \} \) in terms of trade shares. We start with

\[
\lambda_{js} = T_{js} c_{js}^{-\theta_s} / (\gamma_s P_{js}^{-\theta_s}),
\]

which implies that

\[
\ln P_{is} = \ln \left( \gamma_s^{-1} (T_{is} / \lambda_{ii})^{-1/\theta_s} w_{is}^{-1-\alpha_{is}} \right) + \sum_k \alpha_{iks} \ln P_{ik}.
\]

Letting \( A_i \equiv \{ \alpha_{iks} \}_{k=1, \ldots, S} \) (an \( S \times S \) matrix), \( B_i \equiv \left\{ \ln \left( \gamma_s^{-1} (T_{is} / \lambda_{ii})^{-1/\theta_s} w_{is}^{-1-\alpha_{is}} \right) \right\}_{s=1, \ldots, S} \) (an \( S \times 1 \) matrix) and \( X_i \equiv \{ \ln P_{is} \}_{s=1, \ldots, S} \) (an \( S \times 1 \) matrix), then we have

\[
X_i = (I - A_i^T)^{-1} B_i,
\]

where \( I \) is the \( S \times S \) identity matrix. Letting \( \tilde{a}_{ik} \) be the typical element of \( (I - A_i^T)^{-1} \), then we see that

\[
P_{is} = \prod_k \left( \gamma_s^{-1} (T_{ik} / \lambda_{ik})^{-1/\theta_s} w_{ik}^{1-\alpha_{ik}} \right)^{\tilde{a}_{ik}}.
\]

This implies that welfare changes for group \( ig \) are given by

\[
\frac{\dot{Y}_{ig}}{\dot{P}_i} = \frac{\hat{\Phi}_{ig}^{1/\kappa_{ig}}}{\prod_{s,k} \left( \hat{\lambda}_{ik}^{-1/\theta_s} \hat{w}_{ik}^{1-\alpha_{ik}} \right)^{\beta_{is}\tilde{a}_{is}}}.
\]

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

\[
\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{1}{\prod_{s,k} \left( \hat{\lambda}_{ik}^{1/\theta_s} \hat{\Phi}_{ig}^{-(1-\alpha_{ik})/\kappa_{ig}} \hat{\beta}_{is}^{1-\alpha_{ik}} \right)^{\beta_{is} \tilde{a}_{isk}}}.
\]

But then, using \( \hat{\omega}_{is} \hat{\Phi}_{ig}^{1/\kappa_{ig}} = \hat{\pi}_{ig}^{1/\kappa_{ig}} \), we get

\[
\frac{\hat{Y}_{ig}}{\hat{P}_i} = \frac{1}{\prod_{s,k} \left( \hat{\lambda}_{ik}^{1/\theta_s} \hat{\pi}_{ig}^{-(1-\alpha_{ik})/\kappa_{ig}} \hat{\beta}_{is}^{1-\alpha_{ik}} \right)^{\beta_{is} \tilde{a}_{isk}}}.\]

This establishes the result in Proposition 3.

**Appendix E  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 \( \kappa \) and \( A_{ish} \). Workers are fully described by a matrix \( z = \{z_{hs}\} \) 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 \( \zeta_{igh} \), with \( \zeta_{igg} = 1 \) and \( \zeta_{igh} \leq 1 \) for all \( i,g,h \). Thus, a worker from \( g \) that works in region \( h \) in sector \( s \) has income of \( w_{is} \zeta_{igh} z_{hs} \).

We now let

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

A worker with productivity matrix \( z \) from region \( g \) in country \( i \) will choose region-sector \((f,s)\) iff \( z \in \Omega_{igfs} \). The following lemma characterizes the labor supply side of the economy: The share of workers in group \( g \) in country \( i \) that choose to work in \((f,s)\) is

\[
\pi_{igfs} = \int_{\Omega_{igfs}} dF(z) = \frac{A_{fs} (\zeta_{gf} w_{is})^\kappa}{\Phi_{ig}^\kappa},
\]

where \( \Phi_{ig}^\kappa \equiv \sum_{h,k} A_{hk} (\zeta_{gh} w_{ik})^\kappa \). The efficiency units supplied by this group in sector
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

$$E_{i,g,s} \equiv L_{ig} \int_{z_{fg,s}} z_{fs} dF_i(z) = \pi_{igfs} \gamma L_{ig} \frac{\Phi_{ig}}{w_{igfs}}.$$  

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

Let $\mu_{igh} \equiv \sum_s \pi_{ihs}$ be the share of workers from $g$ that work in $h$. It is easy to verify that $\pi_{ihs}/\mu_{igh} = \pi_{ihs}/\mu_{ihh}$ 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 $\pi_{ihs} \equiv \pi_{ihs}/\mu_{igh}$. The shares $\pi_{ihs}$ and $\mu_{igh}$ 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

$$E_{L,D_{is}} = \frac{1}{w_{is}} \sum_j \lambda_{ij,s} \beta_{js} Y_j - \sum_{g,h} E_{i,g,s}.$$  

Noting that $\lambda_{ij,s}, Y_j$ and $E_{i,g,s}$ are functions of the whole matrix of wages $w \equiv \{w_{is}\}$, the system $E_{L,D_{is}} = 0$ for all $i, s$ is a system of equations in $w$ 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

$$\sum_{g,h} \hat{\pi}_{ihs} \hat{\Phi}_{ig} \mu_{igh} \pi_{ihs} Y_{ig} = \sum_j \lambda_{ij,s} \hat{\lambda}_{ij,s} \beta_{is} \sum_y \hat{\Phi}_{jg} Y_{jg}$$  

(27)

with $\hat{\Phi}_{ig} = \sum_{h,s} \mu_{igh} \pi_{ihs} \hat{w}_{is}$, (9) and $\hat{\pi}_{ihs} = \hat{\pi}_{ihs}/\hat{\mu}_{igh}$, $\hat{\pi}_{ihs} = \hat{w}_{is}/\hat{\Phi}_{ig}$, and $\hat{\mu}_{igh} = \sum_s \pi_{ihs} \hat{\pi}_{ihs}$. Equation (27) can be solved for $\hat{w}_{is}$ given data on income levels, $Y_{ig}$, trade shares, $\lambda_{ij,s}$, migration shares $\mu_{igh}$, employment shares $\pi_{ihs}$, and the shocks, $\hat{\tau}_{ij,s}$ 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 \( \hat{\pi}_{ish} \) 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 4.** Given some trade shock, the ex-ante percentage change in the real wage of group \( g \) in country \( i \) is given by

\[
\hat{W}_{ig} = \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta} \cdot \prod_s (\hat{\mu}_{ig} \hat{\pi}_{ish})^{-\beta_{is}/\kappa}.
\]

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 \( I_g \equiv \sum_s v_{igs} \hat{\beta}_{is} \), where \( v_{igs} \equiv \sum_h \hat{\mu}_{igh} \hat{\pi}_{ish} \) is the share of workers from region \( g \) that work in sector \( s \).