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

Simon Galle  
UC Berkeley

Andrés Rodríguez-Clare  
UC Berkeley & NBER

Moises Yi  
UC Berkeley

June 2015

Preliminary and Incomplete

Abstract

This paper develops and applies a framework to quantify the effect of trade on aggregate welfare as well as the distribution of this aggregate effect across different groups of workers. The framework combines a multi-sector gravity model of trade with a Roy-type model of the allocation of workers across sectors. By opening to trade, a country gains in the aggregate by specializing according to its comparative advantage, but the distribution of these gains is unequal as labor demand increases (decreases) for groups of workers specialized in export-oriented (import-oriented) sectors. The model generalizes the specific-factors intuition to a setting with labor reallocation, while maintaining analytical tractability for any number of groups and countries. Our new notion of “inequality-adjusted” welfare effect of trade captures the full cross-group distribution of welfare changes in one measure, as the counterfactual scenario is evaluated by a risk-averse agent behind the veil of ignorance regarding the group to which she belongs. The quantitative application uses trade and labor allocation data across regions in the US and Germany to compute the aggregate and distributional effects of a shock to trade costs or foreign technology levels. For the extreme case in which the country moves back to autarky we find that inequality-adjusted gains from trade are larger than the aggregate gains for both countries, as between-group inequality falls with trade relative to autarky, but the opposite happens for the shock in which China expands in the world economy.

*We are grateful to seminar participants at Columbia, Edinburgh, LSE, Rochester, UC Berkeley, UC Merced, USC and the World Bank for helpful comments and suggestions. We also benefited from useful discussions with Arnaud Costinot, Kerem Cosar, Pablo Fajgelbaum, Patrick Kline and Jonathan Vogel. Román Zárate provided excellent research assistance. All errors remain our own.
1 Introduction

While existing gravity models of international trade provide a transparent approach to quantify the aggregate welfare effects of trade (Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2014), they remain silent on the associated distributional effects due to the standard representative-agent assumption. Yet, a growing empirical literature shows that trade has sharply different effects on real incomes across different groups of agents (e.g. Autor et al. (2013, 2014); Dix-Carneiro and Kovak (2014); Faber (2014)). Implicitly, these two strands of the literature are reconciled by assuming that the winners compensate the losers, but then all we can say is that everybody gains from trade and not how large the social gains are. Ultimately, we want to know how the aggregate gains from trade compare with its distributional implications.

In this paper we present an integrated framework to quantify the effect of trade on the size of the pie and on the way it is sliced and divided across different groups of workers. Assuming the existence of a social welfare function, we can then further quantify the effect of trade on social welfare by adjusting for its effect on between-group inequality. The distributional effects in our model arise from a Roy (1951) structure of the labor market, where trade differentially affects incomes of workers with skills that align with exportable or import-competing sectors. At the heart of the analysis is a simple expression for the change in real income due to a foreign shock (i.e. a change in trade costs or foreign technology levels) for group $g$ in country $i$,

$$\hat{W}_{ig} = \prod_{s} \lambda_{is}^{-\beta_{is}/\theta} \cdot \prod_{s} \pi_{igs}^{-\beta_{is}/\kappa},$$

where we use “hat change notation” $\hat{x} \equiv x'/x$. The first term on the right-hand side captures the change in prices given wages and is standard in the literature. As in Arkolakis et al. (2012) - henceforth ACR, this is given by a geometric average of the changes in the sector-level domestic trade shares elevated to the negative of the inverse of the trade elasticity, $\lambda_{is}^{-1/\theta}$. The second term captures the effect on the real income of group $g$ caused by the movement in sector-level wages. It is given by a geometric average of changes in sectoral employment shares elevated to the negative of the inverse of the labor-supply elasticity to each sector, $\pi_{igs}^{-1/\kappa}$. In our Roy model, the elasticity of labor supply to each sector, $\kappa$, is equal to the shape parameter of the Fréchet distribution that we assume governs the productivity levels that each worker draws for each sector. For both the first and second terms in Equation 1, the averaging weights are the Cobb-Douglas expenditure shares $\beta_{is}$.

This framework extends the existing analysis of Ricardian sector-level comparative advantage in Costinot et al. (2012) - henceforth CDK - to incorporate an upward sloping labor-supply curve to each sector. In fact, as $\kappa \to \infty$, our model collapses to CDK. With a finite $\kappa$ workers are heterogeneous in their sector-level productivities, so trade shocks that lead to the expansion of some sectors and the contraction of others have effects that vary across workers. The intuition here is similar to the one in the specific-factors model. In fact, as $\kappa \to 1$ our model is equivalent to one in which workers are perfectly immobile across sectors. The fact that our model nests CDK and the specific-factors model as $\kappa$ moves from infinity to one implies that $\kappa$ is a key parameter in the determination of the welfare effects of trade. Indeed, as we can see from Equation 1, given changes in sectoral employment shares, $\pi_{igs}$, a lower $\kappa$ implies a higher between-group variance in the welfare effects of trade shocks. The case

---

1 Notable exceptions are Fajgelbaum and Khandelwal (2014), which studies the differential effect of trade on rich and poor households, and Burstein and Vogel (2012), which analyzes the effect of trade on the skill premium.

2 CDK extend the seminal Eaton and Kortum (2002) framework to a multi-sector environment. As shown in ACR, a multi-sector version of the Armington model would be a workable substitute for the CDK-side of the model. The Krugman (1980) model or the Melitz (2003) model with a Pareto distribution (as in Chaney (2008)) would also work, though these models would introduce extra terms because of entry effects.

3 This paper belongs to the Ricardian revival in international trade, nicely surveyed by Costinot and Vogel (2014). Their terminology of Ricardo-Roy models succinctly summarizes the framework of our model: Ricardo on the trade-side and Roy on the labor-side, capturing the source of comparative advantage at the country and worker-level respectively.

4 For the specific-factors model (i.e., the model in which labor is sector specific), the formula in Equation 1 is valid for $\kappa = 1$ if we define $\pi_{ig}$ as the share of earnings of group $g$ that comes from sector $s$. In the Roy-Fréchet model, thinking of $\pi_{igs}$ as employment shares or earning shares is equivalent. This implies that the equivalence between our model with $\kappa \to 1$ and the specific-factors model does not extend to the number of workers across sectors – in particular, for $\kappa \to 1$ the elasticity of labor supply to any particular sector with respect to the wage in that sector goes to 1 in our model but is zero in the specific-factors model.
\( \kappa \to 1 \) is noteworthy because then the group-level change in welfare is equal to the aggregate welfare effect multiplied by the inverse of the change in a Bartik-style index of group-level import competition.

The term labeled “Group-level Roy” in equation 1 is equal to the change in the degree of specialization of each group elevated to the power \( 1/\kappa \), \( S_{ig}^{1/\kappa} \), with the group-level degree of specialization \( S_{ig} \) defined as the exponential of the Kullback-Leibler divergence of the employment shares (\( \pi_{igs}, s = 1, ..., S \)) from the expenditure shares (\( \beta_{is}, s = 1, ..., S \)). Thus, shocks that reduce a group’s specialization have less beneficial welfare effects. As an example, the removal of import quotas on apparel imports from China would likely reduce the degree of specialization for a US group that specializes in apparel, exerting downward pressure on the group’s welfare. Moreover, since the United States is a net importer of apparel, this group would gain from an increase in specialization if the US were to move to autarky. This formalizes the idea that groups that are specialized in import-competing sectors gain less from trade.

We use the concept of “inequality-adjusted” welfare in Jones and Klenow (2015) to measure the aggregate welfare effect of a shock that has heterogeneous effects across groups when there is no compensation for losers. One interpretation of this measure is that it captures the utility of a risk-averse agent who is behind the veil of ignorance regarding the group to which she belongs. Loosely speaking, if a shock increases inequality then the inequality-adjusted welfare effect is less favorable than the one implied by the standard aggregation, which corresponds to our measure when the coefficient of inequality aversion goes to zero.

While our methodology can be applied to several different categorizations of workers into “groups” (e.g., education, age or gender), our empirical application uses a geographical categorization. This is motivated by a growing body of empirical work documenting substantial variation in local labor-market outcomes in response to national-level trade shocks (Autor et al., 2013; Dauth et al., 2014; Dix-Carneiro and Kovak, 2014; Kovak, 2013; McLaren and Hakobyan, 2010; Topalova, 2010). Our model provides a tractable general-equilibrium framework to analyze this heterogeneous impact of trade shocks, which makes our paper a structural complement to the existing set of empirical papers. We use administrative data to obtain sectoral employment shares across 15 manufacturing sectors for each of 265 regions (our groups in this application) at the Kreise level in Germany, and we combine this with data on bilateral trade flows and sectoral output from OECD STAN or the World Input-Output Database. We use this data to perform counterfactual analysis using the approach proposed by Dekle, Eaton and Kortum (2008) for different values of our two key parameters, \( \theta \) and \( \kappa \).

Our first exercise is to compute the gains from trade for each region and for the country as a whole (with the standard aggregation as the population-weighted mean of regional gains), as well as the inequality-adjusted gains from trade. As expected, the aggregate gains from trade and their dispersion are higher for low values of \( \kappa \), with some regions actually losing from trade. Interestingly, we find that the Bartik-style index of region-level import competition perfectly predicts the ranking across regions in the gains from trade. We also find that the inequality-adjusted gains from trade are higher than the aggregate gains, as income levels become less dispersed with trade than in autarky. This is a reflection of a positive cross-region correlation in the data between earnings per worker and import competition (in manufacturing). We also find this to be the case for the United States when we use commuting zones as the definition of regions. These results suggest that trade is pro-poor in these two countries, at least from a regional perspective.

Our second exercise is to compute the welfare effects for Germany of a sector-neutral increase in productivity in China. Of particular note here is that the inequality-adjusted welfare gain is lower than the aggregate gain, a consequence of the fact that inequality across regions increases with the China shock. Hence, while trade is found to be pro-poor when compared to autarky, the rise of China is

\[ S_{ig} = \exp \left[ D_{KL}(\pi_{igs} \parallel \beta_{is}) \right] = \exp \sum_{s} \beta_{is} \ln(\beta_{is}/\pi_{igs}). \]

\[ D_{KL}(\pi_{igs} \parallel \beta_{is}) \]

\[ \kappa \to 1 \]
Our paper is related to several research areas in trade. In addition to the above-mentioned research on trade and local-labor markets (Autor et al., 2013; Dauth et al., 2014; Dix-Carneiro and Kovak, 2014; Kovak, 2013; McLaren and Hakobyan, 2010; Topalova, 2010), there is a large literature on the unequal effects of trade on labor-market outcomes – see for example Autor et al. (2014); Burstein and Vogel (2011, 2012); Helpman et al. (2012); Krishna et al. (2012). A literature focusing specifically on the effect of trade shocks on the reallocation of workers across sectors finds significant effects for developed countries (Artuc et al., 2010; Revenga, 1992), which is the focus of our analysis.

Artuc et al. (2010) and Dix-Carneiro (2014) use a Roy model of the allocation of workers across sectors to offer a structural analysis of the dynamic adjustment to trade liberalization in a small economy. We complement these papers by linking the Roy model for the labor market with a gravity model of trade and by using the resulting framework to provide a simple and transparent way to quantify the aggregate and distributional welfare effects of trade. Other structural analyses of trade liberalization and labor market adjustments are Coşar (2013), Coşar et al. (2013), Kambourov (2009) and Ritter (2012). While all these papers focus on the differential impact of trade through the earnings channel, another set of papers focus on the expenditure channel, as in Atkin and Donaldson (2014), Faber (2014), Fajgelbaum and Khandelwal (2014) and Porto (2006).

Our paper also relates to the renewed attention to Roy models in various fields of economics – see for example Lagakos and Waugh (2013) for a recent application to development, and Young (2014) and Hsieh et al. (2013) for the productivity literature. Closer to our paper, Burstein et al. (2015) utilize a Roy model with a Fréchet distribution of worker abilities across occupations to decompose the changes in between-group earnings inequality into various channels, focusing on the role of technological change in explaining the evolution of the skill premium.

Finally, it is worth commenting how our model relates to the one in Autor et al. (2013). They present a multi-sector gravity model of trade with homogeneous and perfectly mobile workers across sectors (as in CDK), but with each local economy (our groups) modeled as a separate economy. In this case all the variation in the effects of a shock across regions arise because of different terms of trade effects. In our model technologies are national and there are no trade costs among groups within countries, so terms of trade are the same for all groups. Heterogeneity of workers 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.

The rest of this paper is structured as follows. In Section 2 we start out with a short empirical overview of the relation between trade and sectoral reallocation in Germany. Section 3 provides the baseline model and its extensions. The data is described in Section 4, while Section 5 presents our counterfactual analysis of a German return to autarky and of a Chinese technology shock for different values of $\kappa$. Section 6 discusses various approaches for the estimation of $\kappa$, provides some preliminary results, and finally uses a Bartik-style methodology as in Autor et al. (2013) to compare the distributional implications of the China trade shock in our model with those in the data. The concluding section is yet to be written.

## 2 Trade and Sectoral Reallocation in the Data

To understand the relation between trade and sectoral reallocation, we start by a short exploration of the related empirical patterns in Germany. First, we provide descriptives on the changing composition of output across sectors and how these compositional changes are related to trade. Specifically, we decompose the changes in sectoral shares of total output into changes in domestic demand and changes in net exports. This descriptive exercise will demonstrate the substantial magnitude of sectoral reallocation, and at the same time quantify the relative importance of changes in net exports in this reallocation. We

---

9See also Gourinchas (1999) and Kline (2008) for evidence of substantial reallocation in response to sectoral (but not trade) price shocks.

