Essays in Labor Economics and International Trade

by

Moises Yi

A dissertation submitted in partial satisfaction of the requirements for the degree of

Doctor of Philosophy

in

Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor David E. Card, Chair
Professor Enrico Moretti
Professor Patrick M. Kline
Professor Andres Rodriguez-Clare
Professor Reed Walker

Spring 2016
Abstract

Essays in Labor Economics and International Trade

by

Moises Yi

Doctor of Philosophy in Economics

University of California, Berkeley

Professor David E. Card, Chair

This dissertation employs tools from Labor Economics and International Trade to study how workers and labor markets adjust to economic shocks arising from trade liberalization and technological change. It contributes to the existing literature by studying several economic mechanisms that determine the magnitudes (and heterogeneity) of these adjustments.

The first chapter of this dissertation analyzes the roles that skill transferability and the local industry mix have on the adjustment costs of workers affected by negative trade shocks. Using rich administrative data from Germany, we construct novel measures of economic distance between sectors based on the notion of skill transferability. We combine these distance measures with sectoral employment shares in German regions to construct an index of labor market flexibility. This index captures the degree to which workers from a particular industry will be able to reallocate into other jobs. We then study the role of labor market flexibility on the effect of import shocks on the earnings and the employment outcomes of German manufacturing workers. Among workers living in inflexible labor markets, the difference between a worker at the 75th percentile of industry import exposure and one at the 25th percentile of exposure amounts to an earnings loss of roughly 11% of initial annual income (over a 10 year period). The earning losses of workers living in flexible regions are negligible. These findings are robust to controlling for a wide array of region level characteristics, including region size and overall employment growth. Our findings indicate that the industry composition of local labor markets plays an important role on the adjustment processes of workers.

In the second chapter, we develop and apply 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 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.

In the third chapter, we use detailed production data from a large Latin American garment manufacturer to study the process of technology adoption and resulting productivity changes within a firm. We find that the adoption of modern manufacturing techniques increases productivity through two channels, a direct effect and a spillover effect across adjacent production units. By exploiting the gradual introduction of new manufacturing techniques across independent production units, we estimate a direct effect on productivity of roughly 30%. We also estimate large spillovers to neighboring untreated units which amount to a 25% increase in productivity. Both of these effects accumulate slowly over time. The timing and the magnitudes of the estimated spillover effects corroborate qualitative evidence consistent with knowledge diffusion, learning and imitation.
To My Parents
### Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>List of Figures</td>
<td>iv</td>
</tr>
<tr>
<td>List of Tables</td>
<td>v</td>
</tr>
<tr>
<td>1 Industry Mix, Local Labor Markets, and the Incidence of Trade Shocks</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Theoretical Framework</td>
<td>7</td>
</tr>
<tr>
<td>1.2 Data</td>
<td>9</td>
</tr>
<tr>
<td>1.3 Skill Transferability and Sectoral Distances</td>
<td>10</td>
</tr>
<tr>
<td>1.4 Measures of Labor Market Flexibility</td>
<td>16</td>
</tr>
<tr>
<td>1.5 Import Shocks and Worker Adjustment</td>
<td>18</td>
</tr>
<tr>
<td>1.6 Conclusion</td>
<td>25</td>
</tr>
<tr>
<td>2 Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade</td>
<td>27</td>
</tr>
<tr>
<td>2.1 Trade and Sectoral Reallocation in the Data</td>
<td>32</td>
</tr>
<tr>
<td>2.2 Theory: Baseline Model</td>
<td>36</td>
</tr>
<tr>
<td>2.3 Data</td>
<td>49</td>
</tr>
<tr>
<td>2.4 Counterfactual simulations</td>
<td>50</td>
</tr>
<tr>
<td>2.5 Estimation of Parameter $\kappa$</td>
<td>60</td>
</tr>
<tr>
<td>2.6 Conclusion</td>
<td>64</td>
</tr>
<tr>
<td>3 Productivity Spillovers: Evidence from Inside a Firm</td>
<td>65</td>
</tr>
<tr>
<td>3.1 Literature Review</td>
<td>67</td>
</tr>
<tr>
<td>3.2 Context</td>
<td>70</td>
</tr>
<tr>
<td>3.3 Data</td>
<td>74</td>
</tr>
<tr>
<td>3.4 Empirical strategy</td>
<td>78</td>
</tr>
<tr>
<td>3.5 Results</td>
<td>83</td>
</tr>
<tr>
<td>3.6 Conclusion</td>
<td>88</td>
</tr>
<tr>
<td>Bibliography</td>
<td>91</td>
</tr>
</tbody>
</table>
## A Industry Mix, Local Labor Markets, and the Incidence of Trade Shocks