10In contrast, the evidence for developing countries suggests that reallocation in response to trade shocks is at best very sluggish – see Goldberg and Pavcnik (2007), Menezes-Filho and Muenler (2011)), and Dix-Carneiro (2014).

11There is also a broad literature on the impact of trade on poverty and the income distribution using a Computable General Equilibrium (CGE) methodology. Savard (2003) offers an overview of the different approaches for counterfactual analysis of the income distribution within this CGE literature, while Cockburn et al. (2008) integrate multiple chapters on methodology and empirical findings of the CGE approach into a book-length discussion.

---

3
then examine how the observed changes in output shares translate into shifts in sectoral employment shares.

In a second step, we move beyond the descriptive exercise, and present evidence on how trade-shocks affect sectoral output and employment shares. This is a first illustration of the relevance of the model, where sectoral reallocation in response to trade shocks will have smaller or larger welfare effects depending on the dispersion of comparative advantage.

2.1 Decomposition of Sectoral Reallocation

We start from the accounting identity

\[ E_{is}^t = Y_{is}^t - X_{is}^t + M_{is}^t, \]

where \( E_{is}^t \) is country \( i \)'s expenditure in sector \( s \) at time \( t \), \( Y_{is}^t \) is production, \( X_{is}^t \) is exports and \( M_{is}^t \) is imports. Rearranging and dividing both sides by total expenditure in country \( i \) yields

\[ \frac{Y_{is}^t}{E_i^t} = \frac{E_{is}^t - M_{is}^t + X_{is}^t}{E_i^t} = \beta_{is}^t \lambda_{is}^t + \frac{X_{is}^t}{E_i^t}, \]

where \( \beta_{is}^t \equiv \frac{E_{is}^t}{E_i^t} \) are expenditure shares across goods and \( \lambda_{is}^t \equiv \frac{E_{is}^t - M_{is}^t}{E_i^t} \) is the domestic trade share in sector \( s \). Changes over time in \( y_{is}^t \equiv \frac{Y_{is}^t}{E_i^t} \) can be decomposed as

\[ y_{is}^t - y_{is}^{t-1} = (\beta_{is}^t - \beta_{is}^{t-1}) \lambda_{is}^t + (\lambda_{is}^t - \lambda_{is}^{t-1}) \beta_{is}^{t-1} + \frac{X_{is}^t}{E_i^t} - \frac{X_{is}^{t-1}}{E_i^{t-1}}. \]

To bring this equation to the data, we focus on Germany and set \( t = 2007, t - 1 = 2000 \). We first visualize the decomposition of changes in output shares in Figure 1, for 15 manufacturing sectors at the 2-digit level of aggregation.\(^{12}\) We see that both trade-induced and home-induced reallocation are strongly correlated with output-share reallocation. The sector with the highest output-share reallocation, with an increase of 3.9 percentage points, is the sector producing “Motor Vehicles, Trailers, and Semi-Trailers.”

![Figure 1: Decomposition of Changes in Output Shares](image)

We now quantify the share of trade-induced and home-induced reallocation in the output-share reallocation. Define

\[ G_{is}^t \equiv y_{is}^t - y_{is}^{t-1}, \quad H_{is}^t \equiv (\beta_{is}^t - \beta_{is}^{t-1}) \lambda_{is}^t, \quad T_{is}^t \equiv (\lambda_{is}^t - \lambda_{is}^{t-1}) \beta_{is}^{t-1} + \frac{X_{is}^t}{E_i^t} - \frac{X_{is}^{t-1}}{E_i^{t-1}}. \]

\(^{12}\)Section 4 provides a detailed discussion of the data.
that $G_{ts}^t = H_{ts}^t + T_{ts}^t$. We want to know what share of the variance of changes in output shares ($G_{ts}^t$) is home-induced (related to $H_{ts}^t$), and what share is trade-induced (related to $T_{ts}^t$). We can answer this question by running two separate regressions where we either regress $H_{ts}^t$ on $G_{ts}^t$, or $T_{ts}^t$ on $G_{ts}^t$. The results are shown in Table 1. Around 64% of the variance of changes in output shares is due to changes in trade-induced reallocation, while the remainder is related to home-induced reallocation.

### Table 1: Decomposition of Changes in Output Shares

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output-share Reallocation</td>
<td>0.643***</td>
<td>0.357***</td>
</tr>
<tr>
<td></td>
<td>(0.0583)</td>
<td>(0.0583)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00174</td>
<td>-0.00174</td>
</tr>
<tr>
<td></td>
<td>(0.000927)</td>
<td>(0.000927)</td>
</tr>
<tr>
<td>Observations</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As a final step, we ask to what extent changes in output shares, $y_{ts}^t - y_{ts}^{t-1}$, are correlated to changes in employment shares, $\pi_{ts}^t - \pi_{ts}^{t-1}$ with $\pi_{ts}^t \equiv L_{ts}^t / L_t^t$. Empirically, we find that there is a correlation of 56.8% between changes in sectoral output shares and changes in employment shares. We visualize this relation in Figure 2.

### Figure 2: Relation between Sectoral Output and Employment Shares

2.2 Sectoral Reallocation In Response to Trade Shocks

The next step is to examine if we can document a causal effect of foreign trade shocks on sectoral reallocation in Germany. After all, what we call “trade-induced” reallocation above could in principle be the consequence of domestic preference or technology shocks. To examine the causal effect of foreign shocks, we utilize the trade-shock variable constructed by Dauth et al. (2014). Specifically, for each sector $s$, we construct an import penetration measure $\Delta M_{st}^{East\rightarrow Other}$ as the change in net import flows, normalized by sectoral employment, from China and Eastern Europe to a group of “similar countries” during time period $t$. Formally,

Formally, we run the following regressions: $H_{ts}^t = \alpha + \beta_1 G_{ts}^t + \epsilon$; $T_{ts}^t = \alpha + \beta_2 G_{ts}^t + \epsilon$, so $\beta_1 = \text{cov}(G_{ts}^t, H_{ts}^t) / \text{var}(G_{ts}^t)$, $\beta_2 = \text{cov}(G_{ts}^t, T_{ts}^t) / \text{var}(G_{ts}^t)$ and $\beta_1 + \beta_2 = 1$.

The instrument group employed by Dauth et al. (2014) consists of Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. Countries were selected based on having a similar income level as Germany.
\[ \Delta IP_{st}^{\text{East} \rightarrow \text{Other}} = \frac{\Delta M_{st}^{\text{East} \rightarrow \text{Other}}}{L_{st}^{\text{Germany}}} , \]

where \( L_{st}^{\text{Germany}} \) is the number of workers in Germany employed in industry \( s \) at the beginning of time period \( t \). We run the OLS regressions

\[ v_{st} = \gamma \Delta IP_{st}^{\text{East} \rightarrow \text{Other}} + \varepsilon_{st}, \]

with dependent variable \( v_{st} = z_{st} - z_{s,t-1} \) or \( v_{st} = \frac{z_{st}}{z_{s,t-1}} - 1 \) computed for either output shares (i.e., \( z_{st} \equiv y_{st} \)) or employment shares (i.e., \( z_{st} \equiv \pi_{st} \)).

In spite of the fact that we only have 15 sectors, we find that foreign trade shocks have the expected negative sign in all specifications, with a borderline significance for the case in which the dependent variable is the change in employment shares or the growth rate of output shares, and with a strong level of statistical significance in the case in which the dependent variable is the growth rate of the employment share.

**Table 2: Output and Labor Reallocation in Response to Trade Shock**

<table>
<thead>
<tr>
<th>( \Delta IP_{st}^{\text{East} \rightarrow \text{Other}} )</th>
<th>Difference Growth Rate</th>
<th>Difference Growth Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>(-0.0128)</td>
<td>(-0.00304)</td>
<td>(-0.00839)</td>
</tr>
<tr>
<td>((0.0156))</td>
<td>((0.00184))</td>
<td>((0.00421))</td>
</tr>
<tr>
<td>Observations: 15</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>(R^2): 0.046</td>
<td>0.164</td>
<td>0.221</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
The independent variable is measured in 1000 EURO per worker.
The output and employment share are expressed in percentage terms.
* \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \)

This section has made the case that trade shocks lead to a reallocation of sectoral output and employment shares at the national level. In the theoretical section, we present a model that predicts the observed reallocation patterns both at the national and the group level. In addition, the model allows to understand and quantify the aggregate and distributional welfare consequences of a given trade reform through its impact on reallocation.

### 3 Theory: Baseline Model

We present a multi-sector, multi-country, Ricardian model of trade with heterogeneous workers. There are \( N \) countries indexed by \( i,j \) and \( S \) sectors indexed by \( s,k \), each with a continuum of goods indexed by \( \omega \in [0,1] \). Each sector is modeled as in Eaton and Kortum (2002 – henceforth EK): preferences across the continuum of goods in each sector are CES with elasticity of substitution \( \sigma \) and technologies have constant returns to scale and productivities that are distributed Fréchet with shape parameter \( \theta > \sigma - 1 \) 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 \( \tau_{ij,s} \geq 1 \) to export goods in sector \( s \) from country \( i \) to country \( j \).

On the labor side, we assume that there are \( G \) groups of workers indexed by \( g,h \). A worker from group \( g \) in country \( i \) has a number of efficiency units \( z \) in sector \( s \) drawn from a Fréchet distribution with shape parameter \( \kappa > 1 \) and level parameters \( A_{igs} \) that can vary with \( g \). Thus, workers within but all direct neighbors and members of the European Monetary Union were excluded. The intuition behind the instrument is that the “rise of the East” is an exogenous event, affecting trade for all countries at comparable levels of development as Germany in a similar way. For a discussion on the robustness of this instrument, see Dauth et al. (2014).

\[15\] We can easily extend the analysis to allow the Fréchet parameters \( \theta \) and \( \kappa \) to differ across sectors and groups, respectively, but choose not to do so for now to avoid notational clutter.
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 group $a$ is fixed and denoted by $L_{ig}$. Labor supply is inelastic – workers simply choose the sector to which they supply their entire labor endowment.

If $\kappa \to \infty$ and $A_{igs} = 1$ for all $g$ and $s$, the model collapses to the multi-sector EK model developed in CDK. On the other hand, if $\tau_{ij} \to \infty$ for all $j$ and $s$ then economy $i$ is in autarky and collapses to the Roy model in Lagakos and Waugh (2013) (see also Hsieh et al. (2013)).

### 3.1 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 are national, wages cannot differ across groups. Let wages per efficiency unit in sector $s$ differ across sectors. Howev-

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

$$P_{js} = \eta^{-1} \left( \sum_i T_{is} \left( \tau_{ij} w_{is} \right)^{-\theta} \right)^{-1/\theta},$$

where $\eta \equiv \Gamma(1 - \frac{1}{\rho})^{1/(1-\sigma)}$.

Labor supply is determined by workers’ choices regarding which sector to work in. Let $z = (z_1, z_2, ..., z_S)$ and let $\Omega_s \equiv \{ z \text{ s.t. } w_{is} z_s \geq w_{ik} z_k \text{ for all } k \}$. A worker with productivity vector $z$ in country $i$ will choose sector $s$ if $z \in \Omega_s$. Let $F_{ig}(z)$ be the joint probability distribution of $z$ for workers of group $g$ in country $i$. The following lemma (which replicates results in Lagakos and Waugh (2013)) characterizes the labor supply side of the economy:

**Lemma 1.** The share of workers in group $g$ in country $i$ that choose to work in sector $s$ is

$$\pi_{igs} \equiv \int_{\Omega_s} dF_{ig}(z) = \frac{A_{igs} w_{is}^{\kappa}}{\Phi_{ig}^{\kappa}},$$

where $\Phi_{ig}^{\kappa} \equiv \sum_k A_{igk} w_{ik}^{\kappa}$. The supply of efficiency units by this group to sector $s$ is given by

$$E_{igs} \equiv L_{ig} \int_{\Omega_s} z_s dF_{ig}(z) = \frac{\gamma \Phi_{ig}^{\kappa}}{w_{is}} \pi_{igs} L_{ig},$$

where $\gamma \equiv \Gamma(1 - 1/\kappa)$.

---

16There are two sources of comparative advantage in this model: first, as in CDK, differences in $T_{is}$ drive sector-level (Ricardian) comparative advantage; second, differences in $L_i/L_i$ and $A_{igs}$ 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.

17Lemma 1 generalizes easily to a setting with correlation in workers’ ability draws across sectors. In this case, the dispersion parameter $\kappa$ is replaced by $\kappa/(1 - \rho)$, where $\rho$ measures the correlation parameter of ability draws across sectors for each worker. All our results below extend to this case with $\kappa$ replaced $\kappa/(1 - \rho)$.
One implication of this lemma is that income levels per worker are equalized across sectors. That is, for group $g$, we have

$$w_{is}E_{igs}/\pi_{igs}L_{ig} = \gamma \Phi_{ig}.$$  

This is a special implication of the Frechet distribution and it implies that the share of income obtained by workers of group $g$ in country $i$ in sector $s$ (i.e., $w_{is}E_{igs}/\sum w_{ik}E_{ikg}$) is also given by $\pi_{igs}$. Note also that total income of group $g$ in country $i$ is $Y_{ig} \equiv \sum_s w_{is}E_{igs} = \gamma L_{ig}\Phi_{ig}$. In turn, total income in country $i$ is $Y_i \equiv \sum_g Y_{ig}$.

Putting the supply and demand sides of the economy together, we see that excess demand for efficiency units in sector $s$ of country $i$ is

$$ELD_{is} \equiv \frac{1}{w_{is}} \sum_j \lambda_{ij}s \beta_{js} Y_j - \sum_g E_{igs}.$$  \hspace{1cm} (4)

Since that $\lambda_{ij}s, Y_j$ and $E_{igs}$ are functions of the whole matrix of wages $w \equiv \{w_{is}\}$, the system $ELD_{is} = 0$ for all $i, s$ is a system of equations in $w$ whose solution gives the equilibrium wages for some choice of numeraire.

### 3.2 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 $\hat{\tau}_{ij}s$ and $\hat{T}_{js}$ for $i \neq j$ while keeping all other parameters constant (i.e., $\hat{A}_{igs} = 1$ for all $i, g, s$ and $\hat{L}_{ig} = 1$ for all $i, g$). The counterfactual equilibrium entails $ELD'_{is} = 0$ for all $i, s$. Noting that $w_{is}'E'_{igs} = \pi_{igs}\hat{\Phi}_{ig}\pi_{igs}Y_{ig}$, equation $ELD'_{is} = 0$ can be written as

$$\sum_g \hat{\pi}_{igs}\hat{\Phi}_{ig}\pi_{igs}Y_{ig} = \sum_j \hat{\lambda}_{ij}s\hat{\lambda}_{ij}s\beta_{js} \sum_g \hat{\Phi}_{jg}Y_{jg}$$  \hspace{1cm} (5)

with

$$\hat{\Phi}_{ig} = \left(\sum_k \pi_{ikg}w_{ik}^\kappa\right)^{1/\kappa},$$  \hspace{1cm} (6)

$$\hat{\lambda}_{ij}s = \frac{\hat{T}_{is}\left(\hat{\tau}_{ij}s\hat{w}_{is}\right)^{-\theta}}{\sum_k \lambda_{kjs}\hat{T}_{ks}\left(\hat{\tau}_{kjs}\hat{w}_{ks}\right)^{-\theta}},$$  \hspace{1cm} (7)

and

$$\hat{\pi}_{igs} = \frac{\hat{w}_{ik}^\kappa}{\sum_k \pi_{ikg}w_{ik}^\kappa}.$$  

This equation can be solved for $\hat{w}_{is}$ given data on income levels, $Y_{ig}$, trade shares, $\lambda_{ij}s$, expenditure shares, $\beta_{is}$, labor allocation shares $\pi_{igs}$, and labor endowments, $L_{ig}$, and the trade-cost shocks, $\hat{\tau}_{ij}s$. From the $\hat{w}_{is}$ we can then solve for all other relevant changes, including changes in trade shares using (7) and changes in employment shares using (8).

### 3.3 Welfare Effects

Our measure of welfare is ex-ante real income, $W_{ig} \equiv Y_{ig}/L_{ig}$. We are interested in the change in $W_{ig}$ caused by a shock to trade costs or foreign technology levels, henceforth simply referred to as a “foreign shock.” Cobb-Douglas preferences combined with $Y_{ig} = \gamma L_{ig}\Phi_{ig}$ imply that

$$\tilde{W}_{ig}/\tilde{P}_{ig} = \hat{\Phi}_{ig} \prod_s \tilde{P}_{is}^{-\beta_{is}}.$$  \hspace{1cm} (9)

From (3) and (7) and given $\hat{T}_{is} = 1$ for all $s$ we have $\tilde{P}_{is} = \hat{w}_{is}\hat{\lambda}_{is}^{1/\theta}$ while from (6) and (8) we have $\hat{w}_{is}/\hat{\Phi}_{ig} = \hat{\lambda}_{is}^{1/\kappa}$. Combining these two results with (9) we arrive at the following proposition:
Proposition 1. Given some shock to trade costs or foreign technology levels, the ex-ante percentage change in the real wage of group $g$ in country $i$ is given by

$$W_{ig} = \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta} \cdot \prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa}. \quad (10)$$

The RHS of the expression in (10) has two components: the term $\prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta}$ is common across groups, while all the variation across groups comes from the second term, $\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa}$. If $\kappa \to \infty$, this second term converges to one, and the gains for all groups are equal to $\prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta}$, which is the multi-sector formula for the welfare effect of a trade shock in ACR once we note that $\theta$ is the trade elasticity in all sectors in this model. It is easy to show that the term $\prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta}$ corresponds to the change in real income given wages while the term $\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa}$ corresponds to the change in real income for group $g$ coming exclusively from changes in wages $\hat{w}_{is}$ for $s = 1, ..., S$.

The aggregate welfare effect can be obtained from Proposition 1 as $\hat{W}_i = \hat{Y}_i / \hat{P}_i = \sum_g (Y_{ig} / Y_i) \hat{W}_{ig}$, where $Y_{ig} / Y_i$ is group $g$’s share of income. This can be written explicitly as

$$\hat{W}_i = \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta} \cdot \sum_g \left( \frac{Y_{ig}}{Y_i} \right) \prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa}. \quad (11)$$

The aggregate welfare effect of a trade shock is no longer given by the multi-sector ACR term (i.e., $\hat{W}_i \neq \prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta}$). 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. Of course, the group level welfare effect can be seen as the product of the aggregate welfare effect and the group’s relative income effect, $\hat{W}_{ig} = \hat{W}_i \cdot \left( \hat{Y}_{ig} / \hat{Y}_i \right)$. This implies

$$\frac{\hat{Y}_{ig}}{\hat{Y}_i} = \frac{\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa}}{\sum_h \left( \frac{Y_{ih}}{Y_i} \right) \prod_s \hat{\pi}_{ihs}^{-\beta_{is}/\kappa}}. \quad (11)$$

The term $\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa}$ is related to the change in the degree of specialization of group $g$. We use the Kullback-Leibler (KL) divergence as a way to define the degree of specialization of a group. Formally, the KL divergence of $\pi_{ig} = \{\pi_{i1g}, \pi_{i2g}, ..., \pi_{ihg}\}$ from $\beta_i = \{\beta_{i1}, \beta_{i2}, ..., \beta_{iS}\}$ is given by $D_{KL}(\pi_{ig} \parallel \beta_i) = \sum_s \beta_{is} \ln(\beta_{is} / \pi_{igs})$. Note that if group $g$ in country $i$ was in full autarky (i.e., not trading with any other group or country) then $\pi_{igs} = \beta_{is}$. 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

$$\prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa} = \exp \left( \frac{1}{\kappa} \left[ D_{KL}(\pi_{ig} \parallel \beta_i) - D_{KL}(\pi_{ig} \parallel \beta_i) \right] \right).$$

This implies that the welfare effect of a trade shock on a particular group is determined by the change in the degree of specialization of that group as measured by the KL divergence (modulo $\prod_s \hat{\lambda}_{iis}^{-\beta_{is}/\theta}$). Consider a group $g$ in country $i$ 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 $g$ would be highly specialized in $s$ when the country is in autarky (but groups trade among themselves) 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 $g$, implying lower gains relative to other groups in the economy.

3.4 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: $GT_i \equiv 1 - W_i^A$ and $GT_{ig} \equiv 1 - W_{ig}^A$. A move to autarky for country $i$ entails $\hat{\tau}_{ijs} = \infty$ for all $s$ and all $i \neq j$. Conveniently, solving for changes in wages
in country $i$ (i.e., solving for $\hat{w}_{is}$ for $s = 1, ..., S$) from Equation (5) only requires knowing the values of trade and employment shares for country $i$, namely $\lambda_{iis}$ for all $s$ and $\pi_{igs}$ for all $g, s$. This can be seen by letting $\hat{r}_{ij} \to \infty$ in Equation (5), which yields
\[
\sum_g \hat{x}_{igs} \hat{\Phi}_{ig} \pi_{igs} Y_{ig} = \beta_{is} \sum_g \hat{\Phi}_{ig} Y_{ig}.
\]

(12)

**Proposition 2.** For a finite $\kappa$, the aggregate gains from trade are higher than those in the model with $\kappa \to \infty$.

To understand this result, it is useful to consider the simpler case with a single group of workers, $G = 1$. For a move back to autarky, in this case we would have
\[
\hat{W}_i^A = \prod_s \lambda_{iis} \cdot \exp \left[ \frac{1}{\kappa} D_{KL}(\pi_i \parallel \beta_i) \right].
\]

Since $D_{KL}(\pi_i \parallel \beta_i) > 0$, then (given $\pi_i$) a lower $\kappa$ implies a lower $\hat{W}_i$. Intuitively, a finite $\kappa$ 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, – see Costinot and Rodríguez-Clare (2014). Proposition 2 establishes that this result generalizes to the case $G > 1$.

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 $g$ in country $i$ are
\[
GT_{ig} = 1 - \prod_s \lambda_{iis} \cdot \exp \left( \frac{1}{\kappa} \left[ D_{KL}(\pi_{ig}^A \parallel \beta_i) - D_{KL}(\pi_{ig} \parallel \beta_i) \right] \right).
\]

The term $D_{KL}(\pi_{ig}^A \parallel \beta_i) - D_{KL}(\pi_{ig} \parallel \beta_i)$ could be positive or negative, depending on whether group $g$ in country $i$ becomes more or less specialized with trade as measured by the KL divergence. Intuitively, if a group happens to be specialized in industries that face strong import competition, this would imply that $D_{KL}(\pi_{ig} \parallel \beta_i) < D_{KL}(\pi_{ig}^A \parallel \beta_i)$, and hence lower gains from trade.

### 3.5 A Limit Case

An interesting case arises in the limit as $\kappa \to 1$, where the model becomes isomorphic to one in which labor cannot move across sectors (i.e., where $L_{igs}$ is fixed). In this case we can easily get that for a foreign shock we have
\[
\lim_{\kappa \to 1} \hat{Y}_{ig} = \sum_s \pi_{igs} \hat{w}_{is}.
\]

Letting $r_{is} \equiv \sum_g \pi_{igs} Y_{ig} / Y_i$ be the share of sector $s$ in total output in country $i$, we then have
\[
\lim_{\kappa \to 1} \hat{r}_{is} = \frac{\hat{w}_{is}}{\sum_k \hat{r}_{ik} \hat{w}_{ik}}.
\]

Combined with $\lim_{\kappa \to 1} \hat{Y}_i = \sum_k \hat{r}_{ik} \hat{w}_{ik}$ we finally get
\[
\lim_{\kappa \to 1} \hat{Y}_{ig} / \hat{Y}_i = \sum_s \pi_{igs} \hat{r}_{is}.
\]

(14)

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 compute the implied relative income changes across groups. Following Autor et al. (2013), we can instrument the group-level Bartik-style variable $\sum_s \pi_{igs} \Delta L_{s}^{East \to Other}$ and run an IV regression of observed $\hat{Y}_{ig} / \hat{Y}_i$ on $\sum_s \pi_{igs} \hat{r}_{is}$. If $\kappa$ was indeed very close to 1 then this regression should yield a coefficient close to one. We expect that the coefficient will
be lower than one precisely because workers can and would move across sectors in response to relative wage changes.\footnote{The coefficient could be higher than one if there is mobility across regions or if the labor supply to the manufacturing sector is not perfectly inelastic. Below we present extensions of the model to allow for these two possibilities, which we plan to explore quantitatively in the near future.} We will check this result in the empirical section.

The case $\kappa \to 1$ also leads to a sharp result for the change in relative income levels across groups in a move back to autarky. From Equation (12) combined with (8) we get

$$
\hat{w}_{is} \sum_{g} \Phi_{ig}^{1-\kappa} \pi_{igs} Y_{ig} = \beta_{is} \hat{Y}_i \quad \forall i
$$

Setting $\hat{Y}_i = 1$ by choice of numeraire and setting $\kappa = 1$ yields $\hat{w}_{is} = \beta_{is} / r_{is}$.\footnote{In the case of $\kappa = 1$, where there is no labor reallocation under a return to autarky, the change in wages has to offset the factor content of trade $FCT_{is} \equiv L_{is} (1 - \beta_{is} / r_{is})$, such that $\hat{w}_{is} = \beta_{is} / r_{is} = 1 - FCT_{is} / L_{is}$.} Plugging into (13) yields

$$
\lim_{\kappa \to 1} \frac{\hat{Y}_{ig}^{A}}{\hat{Y}_{ig}^{A}} = I_{ig} \equiv \sum_{s} \pi_{igs} \beta_{is} / r_{is}.
$$

(15)

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, in the limit as $\kappa \to 1$, the change in relative income levels across groups is simply given by the index of import competition that we can directly observe in the data. Things are more complicated in the general case with $\kappa > 1$, but we will see that $I_{ig}$ remains a good proxy for whether $\hat{Y}_{ig}^{A} / \hat{Y}_{ig}^{A} \geq 1$ and that the variance of $\hat{Y}_{ig}^{A} / \hat{Y}_{ig}^{A}$ across $g$ falls with $\kappa$. Of course, one can also use the result in (15) to rewrite the result in (14) and get an expression for any foreign shock as

$$
\lim_{\kappa \to 1} \frac{\hat{Y}_{ig}}{\hat{Y}_{ig}} = \frac{1}{I_{ig}}.
$$

3.6 Inequality-Adjusted Welfare Effects

Consider an agent "behind the veil of ignorance" who doesn’t know what group she will belong to. Since there are $L_{ig}$ workers in group $g$, the probability that our agent behind the veil will end up in group $g$ is $l_{ig} \equiv L_{ig} / L_i$. Let $\rho$ denote the degree of relative risk aversion. The certainty-equivalent real income of an agent behind the veil is

$$
U_{i} \equiv \left( \sum_{g} l_{ig} W_{ig}^{1-\rho} \right)^{1/(1-\rho)}.
$$

We can think of $V_{i} \equiv W_{i} / U_{i}$ as a measure of the cost of inequality for an agent behind the veil of ignorance. Consistent with this idea, $V_{i}$ is equal to one if $\rho = 0$ and is increasing in $\rho$, reaching $W_{i} / \min_{g} W_{ig}$ when $\rho \to \infty$.\footnote{Related welfare measures are examined by Cordoba and Verdier (2008); Heathcote et al. (2008) and Jones and Klenow (2015), who incorporate income risk into the analysis of aggregate welfare in macro models without trade.}

In the quantitative section below we will present results for "inequality-adjusted" welfare effects of a foreign shock, defined as $\hat{U}_{i}$ for any foreign shock, and "inequality adjusted" gains from trade, defined as $IGT_i \equiv 1 - \hat{U}_{i}^{A}$ for a shock that takes the economy back to autarky.\footnote{These inequality-adjusted welfare effects focus on between-group inequality. For within-group inequality, the model implies that the distribution of worker income $q$ follows $Pr(q \leq Q) = e^{-\kappa s Q^{-\kappa}}$. Hence, inequality measures which are invariant to the scale of the Fréchet are unaffected by the trade shocks.} We will compare these effects with the standard ones, $\hat{W}_{i}$ and $GT_{i} \equiv 1 - \hat{W}_{i}^{A}$. Given our definition of $V_i$, we have $\hat{U}_{i} = \hat{W}_{i} / \hat{V}_{i}$ and $IGT_{i} = 1 - \frac{1 - GT_{i}}{\hat{V}_{i}^{A}}$. If the foreign shock increases inequality ($\hat{V}_{i} > 1$) then $\hat{U}_{i} < \hat{W}_{i}$ while if inequality falls ($\hat{V}_{i} < 1$) then $\hat{U}_{i} > \hat{W}_{i}$. Similarly, if inequality is higher in the observed equilibrium than in autarky then $IGT_{i} < GT_{i}$, while in the opposite case $IGT_{i} > GT_{i}$.