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>A.1 Data Appendix</td>
<td>99</td>
</tr>
<tr>
<td>A.2 Selection Model - First Stage</td>
<td>101</td>
</tr>
<tr>
<td>A.3 Selection Model - Second Stage</td>
<td>107</td>
</tr>
<tr>
<td>A.4 $LMF_{rt}$ Decomposition</td>
<td>110</td>
</tr>
<tr>
<td>A.5 Earnings and Employment Reallocation by Industry</td>
<td>113</td>
</tr>
<tr>
<td>A.6 Alternative $LMF_{rt}$ based on employment shares</td>
<td>114</td>
</tr>
<tr>
<td>A.7 Additional Results</td>
<td>116</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>B.1 First-stages of estimation procedures</td>
<td>117</td>
</tr>
</tbody>
</table>
## List of Figures

1.1 Distribution of $LMF_{rt}$ .................................................. 18
1.2 Dynamic Effect on Earnings and Transitions out of Manufacturing ........ 23

2.1 Decomposition of Changes in Output Shares .................................. 33
2.2 Relation between Sectoral Output and Employment Shares ..................... 34
2.3 Germany move to autarky .......................................................... 52
2.4 Distribution of Gains by Region .................................................. 53
2.5 Inequality-adjusted gains from trade ............................................. 55
2.6 Relation between import-competition and earnings per worker ................. 55
2.7 Distribution of Gains by Region .................................................. 56
2.8 Welfare-effects and changes in import-competition ........................... 58
2.9 Relation between $\ln \sum_s \pi_{gs} \hat{r}_{is}$ and $\kappa$ .......................... 58
2.10 Inequality-Adjusted welfare-effects from the China shock .................... 59
2.11 Relation between income per worker and $\ln \hat{I}_g$ - China shock .......... 60

3.1 Hierarchical organization of production. ....................................... 71
3.2 Layout of the production hall. ................................................... 72
3.3 Production process before and after the introduction of modern manufacturing techniques .................................................. 73
3.4 Timing of the introduction of modern manufacturing techniques ........... 75
3.5 Phase-in of modern manufacturing techniques in the production hall ....... 76
3.6 Daily average utilization in production hall 1 over time ....................... 81
3.7 Prior productivity and the introduction of modern manufacturing ........... 82
3.8 Daily mean utilization in production hall 1 by division ......................... 84
3.9 Distribution of daily productivity ............................................... 86
3.10 Direct effect ................................................................. 87
3.11 Spillover effects ............................................................. 87
3.12 Spillover effects ............................................................. 89

A.1 Geographic Distribution of $LMF_{rt}$ ...................................... 111

B.1 First stage for Table 2.8 ..................................................... 117
B.2 First stage for Table 2.9 ..................................................... 118
# List of Tables