3.7 Alternative Models and Extensions

In this section we extend the model to allow for an upward sloping labor supply to the whole manufacturing sector (Section 3.7.1), intermediate goods (Section 3.7.2), and mobility across groups, which is particularly relevant to the case in which groups correspond to geographic regions (Section 3.7.3).
3.7.1 Upward sloping labor supply

We extend the model by introducing a new sector in which goods can only be traded within each group. This non-tradable sector is identical to all other sectors regarding the labor and technology dimensions, with the main difference being that the elasticity of substitution in consumption between this sector and the rest can be different than one. As we show next, if the elasticity of substitution between tradables and non-tradables is higher than one then the labor supply to the tradable sector is increasing in the real wage in the tradable sector. We discuss this further below.

The wage in the non-tradable sector (indexed by \( s = 0 \)) can differ across groups (i.e., \( w_{ig0} \neq w_{ih0} \) for \( g \neq h \)). Lemma 1 still applies, and the equilibrium system is similar to what we had above, except that now expenditure shares vary across groups. Letting \( \xi_{ig} \) denote the share of total expenditure in tradables for group \( g \) in country \( i \), the excess labor demand in sector \( s \geq 1 \) is now

\[
ELD_{is} = \frac{1}{w_{is}} \sum_{j,g} \lambda_{igj} \beta_{j} \xi_{ig} Y_{jg} - \sum_g E_{ig}s,
\]

while in sector \( s = 0 \) the excess labor demand in group \( g \) in country \( i \) is have

\[
ELD_{ig0} = \frac{1}{w_{ig0}} (1 - \xi_{ig}) Y_{ig} - E_{ig}s.
\]

In turn, letting \( \chi \) denote the elasticity of substitution in consumption between tradables and non-tradables, the expenditure shares on tradable goods are given by

\[
\xi_{ig} = \frac{\left( \prod_{s=1}^{S} P_{is}^{\beta_{s}} \right)^{1-\chi}}{\left( \prod_{s=1}^{S} P_{is}^{\beta_{s}} \right)^{1-\chi} + P_{ig0}^{1-\chi}},
\]

with \( P_{is} \) for \( s \geq 1 \) still given 3 and \( P_{ig0} = \eta^{-1} T_{i0}^{-1/\gamma} w_{ig0} \). Without loss of generality we assume henceforth that \( T_{i0} = \eta^{-1} \) for all \( i \), so that \( P_{ig0} = w_{ig0} \).

Noting that \( \lambda_{igj}, \xi_{ig}, Y_{jg} \) and \( E_{ig}s \) are all functions of the matrix of wages \( \mathbf{w}^{T} \equiv \{ w_{is} \} \) for all \( i \) and \( s = 1, ..., S \) and the vector \( \mathbf{w}^{NT} \equiv \{ w_{ig0} \} \) for all \( ig \), the system \( ELD_{is} = 0 \) for all \( i, s \) and \( ELD_{ig0} \) for all \( ig \) is a system of equations in \( \mathbf{w}^{T} \) and \( \mathbf{w}^{NT} \) whose solution gives the equilibrium wages for some choice of numeraire. We can proceed as above and write down the equations for the hat changes in wages given some shock to trade costs or technology levels – see the Appendix for details. Here we are interested in showing how the value of \( \chi \) determines the slope of the labor supply to the tradable sector.

The condition \( ELD_{ig0} = 0 \) is simply \( 1 - \xi_{ig} = \pi_{ig0} \). Assuming without loss of generality that \( A_{i0} = 1 \) for all \( i \), and letting \( w_{igM} \equiv \left( \sum_{s \geq 1} A_{igS} \mathbf{w}_{igS}^{\kappa} \right)^{1/\kappa} \), this can be rewritten as

\[
\frac{(w_{ig0}/w_{igM})^{1-\chi}}{(w_{igM}/\prod_{s \geq 1} P_{is}^{\beta_{s}})^{\chi-1} + (w_{ig0}/w_{igM})^{1-\chi}} = \frac{(w_{ig0}/w_{igM})^{\kappa}}{1 + (w_{ig0}/w_{igM})^{\kappa}}.
\]

If \( \chi > 1 \) then the LHS is decreasing in \( w_{ig0}/w_{igM} \) (demand curve) while the RHS is increasing in \( w_{ig0}/w_{igM} \) (supply curve). A decrease in the real manufacturing wage \( w_{igM}/\prod_{s \geq 1} P_{is}^{\beta_{s}} \) implies shift to the right of the demand curve, leading to an increase in the equilibrium \( w_{ig0}/w_{igM} \) and an increase in \( \pi_{ig0} \). Thus, a shock that decreases the real manufacturing wage also leads to an increase in the share of people that move into the non-tradable sector.

As mentioned above, we think of the addition of the non-tradable sector as a particularly convenient way to get the labor supply curve to the manufacturing sector to be upward sloping in the real manufacturing wage. This requires that \( \chi > 1 \), which could seem contrary to the standard custom in the international macroeconomics literature to assume that the elasticity of substitution between tradables and non-tradables is lower than one. A better way to justify \( \chi > 1 \) is to think of sector \( s = 0 \) as “home production.” Indeed, a recent literature in macroeconomics concludes that adjustment in hours devoted
to home production may explain the variation in market hours over the business cycle, with a central value of $\chi = 2.5$ – see Aguiar, Hurst, and Karabourbunis (2013). In the quantitative analysis below we will show results with the model extended to allow for home production using this value of $\chi$.

### 3.7.2 Intermediate Goods

Consider again the basic model but now with an input-output structure as in Caliendo and Parro (2014). This extension is important because a significant share of the value of production in a sector originates from other sectors, and taking this into account may affect the effects of trade on wages $\hat{w}_{is}$ and hence the welfare effects across groups.

The labor supply of the model is exactly as in the main model (as characterized by Lemma 1), and trade shares and the price indices are given as in (2) and (3), except that instead of $\hat{w}_{is}$ we now have $c_{is}$, where $c_{is}$ is given by

$$ c_{is} = w_{is}^{1-\alpha_{is}} \prod_k P_{ik}^{\alpha_{iks}}. \tag{16} $$

Here the $\alpha_{iks}$ are the 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 $\alpha_{is} = \sum_k \alpha_{iks}$. Combining this expression for $c_{is}$ with (3) (but with $\hat{w}_{is}$ replaced by $c_{is}$) yields

$$ P_{js} = \eta^{-1} \left( \sum_k T_{is} \tau_{ij}s w_{is}^{(1-\alpha_{is})} \prod_k (P_{ik}^{-\theta})^{\alpha_{iks}} \right)^{-1/\theta}. $$

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 $\lambda_{ij}$. This implies that trade shares are an implicit function of wages.

Let $X_{js}$ and $R_{js}$ be total expenditure and total revenues for country $j$ on sector $s$. We know that $R_{is} = \sum_j \lambda_{ij} X_{js}$ while Cobb-Douglas preferences and technologies imply $X_{js} = \beta_{js} Y_j + \sum_{k=1}^S \alpha_{jsk} R_{jk}$. Combining these equations we get a system of linear equations that we can use to solve for revenues given income levels and trade shares,

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

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

$$ ELD_{is} = R_{is} - \sum_g E_{igs}. $$

As in the baseline model, the system $ELD_{is} = 0$ for all $i, s$ 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

$$ \sum_g \hat{\pi}_{i gs} \hat{\Phi}_{ig} \pi_{igs} Y_{ig} = (1 - \alpha_{is}) \sum_{j=1}^n \lambda_{ij} \hat{\lambda}_{ij} \left( \beta_{js} \sum_g \hat{\Phi}_{j g} Y_{jg} + \sum_{k=1}^S \alpha_{jsk} \hat{R}_{jk} R_{jk} \right), $$

where $\hat{\Phi}_{ig}$ is as in (6) and

$$ \hat{\lambda}_{ij} = \frac{\left( \hat{\tau}_{ij}s \hat{w}_{is}^{1-\alpha_{is}} \prod_k \hat{P}_{ik}^{\alpha_{iks}} \right)^{-\theta}}{\sum_l \lambda_{ilj} \left( \hat{\tau}_{ij}s \hat{w}_{is}^{1-\alpha_{is}} \prod_k \hat{P}_{ik}^{\alpha_{iks}} \right)^{-\theta}}, $$

$$ \hat{P}_{js}^{-\theta} = \sum_k \lambda_{ij} \hat{\tau}_{ij}s \hat{w}_{is}^{(1-\alpha_{is})} \prod_k (\hat{P}_{ik}^{-\theta})^{\alpha_{iks}}. $$
Lemma 2. A worker with productivity matrix

\[
R_{is} = \sum_j \lambda_{ij} \Delta_{ij} \left( \beta_{j} \sum_g \phi_{ig} Y_{jq} + \sum_{k=1}^{S} \alpha_{j} \phi_{jk} R_{jk} \right).
\]

Analogous to Proposition 1, from the hat algebra we find the following result:

Proposition 3. Given some trade shock, the ex-ante percentage change in the real wage of group \(g\) in country \(i\) is given by

\[
\dot{W}_{ig} = \prod_{s,k} \lambda_{ik}^{-\beta_{s} \alpha_{s} \gamma_{s}} \prod_{s,k} \lambda_{ig}^{-\beta_{g} \alpha_{g} \gamma_{g}} (1-\alpha_{g}/\kappa) \kappa
\]

where \(\tilde{a}_{i,sk}\) is the typical element of matrix \((I - \Phi)^{-1}\) with \(\Phi = \{\alpha_{iks}\}_{k,s=1,...,S}^{}\).

3.7.3 Mobility Across Regions

In our model, the ability of workers can be interpreted as being determined by the fundamentals of the region where they work, in addition to innate characteristics particular to the worker’s region of origin. Under this interpretation, workers have an incentive to move across regions in response to trade shocks, which is something we have not modeled thus far.

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 \(\beta_{hs}\). 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 \(i\) has a proportional adjustment to income determined by \(w_{igs}z_{hks}\), with \(w_{ig} = 1\) and \(w_{ig} \leq 1\) for all \(i, g, h\). Thus, a worker from \(g\) that works in region \(h\) in sector \(s\) has income of \(w_{igs}z_{hks}\).

We now let

\[
\Omega_{igs} \equiv \{z \text{ s.t. } w_{igs}z_{hks} \geq w_{ig} \gamma_{hgs}z_{hks} \text{ for all } h, k\}.
\]

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

Lemma 2. The share of workers in group \(g\) in country \(i\) that choose to work in \((f, s)\) is

\[
\pi_{igfs} = \int_{\Omega_{igs}} dF(z) = \frac{A_{fs}(z_{igs})^{\kappa}}{\Phi_{ig}^{\kappa}},
\]

where \(\Phi_{ig} = \sum_{h,k} \beta_{hs} (w_{igs})^{\kappa}\). The efficiency units supplied by this group in sector \((f, s)\) are given by

\[
E_{ifs} = L_{iq} \int_{\Omega_{igs}} z_{fs} dF(z) = \pi_{igfs} \gamma_{L_{ig}} \frac{\Phi_{ig}}{w_{igs} \gamma_{igs}}.
\]

Total income of group \(g\) in country \(i\) is

\[
Y_{ig} = \sum_{f,s} w_{igs}z_{ifs} E_{ifs} = \gamma_{L_{ig}} \Phi_{ig}.
\]

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 \(Y_{ig}/L_{ig} = \gamma_{ig}\).

---

23 Specifically, there are two ways to interpret our baseline model. First, one could think that the \(z\) is inherent to the worker, something that the worker is born with, and that if she were to migrate to another region this \(z\) would not change. Since wages vary across sectors but not across regions, this interpretation would imply that there are no incentives for workers to migrate. Second, one could think that all workers draw an \(x\) in each sector from a Fréchet distribution with parameters \(\kappa\) and \(\beta_{s}\), and that their efficiency units if they work in \((g, s)\) are \(A_{gs}^{1/\kappa} x_{s}\) (note that this is isomorphic to our current specification because \(Pr(z \leq a) = Pr(A_{gs}^{1/\kappa} x \leq a)\)). In this interpretation, \(A_{gs}^{1/\kappa}\) is a region-sector specific shifter that is common to all workers, and \(x\) is an worker-specific idiosyncratic term that is distributed the same everywhere. If we adopt the second interpretation, then labor income would differ across regions for the same worker, and there would be an incentive to migrate. For example, workers would want to move to regions that have a comparatively high common shifter in sectors whose relative wage increases after the trade shock.

24 There is limited empirical evidence of geographic mobility in response to trade shocks. Autor et al. (2013), Dauth et al. (2014), and Topalova (2010) find that trade shocks induced only small population shifts across regions in the US, Germany, and India, respectively. These studies focus on the short and medium run, while ours focuses on the long run.
Let $\mu_{igh} \equiv \sum_s \pi_{ighs}$ be the share of workers from $g$ that work in $h$. It is easy to verify that $\pi_{ighs}/\mu_{igh} = \pi_{ihhs}/\mu_{ihh}$ for all $i, g, h, s$. Thus, conditional on locating in region $h$, all workers irrespective of their origin have sector employment shares given by $\pi_{ihhs} \equiv \pi_{ighs}/\mu_{igh}$. The shares $\pi_{ihhs}$ 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

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

Noting that $\lambda_{ijs}$, $Y_j$ and $E_{ighs}$ are functions of the whole matrix of wages $w \equiv \{w_{is}\}$, the system $ELD_{is} = 0$ for all $i, s$ is a system of equations in $w$ whose solution gives the 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 to what we did in Section 3.2. Changes in wages can be obtained as the solution to the system of equations given by

$$\sum_{g, h} \tilde{\pi}_{ihhs} \hat{\Phi}_{ig} \mu_{igh} \pi_{ihhs} Y_{ig} = \sum_j \lambda_{ijs} \hat{\lambda}_{ijs} \beta_{hs} \sum_g \hat{\Phi}_{jg} Y_{jg}$$

with $\hat{\Phi}_{ig} = \sum_{h, s} \mu_{igh} \pi_{ihhs} \hat{w}_{is}^\kappa$, (7) and $\hat{\pi}_{ihhs} = \hat{\pi}_{ighs}/\hat{\mu}_{igh}$, $\hat{\pi}_{ihhs} = \hat{w}_{is}^\kappa/\hat{\Phi}_{ig}$ and $\hat{\mu}_{igh} = \sum_s \pi_{ihsh} \hat{\pi}_{ihhs}$. Equation (5) can be solved for $\hat{w}_{is}$ given data on income levels, $Y_{ig}$, trade shares, $\lambda_{ijs}$, migration shares $\mu_{igh}$, employment shares $\pi_{ihhs}$, and the shocks, $\tilde{\tau}_{ijs}$ and $\tilde{T}_{js}$. In turn, given $\hat{w}_{is}$, changes in trade shares can be obtained from (7), while changes in migration and employment shares can be obtained from the expressions for $\pi_{ihhs}$ and $\mu_{igh}$ above.

Given $\hat{w}_{is}$, 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 $\hat{W}_{ig} = \prod_s \hat{\lambda}_{iis}^\beta / \prod_s (\hat{\mu}_{igs} \hat{\pi}_{igs})^{-\beta_s/\kappa}$.**

For the limit case $\kappa \to 1$ we again have $\lim_{\kappa \to 1} \hat{Y}_{ig}/\hat{Y}_i = 1/\hat{\mu}_{ig}$, where $\hat{\nu}_{igs} \equiv \sum_h \mu_{igh} \pi_{ihhs}$ is the share of workers from region $g$ that work in sector $s$.

### 4 Data

National figures on bilateral trade flows, sectoral output and employment shares come mostly from the OECD Database for Structural Analysis (STAN), and are supplemented with data from the World Input-Output Database (WIOD). For Germany, we obtain regional employment shares ($\pi_{igs}$) and output shares (needed to compute $r_{is}$) using data from the German Social Security System. For reasons of convenience we restrict our simulation analysis to the year 2003.25 Our choice of industry classification is also driven by the availability of the data. We aggregate manufacturing industries into 15 groups which roughly correspond to two-digit ISIC Rev. 3 codes ($S = 15$).

For Germany, the geographical units of observation $g$ are German Kreise, which are roughly equivalent to US counties. Each of these regions contains a minimum of 100,000 inhabitants as of December of 2008. In the current version of the data, we observe 265 of these regions (all located in West Germany).26 27

Our measures of trade flows are taken from the OECD-STAN database. To arrive at our measures, we combine values of national sectoral output,28 and total import and export figures by sector. This allows us to obtain consistent values of import penetration by sector ($\lambda_{iis}$).

---

25 We are in the process of reproducing the simulations for other years.

26 The employment counts are based on the job in which workers spent the longest spell during 2003.

27 In cases where $\pi_{igs} = 0$, we imputed a small value to make the data consistent with our model.

28 Output measures $Y_{is}$ are based on STAN variable PROD “Production (gross output)” (see Appendix for detailed description). We acknowledge that there is a mismatch in between the labor data, which corresponds to West German regions, and the trade data, which corresponds to the whole of Germany. We will work on improving this in the near future.
Table 3: List of Industries

<table>
<thead>
<tr>
<th>ISIC Rev. 3 Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>15-16</td>
<td>C15T16 Food products, beverages and tobacco</td>
</tr>
<tr>
<td>17-19</td>
<td>C17T19 Textiles, textile products, leather and footwear</td>
</tr>
<tr>
<td>20</td>
<td>C20 Wood and products of wood and cork</td>
</tr>
<tr>
<td>21-22</td>
<td>C21T22 Pulp, paper, paper products, printing and publishing</td>
</tr>
<tr>
<td>23</td>
<td>C23 Coke, refined petroleum products and nuclear fuel</td>
</tr>
<tr>
<td>24</td>
<td>C24 Chemicals and chemical products</td>
</tr>
<tr>
<td>25</td>
<td>C25 Rubber and plastics products</td>
</tr>
<tr>
<td>26</td>
<td>C26 Other non-metallic mineral products</td>
</tr>
<tr>
<td>27</td>
<td>C27 Basic metals</td>
</tr>
<tr>
<td>28</td>
<td>C28 Fabricated metal products, except machinery and equipment</td>
</tr>
<tr>
<td>29</td>
<td>C29 Machinery and equipment, n.e.c.</td>
</tr>
<tr>
<td>30-33</td>
<td>C30T33 Electrical and optical equipment</td>
</tr>
<tr>
<td>34</td>
<td>C34 Motor vehicles, trailers and semi-trailers</td>
</tr>
<tr>
<td>35</td>
<td>C35 Other transport equipment</td>
</tr>
<tr>
<td>36-37</td>
<td>C36T37 Manufacturing n.e.c. and recycling</td>
</tr>
</tbody>
</table>

\[
\lambda_{is} = \frac{Y_{is} - X_{is}^{\text{WORLD}}}{Y_{is} - X_{is}^{\text{WORLD}} + N_{is}^{\text{WORLD}}}
\]

Employing the sectoral output and trade flow data from the OECD STAN Database, we obtain the consumption shares \( \beta_{is} \) as follows:

\[
\beta_{is} = \frac{Y_{is} - X_{is}^{\text{WORLD}} + N_{is}^{\text{WORLD}}}{\sum_s Y_{is} - X_{is}^{\text{WORLD}} + N_{is}^{\text{WORLD}}}
\]

In our estimations in Section 6, we supplement our trade figures with data from the United Nations Commodity Trade Statistics Database (UN Comtrade) in order to obtain instrumental variables for region-level import penetration consistent with the work by (Dauth et al., 2014).
5 Counterfactual simulations

Using our baseline model and the methodology described in Section 3, in this Section we perform two counterfactual exercises: a move to autarky by Germany and a sector-neutral productivity increase in China. For each of these two cases, we compute the group-level, aggregate and inequality-adjusted welfare effects, \( \hat{W}_{ig} \), \( W_i \) and \( U_i \), respectively, for \( i = \text{Germany} \) and \( g = 1, ..., 265 \). In all the ensuing exercises, we follow Costinot and Rodríguez-Clare (2014) in assuming a value of \( \theta = 5 \), which is the central value for the trade elasticity as reviewed in Head and Mayer (2014).

5.1 A move to autarky

Table 4 summarizes the results for \( \hat{W}_{ig} \) and \( W_i \). For a value of \( \kappa = 3 \), our results indicate an aggregate loss of 11.2%, with a significant dispersion in these losses across regions (a standard deviation of 4.9 percentage points). The most affected regions experience losses of 22.4%, while the least affected regions experience gains of 23.7%. The loss from a return to autarky decreases with \( \kappa \), with an aggregate loss of 13.9% when \( \kappa \to 1 \) and 8% when \( \kappa \to \infty \). The intuition is that a lower \( \kappa \) introduces more curvature to the PPF, making it harder to adjust to autarky.

Table 4: Summary Statistics - Germany’s return Autarky

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>( W_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{W}_{ig}, \kappa \to 1 ) (Specific Factors)</td>
<td>0.876</td>
<td>0.123</td>
<td>0.633</td>
<td>1.963</td>
<td>0.861</td>
</tr>
<tr>
<td>( \hat{W}_{ig}, \kappa = 3 )</td>
<td>0.888</td>
<td>0.049</td>
<td>0.776</td>
<td>1.237</td>
<td>0.886</td>
</tr>
<tr>
<td>( \hat{W}_{ig}, \kappa = 7 )</td>
<td>0.905</td>
<td>0.022</td>
<td>0.852</td>
<td>1.054</td>
<td>0.901</td>
</tr>
<tr>
<td>( \hat{W}_{ig}, \kappa = 15 )</td>
<td>0.913</td>
<td>0.011</td>
<td>0.887</td>
<td>0.982</td>
<td>0.908</td>
</tr>
<tr>
<td>( \hat{W}_{ig}, \kappa \to \infty ) (CDK)</td>
<td>0.920</td>
<td>0.0</td>
<td>0.920</td>
<td>0.920</td>
<td>0.920</td>
</tr>
<tr>
<td>( W_i )</td>
<td>0.876</td>
<td>0.123</td>
<td>0.633</td>
<td>1.963</td>
<td>0.861</td>
</tr>
<tr>
<td>N</td>
<td>265</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3 plots the distribution of regional losses for different values of \( \kappa \). A lower \( \kappa \) leads to higher dispersion in these losses due to a stronger pattern of worker-level comparative advantage. As \( \kappa \) approaches infinity, workers are perfectly substitutable across sectors, and the variance in regional gains from trade gradually disappears.

In our simulations, regions specialized in import-competing sectors tend to lose less than export-oriented regions. Employment shares in the autarky equilibrium are given by expenditure shares, \( r^a_{is} = \beta_{is} \), so the ratio \( \beta_{is}/r_{is} \) proxies the necessary expansion/contraction that a sector has to undergo at the national level as country \( i \) moves to autarky. We can then think of this ratio as a sector-level index of import competition, with \( \beta_{is}/r_{is} > 1 \) (\(< 1\)) indicating an import-competing (export-oriented) sector. Table 5 shows that this index varies considerably across manufacturing industries in Germany, reaching a maximum for sector 23, “Coke, refined petroleum products and nuclear fuel”, with \( \beta_{is}/r_{is} = 9.16 \), and a minimum for sector 29, “Machinery and equipment,” with \( \beta_{is}/r_{is} = 0.65 \). Taken together, this sizable variation in \( \beta_{is}/r_{is} \) implies considerable sectoral reallocation under a return to autarky.

Figure 4 presents the results for group-level gains from trade (in logs, vertical axis) against the Bartik-style region-level index of import competition defined in Section 3.5 , \( I_{ig} \equiv \sum g \pi_{igs} \beta_{is} \) (in logs, horizontal axis). In Section 3.5 we showed that in the limit as \( \kappa \to 1 \) this index perfectly captures the variation in group-level gains from trade, as shown by the slope of 1 in the points corresponding to this case. The figure also shows that although the slope is no longer one when \( \kappa > 1 \), the correlation between \( \log \hat{W}_{ig} \) and \( \log I_{ig} \) is almost one, indicating that the \( I_{ig} \) does a very good job in ranking regions according to their gains from trade. We also see that the most import-competing regions gain in the move to autarky. Gelsenkirchen is the region that gains the most, with an increase in real income of

---

\[ \text{The table displays both } W_i \text{ and the mean value for } \hat{W}_{ig} \text{. The difference between these two values is that the former is a weighted mean across groups, while the latter is an unweighted mean. In general, the two values are closely related, with a maximum difference of 0.9 percentage points, corresponding to the limit } \kappa \to 1. \]
23.7\% when $\kappa = 3$, mainly because it has 18\% of its manufacturing workforce employed in sector 23 “Coke, refined petroleum products and nuclear fuel”.