1.1 Descriptives for Main Estimation Sample ............................................. 13  
1.2 Corrected and Uncorrected Estimates $\beta$ ............................................ 14  
1.3 Regional Employment Shares - 1998 .................................................. 16  
1.4 Descriptives - Full Sample ................................................................. 20  
1.5 Regressions by Quartile of $LMF_{rt}$ .................................................... 21  
1.6 Regressions by Quartile of $LMF_{rt}$ - Robustness Tests ....................... 22  
1.7 Two-Step Estimation Descriptives (First Step) ..................................... 24  
1.8 Two-Step Estimation (Second Step) ..................................................... 25  
2.1 Decomposition of Changes in Output Shares ......................................... 34  
2.2 Output and Labor Reallocation in Response to Trade Shock ..................... 35  
2.3 List of Industries .................................................................................. 49  
2.4 Summary Statistics - Germany’s return Autarky ..................................... 51  
2.5 Index of sectoral import competition ..................................................... 53  
2.6 $\hat{W}_{ig}$ in Germany - $T_{China,s}^{1/9}=5$ ........................................ 57  
2.7 Labor Reallocation in Response to Trade Shock ..................................... 62  
2.8 Reallocation and regional income per worker ......................................... 63  
2.9 Changes in import-competition and regional income per worker .............. 64  
3.1 Summary statistics ............................................................................... 79  
A.1 Descriptives - Coworker Networks ....................................................... 102  
A.2 Multinomial Logit Model ................................................................. 104  
A.3 Multinomial Logit Model - Occupation Restriction ............................... 105  
A.4 Corrected and Uncorrected Estimates $\beta$ - Gender ............................ 107  
A.5 Corrected and Uncorrected Estimates $\beta$ - Apprenticeship ................. 108  
A.6 Corrected and Uncorrected Estimates $\alpha$ ............................................ 109  
A.7 $LMF_{rt}$ Variance Decomposition ....................................................... 112  
A.8 Employment Reallocation - By Quartile of $LMF_{rt}$ ............................ 113  
A.9 Regressions by Quartile of $LMF_{rt}$ - Alternative $LMF_{rt}$ Measure .......... 114  
A.10 Regressions by Quartile of $LMF_{rt}$ - Alternative $LMF_{rt}$ Measure ........ 115  
A.11 Two-Step Estimation (Placebo Tests) ................................................. 116
Acknowledgments

This dissertation would not have been possible without the support of my advisors, co-authors, and colleagues.

I am tremendously grateful to my advisor, David Card, for his support and dedication throughout my graduate (and undergraduate) career. More than anyone, David’s incredible expertise and generosity have benefitted both my research work and career. I will be forever grateful for the countless hours of advice, for all his insights, and most of all for his invaluable guidance from the beginning. I also want to express my deep gratitude to Enrico Moretti for all his advice and support, and for generously helping me while on sabbatical this last year. It is from Enrico’s class and our conversations that many of the ideas for this dissertation took form. His impact can be seen in every chapter of this dissertation, and I have no doubt his influence will show in my future work. I am also very fortunate to have had the opportunity to learn from Pat Kline. His advice was crucial in the formulation of the research designs and methodological approaches for each chapter of this dissertation. His expertise in so many different fields and approaches is unrivaled and my work has benefitted immensely from his guidance. I am also deeply grateful to Andres Rodriguez-Clare. Besides being a great co-author, Andres has been an exceptional mentor and teacher. It is thanks to Andres that I became interested in topics related to labor adjustments and trade liberalization, and I have learned a great deal about research in International Trade from him. I also want to express my gratitude to Reed Walker and Chris Walters for their constant support and for the many hours of helpful discussions. I am very grateful for their advice, both in terms of my research and on how to best frame and present my projects.