Figure 3: Germany move to autarky

Figure 4: Distribution of Gains by Region
Table 5: Index of sectoral import competition

<table>
<thead>
<tr>
<th>$\beta_{is}/r_{is}$</th>
<th>Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.224</td>
<td>$s = C15T16$ Food products, beverages and tobacco</td>
</tr>
<tr>
<td>1.26</td>
<td>$s = C17T19$ Textiles, textile products, leather and footwear</td>
</tr>
<tr>
<td>0.865</td>
<td>$s = C20$ Wood and products of wood and cork</td>
</tr>
<tr>
<td>0.838</td>
<td>$s = C21T22$ Pulp, paper, paper products, printing and publishing</td>
</tr>
<tr>
<td>9.159</td>
<td>$s = C23$ Coke, refined petroleum products and nuclear fuel</td>
</tr>
<tr>
<td>1.342</td>
<td>$s = C24$ Chemicals and chemical products</td>
</tr>
<tr>
<td>0.715</td>
<td>$s = C25$ Rubber and plastics products</td>
</tr>
<tr>
<td>0.989</td>
<td>$s = C26$ Other non-metallic mineral products</td>
</tr>
<tr>
<td>1.11</td>
<td>$s = C27$ Basic metals</td>
</tr>
<tr>
<td>0.706</td>
<td>$s = C28$ Fabricated metal products, except mach. and equip.</td>
</tr>
<tr>
<td>0.647</td>
<td>$s = C29$ Machinery and equipment, n.e.c.</td>
</tr>
<tr>
<td>0.93</td>
<td>$s = C30T33$ Electrical and optical equipment</td>
</tr>
<tr>
<td>1.408</td>
<td>$s = C34$ Motor vehicles, trailers and semi-trailers</td>
</tr>
<tr>
<td>1.162</td>
<td>$s = C35$ Other transport equipment</td>
</tr>
<tr>
<td>0.826</td>
<td>$s = C36T37$ Manufacturing n.e.c. and recycling</td>
</tr>
</tbody>
</table>

Given the distribution of group-level gains from trade, we can compute the inequality-adjusted gains from trade ($IGT$), as described in Section 3.6. Figure 3 shows that for a strictly positive coefficient of relative risk aversion, the $IGT$ for Germany are higher than the standard aggregate gains from trade. Loosely speaking, this comes from the fact that there is less inequality across regions with trade than in the autarky counterfactual. For $\kappa = 3$, the gains from trade are 11.2% while $IGT = 12.8\%$ for a coefficient of inequality aversion of 2. Furthermore, the $IGT$ tends to increase, though not monotonically, with the coefficient of inequality aversion.

In Figure 6 we provide some insight into why $IGT > GT$. In the data, the correlation between import-competition and average earnings per worker is positive at 0.33, which explains why trade is on average pro-poor. In addition, the bottom percentiles of the income distribution predominantly feature export-oriented regions, and these regions gain more from trade than the average region. This means
that certainly for high \( \rho, \) \( IGT > GT. \)\(^{30}\)

\[\text{Figure 6: Relation between import-competition and earnings per worker}\]

![Figure 6: Relation between import-competition and earnings per worker](image)

For the US, we find broadly similar patterns, with \( IGT \) larger than regular gains of trade, and increasingly so for higher coefficients of relative risk aversion. These patterns are displayed in Figure A.6.

### 5.2 Productivity increase in China

Motivated by recent research on the rise of China and its distributional impact on US (Autor et al., 2013) or German (Dauth et al., 2014) labor markets, we simulate counterfactual equilibria after an increase in China’s technology level. Specifically, we study the effects the a sector-neutral productivity increase in China with \( \hat{T}_{i_s}^{1/\theta} = 5 \) for \( i = \text{China} \) and all \( s.\)\(^{31}\) We employ data from the World Input-Output Database (WIOD) for the year 2003 and focus on the manufacturing sector, as in the autarky exercise.\(^{32}\)

As shown in Table 6, the distributional effects of the productivity increase in China become quite strong for \( \kappa \to 1, \) with the standard deviation of the gains being almost twice the mean. In this limit case there are also substantial outliers in terms of group-level gains, with maximum losses and gains at 16.4% and 18% respectively. The dispersion of these gains falls quickly with \( \kappa. \) For \( \kappa = 3 \) the standard deviation of the gains is almost equal to the mean and it falls to one fifth of the mean for \( \kappa = 15 \) – see Figure 7.

The degree to which regions win or lose from the China shock depends on the change in their level of import-competition, as explained in section 3.5. Based on equation 14 and \( \hat{W}_{ig} = \hat{W}_i \hat{Y}_{ig}/\hat{Y}_i, \) in the limit as \( \kappa \to 1 \) we have

\[\ln \hat{W}_{ig} = \ln \hat{W}_i + \ln \sum_s \pi_{igs} \hat{r}_{is}. \tag{19}\]

In Figure 8, we display this relationship between \( \ln \hat{W}_{ig} \) and \( \ln \sum_s \pi_{igs} \hat{r}_{is}, \) the regional exposure to the

\(^{30}\)We are in the process of exploring the robustness of these data patterns.

\(^{31}\)This counterfactual is closely related to the analysis in Hsieh and Ossa (2011), which examines how China’s productivity growth affects worldwide real incomes. Hsieh and Ossa (2011) estimate annual sectoral productivity growth rates in China that range from 7.4% to 24.3%, with an average of 13.8%. The value of \( \hat{r}_{i_s}^{1/\theta} = 5 \) is on the high side of these estimates.

\(^{32}\)The WIOD dataset is discussed in Timmer et al. (2015).
Table 6: $\hat{W}_{ig}$ in Germany - $\forall s: \hat{I}_{China,s}^{1/\theta} = 5$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>$W_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{W}_{ig}, \kappa \to 1$ (Specific Factors)</td>
<td>1.022</td>
<td>0.04</td>
<td>0.836</td>
<td>1.18</td>
<td>1.034</td>
</tr>
<tr>
<td>$\hat{W}_{ig}, \kappa = 3$</td>
<td>1.009</td>
<td>0.008</td>
<td>0.965</td>
<td>1.046</td>
<td>1.011</td>
</tr>
<tr>
<td>$\hat{W}_{ig}, \kappa = 7$</td>
<td>1.005</td>
<td>0.002</td>
<td>0.995</td>
<td>1.013</td>
<td>1.006</td>
</tr>
<tr>
<td>$\hat{W}_{ig}, \kappa = 15$</td>
<td>1.005</td>
<td>0.001</td>
<td>1.002</td>
<td>1.006</td>
<td>1.005</td>
</tr>
<tr>
<td>$\hat{W}_{ig}, \kappa \to \infty$ (CDK)</td>
<td>1.004</td>
<td>0</td>
<td>1.004</td>
<td>1.004</td>
<td>1.004</td>
</tr>
</tbody>
</table>

Figure 7: Distribution of Gains by Region

Figure 8 suggests that this linearity persists for $\kappa > 1$, with a slope decreasing with $\kappa$. More formally, we run the following regression for different values of $\kappa$:

$$\ln \hat{W}_{ig} = \ln \hat{W}_i + \beta \ln \sum_s \pi_{igs} \hat{r}_{is}.$$  (20)

Figure 9 plots the relation between this $\beta$ and $\kappa$ for different values of $\kappa$, and we notice that $\beta$ monotonically decreases with $\kappa$. We will refer back to Figure 9 when we compare the model and data using a Bartik approach in section 6.3.

There is a linear and positive relationship between these two variables for each value of $\kappa$. For $\kappa \to 1$, this is in line with the theoretical result in equation 19. More formally, we run the following regression for different values of $\kappa$:

$$\ln \hat{W}_{ig} = \ln \hat{W}_i + \beta \ln \sum_s \pi_{igs} \hat{r}_{is}.$$  (20)

Figure 9 plots the relation between this $\beta$ and $\kappa$ for different values of $\kappa$, and we notice that $\beta$ monotonically decreases with $\kappa$. We will refer back to Figure 9 when we compare the model and data using a Bartik approach in section 6.3.

\[33\text{It is easy to show that if } \kappa \to 1 \text{ then } \sum_s \pi_{igs} \hat{r}_{is} = 1/\hat{I}_{ig} \text{ (see Section 3.5). Here we use the expression } \sum_s \pi_{igs} \hat{r}_{is} \text{ because of its Bartik structure, which we will use to relate the model implications to those we see in the data.}\]
The coefficient $\beta$, on the vertical axis, is estimated in the following regressions: $\ln \hat{W}_{ig} = \ln \hat{W}_i + \beta \ln \sum_s \pi_{igs} \hat{r}_{is}$, which is run separately for different vectors of $\hat{r}_{is}$. Each vector of $\hat{r}_{is}$ is the outcome of a simulation under a different value of $\kappa$ (horizontal axis).
We now use the distribution of group-level welfare effects from the China shock to compute the inequality-adjusted welfare effect of this shock for Germany. In Figure 10 we plot the inequality-adjusted welfare effect, $\hat{U}_i$ for $i = Germany$. By definition, this is equal to the standard aggregate effect ($\hat{W}_i$) when the coefficient of inequality aversion ($\rho$) is zero. The figure reveals that the inequality-adjusted welfare gain is decreasing in $\rho$, so that for any positive level of $\rho$ we have $\hat{U}_i > \hat{W}_i$. The reason for this is that, as shown in Figure 11, there is a negative covariance between the change in the degree of import competition ($\hat{I}_{ig}$) and the initial income level ($Y_{ig}$).\(^{34}\) This implies that the cross-region distributional impact of the China shock is pro-rich.

Figure 10: Inequality-Adjusted welfare-effects from the China shock

\(^{34}\)As mentioned in the previous footnote, in the limit $\kappa \to 1$ we have $\sum_s \pi_{isg} \hat{r}_{is} = 1/\hat{I}_{ig}$, hence $\ln \hat{W}_{ig} = \ln \hat{W}_i - \ln \hat{I}_{ig}$. 

23
6 Estimation of Parameter $\kappa$

We have demonstrated how the $\kappa$ parameter affects the aggregate and distributional welfare-effects from trade, both theoretically and with counterfactual exercises. In this section, we present two strategies for structurally estimating $\kappa$. Both approaches aim to combine clean identification with solid structural foundations. However, they both present several practical hurdles, which we are in the process of dealing with, and which render the current results preliminary. As in section 5, our empirical analysis focuses on Germany and defines groups in terms of geographical units.

6.1 Labor-supply elasticity

A first estimation strategy is based on the role of $\kappa$ as a labor-supply elasticity in the model. Fixing some normalizing sector $s_0$, Lemma 1 implies

$$\tilde{\pi}_{gst} = \frac{\pi_{gst}}{\pi_{gst0}} = \frac{A_{gst}}{A_{gs0}} \left( \frac{w_{st}}{w_{s0}} \right)^\kappa. $$

Taking logs and first differences, this yields the estimating equation

$$\Delta \ln \tilde{\pi}_{gst} = \kappa \Delta \ln \tilde{w}_{st} + \varepsilon_{gst}, (21)$$

where $\tilde{w}_{st} = \frac{w_{st}}{w_{s0}}$ is the relative sectoral wage per efficiency unit for sector $s$, and $\varepsilon_{gst} = \Delta A_{gst} A_{gs0}^{-1}$. Using equation 21 to estimate $\kappa$ requires three types of data: regional employment shares for each sector (observable), measures of sectoral wages per efficiency unit ($w_{st}$, which are unobserved), and a credible instrument for $\Delta \ln \tilde{w}_{st}$ to deal with the correlation between $\tilde{w}_{st}$ and $\varepsilon_{gst}$ due to supply shocks ($A_{gst} \neq 1$).

Our estimation procedure will therefore consist of several steps. First, we employ worker-level data to obtain estimates of changes in sectoral wages per efficiency unit. Second, we obtain measures of sectoral trade shocks to use as instruments. Lastly, we integrate all these components to estimate $\kappa$ from the

---

35 We have imposed that $\theta$, the main other structural parameter, is equal across sectors. Relaxing this assumption would affect the aggregate gains of trade, but not the distribution of gains. For discussion and estimation of $\theta$, see Caliendo and Parro (2014); Head and Mayer (2014). 

36 In the existing literature, Hsieh et al. (2013) and Burstein et al. (2015) obtain values of $\kappa$ for a Roy-framework applying to worker allocation across occupations rather than sectors. As a robustness test, we will later employ the methodology from Hsieh et al. (2013) to calibrate alternative measures of $\kappa$. Our second estimation approach is based on the strategy in Burstein et al. (2015).
response of sectoral employment shares to changes in wages per efficiency units. We next discuss each step of our analysis.

6.1.1 Efficiency unit wages ($w_{st}$)

To obtain values for $\Delta \ln w_{st}$, we employ a simplified version of the method developed by Heckman and Scheinkman (1987), such that it structurally fits our model. In this procedure, we employ individual-level panel data and assume that the sectoral productivity draw $z_{ns}$ for individual $n$ is fixed over time. In our model, observed earnings for worker $n$ in sector $s$ at periods $t_0$ and $t_1$ can be written as

$$y_{nst} = w_{st} z_{ns} + \xi_{nst}$$

for $t = t_0, t_1$,

where $\xi_{nst}$ is random noise. Solving for $z_{ns}$ we get the estimating equation

$$y_{nst1} = \frac{w_{st1}}{w_{st0}} y_{nst0} + \left[ \frac{w_{st1}}{w_{st0}} \xi_{nst0} \right]$$

(22)

The coefficient from Equation (22) can be estimated separately for workers in each sector $s$. To ensure consistency, we restrict the sample to workers present in sector $s$ on both period $t_0$ and $t_1$. Lastly, we follow Heckman and Scheinkman (1987) and instrument for $y_{nst0}$ using lagged earnings. The intuition behind this procedure is simple: if realized earnings for workers is a combination of their unobserved sectoral ability and a sectoral wage for their ability, then changes in the observed earnings for a fixed sample of workers will reflect changes in $w_{st}$.

Equation 22 above assumes that earnings changes depend solely on changes in the returns to a one dimensional sectoral ability ($z_{ns}$). In reality, changes in the returns to other worker characteristics are likely to influence earnings over time. To address this concern, we first estimate a standard Mincer regression, regressing observed wages for all workers on gender, education, experience and experience squared. We then use the residuals from this regression as measures for $y_{nst}$ in equation 22.

6.1.2 Trade shocks as instruments

We instrument for changes in sectoral wages with trade shocks. Specifically, following the intuition of Autor et al. (2014) (and its application by Dauth et al. (2014) to Germany), we use changes in trade flows from China and Eastern Europe to a group of countries “similar” to Germany as measure of trade shocks. The idea behind this approach is to capture the effect of import-demand shocks arising from growth in China and Eastern Europe on German wages, which is uncorrelated to unobserved local supply shocks. Specifically, the instrument is

$$\Delta IP_{st}^{East \rightarrow Other} = \Delta M_{st}^{East \rightarrow Other} \cdot L_{st}^{Germany}$$

where $L_{st}^{Germany}$ is the number of workers in Germany employed in industry $s$ at the beginning of time period $t$. This instrument has been discussed in greater detail in Section 2.2.

---

37 In Heckman and Scheinkman (1987), there are many productive attributes, observed and unobserved, priced differently in each sector. Our application of their methodology is a simplified version in which we assume there is a single one-dimensional unobserved attribute ($z_{ns}$) with price $w_{st}$ that determines the observed wages of workers.

38 This is necessary to account for the correlation between $y_{nst}$, and the error term in 22.

39 We plan to run this wage regression for workers in all sectors together, restricting the coefficients on each control variable to be the same across sectors, but allowing them to vary by year. The details of this estimation procedure are presented in Appendix B.

40 Eastern Europe is comprised of the following countries: Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the former USSR or its succession states Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

41 We follow Dauth et al. (2014) in defining this set of countries to include Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom.
6.1.3 Estimating equations

Having obtained estimates for the changes in wages and trade shocks, we can use equation 21 to obtain estimates of $\kappa$. Formally, our system of equations is the following:

$$\Delta \ln \tilde{\pi}_{gst} = \kappa \Delta \ln \tilde{w}_{st} + \varepsilon_{gst}$$

$$\Delta \ln \tilde{w}_{st} = \gamma \Delta IP_{st}^{East\rightarrow Other} + \nu_{st}$$

For consistency with the counterfactuals in section 5, industries will be aggregated to match those presented in table 3. 42

6.1.4 Results

We are currently - June 2015 - implementing this labor supply estimation strategy. Preliminary estimations suffer from the combination of a potential weak-instrument problem - the predictive power of trade-shocks on efficiency wages is present, but not necessarily sufficiently strong to yield a high F-statistic - and a small number of clusters ($S = 15$). We are in the process of addressing these challenges.

6.2 Reallocation and regional income per worker

Our second approach is based on the estimation approach in Burstein et al. (2015), and relies on the relationship between region-level income changes $\hat{Y}_{ig}$ and region-level reallocation. The intuition behind this approach is the structural relation between unobserved changes in relative wages and observed relative changes in sectoral shares. This relation implies that there is also a structural relation between $\hat{Y}_{ig}$, which is a function of sectoral wages $\hat{w}_{is}^{\kappa}$, and relative changes in sectoral shares. Moreover, this structural relationship between these two observables is governed by $\kappa$, such that it provides an approach for structural estimation of $\kappa$.

6.2.1 Derivation

Letting $Y_{ig}$ be income for group $g$ in country $i$ and $\pi_{igs}$ be the employment shares of this group across sectors $s = 1, \ldots, S$, we have

$$\hat{Y}_{ig} = \left( \sum_s \pi_{igs} \hat{w}_{is}^{\kappa} \right)^{1/\kappa}$$

We also have $\hat{\pi}_{igs} = \frac{\hat{w}_{is}^{\kappa}}{\hat{\pi}_{i1}^{\kappa}}$ and hence

$$\frac{\hat{w}_{is}^{\kappa}}{\hat{\pi}_{i1}^{\kappa}} = \frac{\hat{\pi}_{igs}}{\hat{\pi}_{ig1}} \quad (23)$$

Combining these expressions we obtain the following equation

$$\ln \hat{Y}_{ig} = \frac{1}{\kappa} \ln \left( \sum_s \pi_{igs} \frac{\hat{\pi}_{igs}}{\hat{\pi}_{ig1}} \hat{w}_{is}^{\kappa} \right) \quad (24)$$

Before we take this equation to the data43, we reduce sensitivity to group-level noise by observing that equation 23 holds for all $g$, such that we can define $\nu_{is}(k) \equiv \exp\left\{ \frac{1}{k} \sum_g \log \frac{\hat{\pi}_{igs}}{\hat{\pi}_{ig1}} \right\}$ and then update equation 24 to

$$\ln \hat{Y}_{ig} = \frac{1}{\kappa} \ln \left( \sum_s \pi_{igs} \nu_{is}(1) \hat{w}_{i1}^{\kappa} \right)$$

42Given our use of instruments for $\Delta \ln \tilde{w}_{st}$, it is not necessary to adjust our standard errors to account for the fact that the $\Delta \ln \tilde{w}_{st}$’s are themselves estimates.

43Note that it simplifies to $\ln \hat{Y}_{ig} = a_i - \frac{1}{k} \ln \hat{\pi}_{ig1}$, with $a_i = \ln \hat{w}_{i1}^{\kappa}$. This equation can be taken to the data, but is sensitive to the choice of reference sector.
In order to eliminate the sensitivity of this relation to the choice of reference sector, we can use the fact that \( \forall k : \hat{w}_{is}^k = \hat{w}_{ik}^k \nu_{is}(k) \), to write \( \hat{w}_{is}^k = (\exp \frac{1}{\kappa} \sum_k \log \hat{w}_{ik}^k) \nu_{is} \), where \( \nu_{is} \equiv \exp \left( \frac{1}{\kappa} \sum_k \log \nu_{is}(k) \right) \). This way, we arrive at the following equation

\[
\sum_s \pi_{igs} \hat{w}_{is}^k = \left( \exp \frac{1}{\kappa} \sum_k \log \hat{w}_{ik}^k \right) \sum_s \pi_{igs} \nu_{is} \tag{25}
\]

### 6.2.2 Estimating equation

We can substitute equation 25 into 24 and obtain our estimating equation,

\[
\ln \hat{Y}_{ig} = b_i + \frac{1}{\kappa} \ln \sum_s \pi_{igs} \nu_{is} + \xi_{ig} \tag{26}
\]

where \( b_i \equiv \frac{1}{\kappa} \left( \frac{1}{S} \sum_k \log \hat{w}_{ik}^k \right) \). Finally, we require exogenous variation in \( \sum_s \pi_{igs} \nu_{is} \). To this end, we use the Bartik-type instrument \( \sum_s \pi_{igs} \Delta IP_{st}^{East \rightarrow Other} \), which turns the sectoral trade shock \( \Delta IP_{st}^{East \rightarrow Other} \), defined in section 2.2, into a regional trade-shock. In fact, this instrument is closely related to the region-level trade-shocks in Autor et al. (2013).

### 6.2.3 Results

Before we discuss the estimates of \( \kappa \), we examine if the trade shocks impact sectoral reallocation at the region-level in Germany. To this end, we run the following regression

\[
\Delta \ln \hat{\pi}_{igst} = \gamma \Delta IP_{st}^{East \rightarrow Other} + \zeta_{st}
\]

with \( \hat{\pi}_{igst} \equiv \frac{\pi_{igst}}{\pi_{igqt}} \). Table 7 presents the estimation results for this regression. For each of the specifications, we find a significantly negative impact of import-competition on the relative growth of a sector. This confirms that our trade-shock variable \( \Delta IP_{st}^{East \rightarrow Other} \) induces sectoral reallocation in the expected direction.

<table>
<thead>
<tr>
<th>( \Delta IP_{st}^{East \rightarrow Other} )</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag = 5</td>
<td>-0.0038*</td>
<td>-0.0039*</td>
<td>-0.0042**</td>
<td>-0.0041**</td>
<td>-0.0042**</td>
</tr>
<tr>
<td>Lag = 6</td>
<td>[0.0749]</td>
<td>[0.0519]</td>
<td>[0.0120]</td>
<td>[0.0340]</td>
<td>[0.0440]</td>
</tr>
<tr>
<td>Lag = 7</td>
<td>3999</td>
<td>3988</td>
<td>3983</td>
<td>3987</td>
<td></td>
</tr>
<tr>
<td>Lag = 8</td>
<td>4002</td>
<td>3999</td>
<td>3988</td>
<td>3983</td>
<td>3987</td>
</tr>
<tr>
<td>Lag = 9</td>
<td>4002</td>
<td>3999</td>
<td>3988</td>
<td>3983</td>
<td>3987</td>
</tr>
</tbody>
</table>

Symmetric p-values from wild cluster bootstrap-t Wald test in brackets.

(1,000 replications, clustered by 14 industry cells, * \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \)).

Data from 1999-2008, \( \Delta IP_{st}^{East \rightarrow Other} = \Delta M_{East \rightarrow Other} - \Delta MF_{East \rightarrow Other} \) in 1000 EURO.

All estimations use sector 1516 as the numeraire sector for the dependent variable.

We now use region-level trade shocks as an instrument in our estimation of \( \kappa \), where we exploit the link between sectoral reallocation and regional income per worker. Table 8 presents preliminary results for this estimation approach.\(^{45}\) For specifications 2-5, which obtain statistical significance, the point estimates for \( \kappa \) range from 2.9 to 4, with a 95% confidence interval for the most precise estimate (specification 3) of 1.1-4.7. For these values of \( \kappa \), the distributional impacts of trade are substantial compared to their aggregate impact (see Section 5).\(^{46}\) For convenience, in the remainder of this section we focus on \( \kappa = 3 \).

\(^{44}\)For each group \( g \) there are \( S - 1 \) degrees of freedom for the reallocation of \( \pi_{igst} \). This is why we normalize to a reference sector \( \pi_{igqt} \).

\(^{45}\)Appendix Figure C.1 plots the scatters for the first stage.

\(^{46}\)It is possible that there is a downward bias on \( \kappa \) (i.e. an upward bias on the regression coefficient of interest), since
Table 8: Reallocation and regional income per worker

<table>
<thead>
<tr>
<th></th>
<th>First Stage</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lag = 5</td>
<td>Lag = 6</td>
<td>Lag = 7</td>
<td>Lag = 8</td>
<td>Lag = 9</td>
</tr>
<tr>
<td>( \sum_s \pi_{is} \Delta IP_{East \rightarrow Other} )</td>
<td>–0.005***</td>
<td>–0.004***</td>
<td>–0.005***</td>
<td>–0.005***</td>
<td>–0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.65</td>
<td>0.55</td>
<td>0.60</td>
<td>0.69</td>
<td>0.70</td>
</tr>
<tr>
<td>( F )-stat</td>
<td>232.19</td>
<td>125.45</td>
<td>145.62</td>
<td>219.13</td>
<td>300.04</td>
</tr>
<tr>
<td>Observations</td>
<td>265</td>
<td>265</td>
<td>265</td>
<td>265</td>
<td>265</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Second Stage</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln \tilde{Y}_{ig} )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \ln \sum_s \pi_{is} \nu_{is} )</td>
<td>0.202</td>
<td>0.293**</td>
<td>0.342***</td>
<td>0.249***</td>
<td>0.292***</td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td>(0.127)</td>
<td>(0.108)</td>
<td>(0.094)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>Implied ( \kappa )</td>
<td>4.957</td>
<td>3.413</td>
<td>2.927</td>
<td>4.019</td>
<td>3.419</td>
</tr>
<tr>
<td></td>
<td>(3.305)</td>
<td>(1.478)</td>
<td>(0.926)</td>
<td>(1.518)</td>
<td>(0.997)</td>
</tr>
<tr>
<td>Observations</td>
<td>265</td>
<td>265</td>
<td>265</td>
<td>265</td>
<td>265</td>
</tr>
</tbody>
</table>

Standard errors in parentheses; * \( p<0.1 \), ** \( p<0.05 \), *** \( p<0.01 \)

Data from 1999-2008, with \( \Delta IP_{East \rightarrow Other} \) denoted in 1000 EURO with base year 2005.

The lag after 1999 indicates the construction of the time-period.

6.3 A Bartik perspective

Finally, we employ a Bartik approach to explore the implied distributional effect of the China productivity shock according to the model, setting \( \theta = 5 \) and \( \kappa = 3 \), and compare it with the effect we see in the data. In Section 5.2 we showed that the China shock, as captured by the impact of the Bartik-style variable \( \sum_s \pi_{is} \hat{r}_{is} \), has an approximately log-linear effect on region welfare, \( \hat{W}_{ig} \), with the slope of this relationship decreasing with \( \kappa \). Here, we run the counterpart of this analysis on real data for the China-shock. For the period starting in 1999 and with lags going from 5 to 9 years, we run the empirical counterpart of equation 20.

\[
\ln \hat{Y}_{ig} = \alpha + \beta \ln \sum_s \pi_{is} \hat{r}_{is} + \varepsilon_{ig}
\]

with \( \sum_s \pi_{is} \Delta IP_{East \rightarrow Other} \) as an instrument for \( \ln \sum_s \pi_{is} \hat{r}_{is} \), in the style of Autor et al. (2013) and Dauth et al. (2014).