Finally, I am also indebted to my many co-authors, each of whom contributed to this work in different ways. I thank Steffen Mueller and Jens Stegmaier for their important insights on German labor markets and for giving me the opportunity to work with German administrative data. I am also very grateful for the opportunity of working with Torsten Walter, from whom I learned a tremendous amount. I also would like to give a special thanks to my friend and co-author Simon Galle, who taught me how to be a better economist, and whose skill set always felt like a perfect complement to mine. I look forward to future collaborations in the years to come. Lastly, I would like to thank all my colleagues in the Berkeley Economics Department, and in particular Carl, David, Hedvig, Attila, Tarso, Edson, Monica, Pierre, Juan Pablo, and Dorian. Thank you for all your support and your friendship these last few years.
Chapter 1

Industry Mix, Local Labor Markets, and the Incidence of Trade Shocks

with Steffen Mueller and Jens Stegmaier
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

Today’s globalized economy has greatly benefited from the rapid pace of technological change and growing trade integration. At the same time, the broad nature of these changes, which in many cases affect entire industries and occupations, have resulted in significant labor market adjustments which often involve workers reallocating into other sectors or occupations. In the German context, for example, manufacturing employment shrank by 25% from 1990 to 2005 (a loss of 2.3 million jobs) while the service sector added 3.9 million jobs during the same period (Bachmann and Burda, 2008). In standard neoclassical models, sectoral reallocation plays a positive role, leading workers into higher productivity industries. These predictions, however, stand in stark contrast with empirical studies in the labor literature, which find significant and persistent effects of sectoral shocks on worker outcomes.1

These large costs highlight the fact that workers are not perfectly mobile across sectors, at least in the short and medium run. This fact has big implications for the trade literature, where reallocation of workers across sectors plays an important role in assessing the effects of trade liberalization. Indeed, there is a recent and growing literature studying the role of sectoral mobility costs on labor market adjustments (Artuc, Chaudhuri, and McLaren, 2010; Dix-Carneiro, 2014; Caliendo, Dvorkin, and Parro, 2015).2 In this paper, we contribute to this literature by studying the roles that skill transferability and the sectoral composition of local labor markets play in determining the adjustment costs resulting from negative import shocks. We employ rich administrative data on German manufacturing workers to directly measure how transferable their skills are across sectors, and to test whether manufacturing workers located in regions with different sectoral employment structures adjust differently in response to increased import competition from China and Eastern Europe.

We hypothesize that there is large heterogeneity in the degree of transferability of skills across different types of jobs. This heterogeneity implies that workers will find it easier to transition into some sectors but not into others (because in the former their skills are highly valued, whereas in the latter they are less useful).3 As a result, the sectoral composition of a local labor market will determine adjustment costs because it determines what types of jobs are available to negatively affected workers.

To empirically test this hypothesis, we proceed in three steps. We begin by estimating novel measures of skill transferability across sectors. These measures capture how valuable the observed skills and human capital of workers are when applied in other sectors. We interpret these as measuring the economic distance between sectors from the workers’ per-

---

1See for example D. Autor et al. (2014) and Walker (2013). These findings are also consistent with extensive literature on the negative effects of job losses (Davis and Von Wachter, 2011; Jacobson, LaLonde, and D. G. Sullivan, 1993)

2An additional body of work on trade and labor market adjustments focuses on different types of frictions: Helpman, Itskhoki, and Redding (2010) on within-industry labor market frictions; Kambourov (2009) and Topalova (2010) on labor market regulations.

3This approach is grounded in the extensive labor literature on the importance of human capital as a determinant of wage growth, and on more recent literature on the specificity of human capital. See Gathmann and Schoenberg (2010), Poletaev and C. Robinson (2008), Neal (1995), Parent (2000), Kambourov and Manovskii (2009), and P. Sullivan (2010).
In the second step, we combine these distances with local industry employment shares to obtain a labor market flexibility index, which captures how easily a worker with a given set of skills will be able to reallocate into other sectors. In the last step, we test how workers in regions with different degrees of labor market flexibility are differentially affected by national import shocks. Our empirical findings confirm our hypothesis. We find there is large heterogeneity in the degree of skill transferability across sectors, and that workers living in regions with many employment opportunities in sectors that value their skills experience smaller adjustment costs in response to import shocks.