Table 6.3 presents the results.\(^{47}\) The coefficient is positive and significantly different from zero for specifications 2-5. This positive and significant relationship in the data is consistent with the theoretical prediction that regional welfare is strongly correlated with \( \sum_s \pi_{is} \hat{r}_{is} \). Moreover, based on Figure 9, the point estimates in specifications 2-5, imply values for \( \kappa \) between 2 and 4. These values are in line with the estimates in Table 8. Finally, the confidence intervals for the coefficients in these specifications are all contained within zero and one, as required by the theory (see discussion in Section 3.5 and illustration in Section 5.2).

\(^{47}\)Appendix Figure C.2 plots the scatters for the first stage.
Table 9: Changes in import-competition and regional income per worker

<table>
<thead>
<tr>
<th></th>
<th>First Stage</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lag = 5</td>
<td>Lag = 6</td>
<td>Lag = 7</td>
<td>Lag = 8</td>
<td>Lag = 9</td>
</tr>
<tr>
<td>$\sum_{s} \pi_{igs} \Delta IP_{East \rightarrow Other}^{s}$</td>
<td>-0.005***</td>
<td>-0.005***</td>
<td>-0.004***</td>
<td>-0.004***</td>
<td>-0.003***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.47</td>
<td>0.44</td>
<td>0.38</td>
<td>0.33</td>
<td>0.24</td>
</tr>
<tr>
<td>F-stat</td>
<td>135.56</td>
<td>174.69</td>
<td>152.07</td>
<td>178.67</td>
<td>106.43</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Second Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sum_{s} \pi_{igs} \hat{r}_{is}$</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>(0.137)</td>
</tr>
<tr>
<td>Observations</td>
<td>265</td>
</tr>
</tbody>
</table>

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data from 1999-2008, with $\Delta IP_{East \rightarrow Other}^{s}$ denoted in 1000 EURO with base year 2005.
The lag after 1999 indicates the construction of the time-period.
References


Faber, B. (2014). Trade Liberalization, the Price of Quality, and Inequality: Evidence from Mexican Store Prices.


A  US version

A.1  Data

For the US, we combine employment data from the County Business Patterns (CBP) dataset and sectoral output data from the NBER CES database. We also employ data on trade flows and regional earnings that were kindly provided by Gordon Hanson.

We follow Autor et al. (2013) - (ADH) in defining regional economies using the concept of Commuting Zones (CZs). Our industry classification follows the 1987 SIC classification codes aggregated to the 2-digit level by an algorithm also provided by ADH, and restricted to manufacturing industries only. This leaves us with a total of 722 CZs and 20 industries. All current figures are for the year 2000.

For employment shares $\pi_{igs}$, we apply the same algorithm as ADH to obtain commuting zone employment shares from the CBP county level data. As in the German case, we currently input very low values ($\pi_{igs} = e^{-10}$) to CZ-industry cells with zero values. Our figures for national sectoral output $Y_{is}$ come directly from the NBER-CES database variable $vship$, which represents the total value of industry shipments. To obtain aggregate earnings in manufacturing at the CZ level ($Y_{ig}$), we employ publicly available data from ADH’s China Syndrome paper. Specifically, we multiply each commuting zone’s weekly average wages in manufacturing by their employment count in manufacturing.

A.2  Decomposition

Here, we implement the same analysis as in Section 2.1, but now for the US, with $t = 2007, t - 1 = 1995$.

Figure A.1: Decomposition of Changes in Output Shares - US

Figure A.1 displays the relation between output-share reallocation and first trade-induced reallocation (Left Panel) and second home-induced reallocation (Right Panel.) One sector is an important outlier in terms of output-share reallocation, namely “Petroleum Refining and Related Industries.” Since this outlier is largely explained by home-induced reallocation, trade-induced reallocation will play a smaller role in the US. This is demonstrated by the regression results in Table A.1., where only 13.6% of output-share reallocation is trade-induced, substantially below the 64.3% in Germany.

Figure A.2. shows the relation between growth rates of sectoral output-shares and growth rates of sectoral employment shares. The correlation of these growth rates is 66.5% in our US data.
Table A.1: Decomposition of Changes in Output Shares

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trade-induced Reallocation</td>
<td>Home-induced Reallocation</td>
</tr>
<tr>
<td>Output-share Reallocation</td>
<td>0.136$^*$</td>
<td>0.864$^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0553)</td>
<td>(0.0553)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.00216</td>
<td>0.00216</td>
</tr>
<tr>
<td></td>
<td>(0.00109)</td>
<td>(0.00109)</td>
</tr>
<tr>
<td>Observations</td>
<td>20</td>
<td>20</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

$^*$ $p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Figure A.2: Relation between Sectoral Output and Employment Shares
A.3 Autarky Exercise - US

Figure A.3: Distributional Gains by Region - Autarky - US

Variation in Regional Losses – US

Autarky Case

Last updated 13 Jun 2015, 20 sectors. tables_graphs_aut_US.do.

Figure A.4: Distributional Gains by Region - Autarky - US

US return to autarky: winners and losers

Log proportional change in real income

Last updated 13 Jun 2015, 20 sectors. tables_graphs_aut_US.do.
Figure A.6 provides insight into why the inequality-adjusted gains from trade are strongly positive in the US. First, the correlation between import-competition and income per capita is positive, at 0.147. Hence, on average poorer regions gain more from trade than richer regions, such that trade is pro-poor. In these bottom percentiles, the export-oriented regions are well represented. These export-oriented regions unambiguously lose from going to autarky, whereas the import-competing regions lose less. As such, inequality among the bottom income percentiles is mitigated under trade, compared to autarky.\footnote{We are in the process of exploring the robustness of these results to model specifications that include capital in the production function or for differences in skills across worker groups and to different measurements of import-competition.}

Figure A.6: Correlation between import-competition and earnings per worker
B Estimation of sectoral efficiency unit wages

The following are our estimation equations:

\[ m_{nst} = \alpha + X'_{nt} \beta_t + y_{nst} \]

where \( m_{nst} \) are the observed daily earnings (in levels) of individual \( n \) in sector \( s \) at time \( t \), and \( y_{nst} \) is the residual. \( X_{nt} \) is a vector of control variables that includes dummies for gender, 7 education categories, and experience and experience squared, all interacted by year dummies. Note that we do not allow for a year-specific intercept. We also restrict the coefficients on each control variable to be the same across sectors, but we allow them to vary by year.

C First-stages of estimation procedures

![Figure C.1: First stage for Table 8](image-url)
D Extensions with home production

D.1 Regional income and reallocation

In Section 6.2 we find coefficient-estimates for $\kappa$ that are below or close to 1, which leads us to worry about a bias in our estimation procedure. Here, we provide an extension of our estimation procedure in Section 6.2, which can potentially account for the downward bias in the $\kappa$-estimate.

D.1.1 Derivation

Start from

$$Y_{igM} \equiv \gamma \sum_{k=1}^{S} A_{igk} \frac{w_{ik}^{\kappa}}{\Phi_{ig}^{\kappa}} L_{ig} = \gamma \Phi_{ig} L_{ig} \pi_{igM}$$

where $\pi_{igM} = \sum_{k=1}^{S} A_{igk} \frac{w_{ik}^{\kappa}}{\Phi_{ig}^{\kappa}}$. This implies

$$\hat{Y}_{igM} = \hat{\Phi}_{ig} \hat{\pi}_{igM}$$

Taking logs:

$$\ln \hat{Y}_{igM} = \ln \hat{\Phi}_{ig} + \ln \hat{\pi}_{igM}$$

This equation is very closely related to our previous approach, except that we now need to update the derivation of the observable counterpart to $\ln \hat{\Phi}_{ig}$ . To this end, note that for $s \geq 1$ we have $\hat{\pi}_{igs} = \hat{u}_{is}^{\kappa} / \hat{\Phi}_{ig}^{\kappa}$ and $\hat{\pi}_{i0} = \hat{u}_{i0}^{\kappa} / \hat{\Phi}_{ig}^{\kappa}$ and hence

$$\frac{\hat{u}_{is}^{\kappa}}{\hat{u}_{i1}^{\kappa}} = \frac{\hat{\pi}_{igs}}{\hat{\pi}_{i1}}$$

Combining these expressions we get

$$\frac{1}{\kappa} \ln \left( \sum_{s} \pi_{igs} \frac{\hat{\pi}_{igs} \hat{u}_{i1}^{\kappa}}{\hat{\pi}_{i1}} \right) = \frac{1}{\kappa} \ln \left( \frac{\hat{u}_{i1}^{\kappa}}{\hat{\pi}_{i1}} \right)$$
The problem is that \( \frac{\hat{w}^\kappa_{ig}}{\hat{w}^\kappa_{i1}} \) would make this very sensitive to the choice of \( g \). We can use the fact that for \( s \geq 1 \) this relation \( \frac{\hat{w}^\kappa_{ig}}{\hat{w}^\kappa_{i1}} = \frac{\hat{\pi}_{ig}}{\hat{\pi}_{i1}} \) holds for all \( g \), so that for \( s \geq 1 \) we have

\[
\frac{\hat{w}^\kappa_{ig}}{\hat{w}^\kappa_{i1}} = \nu_{is}(1)
\]

where for any \( k \geq 1 \) we have

\[
\nu_{is}(k) \equiv \exp \left( \frac{1}{S} \sum_{g} \log \frac{\hat{\pi}_{igs}}{\hat{\pi}_{igk}} \right)
\]

But note that \( \frac{\hat{w}^\kappa_{ig0}}{\hat{w}^\kappa_{i1}} = \frac{\hat{\pi}_{ig}}{\hat{\pi}_{i1}} \) does not mean that \( \frac{\hat{w}^\kappa_{ig0}}{\hat{w}^\kappa_{i1}} = \frac{\hat{\pi}_{ih0}}{\hat{\pi}_{ih1}} \) for \( h \neq g \), so we cannot do this for all \( s \) and say that

\[
\sum_{k=0}^{S} \pi_{igk} \hat{w}^\kappa_{igk} = \hat{w}^\kappa_{i1} \sum_{k=0}^{S} \pi_{igk} \nu_{is}(1)
\]

Instead we need to use:

\[
\pi_{ig0} \hat{w}^\kappa_{ig0} + \sum_{s \geq 1} \pi_{igs} \hat{w}^\kappa_{is} = \hat{w}^\kappa_{i1} \left[ \pi_{ig0} \frac{\hat{\pi}_{ig0}}{\hat{\pi}_{i1}} + \sum_{s \geq 1} \pi_{igs} \nu_{is}(1) \right]
\]

In order to reduce sensitivity to the reference sector 1, we can use that we have for all \( s, k \geq 1 \)

\[
\hat{w}^\kappa_{is} = \hat{w}^\kappa_{ik} \nu_{is}(k)
\]

This implies that

\[
\hat{w}^\kappa_{is} = \left( \exp \left( \frac{1}{S} \sum_{k \geq 1} \log \hat{w}^\kappa_{ik} \right) \right) \nu_{is}
\]

where

\[
\nu_{is} \equiv \exp \left( \frac{1}{S} \sum_{k \geq 1} \log \nu_{is}(k) \right)
\]

We now have

\[
\pi_{ig0} \hat{w}^\kappa_{ig0} + \sum_{s \geq 1} \pi_{igs} \hat{w}^\kappa_{is} = \pi_{ig0} \hat{w}^\kappa_{ig0} + \left( \exp \left( \frac{1}{S} \sum_{k \geq 1} \log \hat{w}^\kappa_{ik} \right) \right) \sum_{s \geq 1} \pi_{igs} \nu_{is}
\]

Using the fact that for any \( k \geq 1 \) we have

\[
\hat{w}^\kappa_{ig0} = \frac{\hat{\pi}_{ig0}}{\hat{\pi}_{igk}} \hat{w}^\kappa_{ik}
\]

we can then write

\[
\hat{w}^\kappa_{ig0} = \exp \log \prod_{k \geq 1} \left( \frac{\hat{\pi}_{ig0}}{\hat{\pi}_{igk}} \right)^{1/S} \prod_{k \geq 1} \left( \hat{w}^\kappa_{ik} \right)^{1/S}
\]

\[
= \left( \exp \left( \frac{1}{S} \sum_{k \geq 1} \log \hat{w}^\kappa_{ik} \right) \right) \phi_{ig}
\]

where

\[
\phi_{ig} \equiv \left( \exp \left( \frac{1}{S} \sum_{k \geq 1} \log \left( \frac{\hat{\pi}_{ig0}}{\hat{\pi}_{igk}} \right) \right) \right)
\]

so finally we have

39
\[ \pi_{ig0} w^r_{ig0} + \sum_{s \geq 1} \pi_{igs} w^r_{is} = \left( \exp \frac{1}{S} \sum_{k \geq 1} \log \hat{u}_{ik}^k \right) \left( \pi_{ig0} \varphi_{ig} + \sum_{s \geq 1} \pi_{igs} \nu_{is} \right) \] (28)

D.1.2 Estimating equation and instruments

We obtain our estimating equation by substituting equation 28 into equation 27:

\[ \ln \hat{Y}_{ig} = b_i + \frac{1}{\kappa} \ln \left( \pi_{ig0} \varphi_{ig} + \sum_{s \geq 1} \pi_{igs} \nu_{is} \right) + \hat{\pi}_{igM} + \varepsilon_{ig} \] (29)

Here, as an instrument for \( \left( \pi_{ig0} \varphi_{ig} + \sum_{s \geq 1} \pi_{igs} \nu_{is} \right) \) we can use the usual Bartik instrument \( \sum_s \pi_{igs} \frac{\Delta IP_{East\rightarrow Other}}{L_{is}} \), while for \( \hat{\pi}_{igM} \), we can instrument with \( \frac{1 - \pi_{ig0} \sum_s \pi_{igs} \frac{\Delta IP_{East\rightarrow Other}}{L_{is}}}{\pi_{igM}} \).