In order to motivate our study, we start by presenting a simple two-period model that features multiple sectors and local labor markets. Each labor market contains heterogeneous workers who differ in their observable skills. These skills are transferable across sectors, but only partially so and with varying degrees depending on the sectors involved. All workers start in manufacturing jobs in the initial period, and choose to reallocate in response to an external shock in the second period. Workers sort into different sectors following a Roy structure, but face different search costs that vary across labor markets. Their final wage outcome depends on their sectoral choice and how valuable their skills are in their new jobs. These features capture the main idea of our study. Varying degrees of skill transferability imply that workers face different economic distances when moving across sectors. At the same time, labor market conditions determine how easily workers can move into certain sectors. These two features result in varying reallocation costs across labor markets. Even workers with similar skills but in different labor markets will be affected differently by a common economic shock.

Following the predictions of this stylized model, we proceed with the empirical analysis. The first step is to estimate how transferable skills are across sectors. We do this by directly observing wage changes for workers who switch from manufacturing into other sectors, and relating these changes to their individual characteristics and skills. Our approach consists of running separate wage regressions for workers moving from manufacturing into each potential target sector, and estimating the returns workers get on their skills after they switch. The major challenge inherent in this type of analysis is the endogenous sorting of workers into sectors. In order to address this issue, we take advantage of the high level of detail and scope of our administrative data. First, we focus on exogenously displaced workers (due to firm closures and mass-layoffs) thereby ensuring workers’ exit from their previous job was involuntary. Then, in order to address worker sorting into sectors we employ a selection correction model (Dahl, 2002; Bourguignon, Fournier, and Gurgand, 2007). In order to identify the relevant parameters, we rely on a novel instrument for industry choice based on

---

4While other measures of economic distance between sectors have been developed in the literature, they mostly focus on distances from the production perspective (e.g. input-output flows or technological proximity based on patents or R&D research) which are not necessarily related to the cost workers face when moving between sectors. For an example of their application, see Greenstone, Hornbeck, and Moretti (2010) and Ellison, Glaeser, and Kerr (2010).

5See Beaudry, Green, and Sand (2012) and Bombardini, Gallipoli, and Pupato (2012) for recent applications of this type of selection model corrections.
the social network of each displaced individual. This instrument is based on the growing literature on the importance of social networks in determining labor market outcomes.\footnote{For recent examples, see Saygin, Weber, and Weynandt (2014), Glitz (2013), and Cingano and Rosolia (2012) on coworker networks; Hellerstein, Kutzbach, and Neumark (2015) on neighborhood networks.} The reasoning behind our selection instrument is that past co-workers can provide information about job openings in their own firms and industries, increasing the likelihood a displaced worker will choose an industry without affecting her wage there (conditional on observed characteristics).

Our procedure allows us to predict wage changes based on the individual characteristics of workers (e.g. experience, education, gender, etc.) and their source and target sectors. We interpret these predicted wage changes, which vary across individual workers and pairs of sectors, as measures of economic distance between sectors. Using these distances, we then construct an index of labor market flexibility for each region in Germany. This index combines sectoral distances with the sectoral composition of each local labor market. It captures the degree to which workers from a particular industry (in this case manufacturing) will be able to reallocate into other jobs. The intuition behind it is that regions with many employment opportunities in “close” sectors will allow workers to better adjust to negative shocks.

Finally, in the last part of the paper, we analyze the relationship between labor market flexibility and workers’ responses to sectoral shocks. We do so by estimating the medium run effects of import shocks on workers, and how these vary across regions with different degrees of labor market flexibility. In this, we build upon the empirical approach developed by D. Autor et al. (2014) (henceforth ADHS), who estimate the effect of trade-induced shocks on workers outcomes. Their approach focuses on workers who were initially employed in manufacturing, and compares the medium term outcomes of those who were exposed to import competition against other manufacturing workers who were not. We expand on ADHS’s approach by allowing the effects of import competition to vary across regions with different degrees of flexibility.

Our findings indicate large heterogeneity in the sectoral distances workers face, even for workers with similar backgrounds and levels of education. For example, we find that for the average manufacturing worker, an extra year of experience is associated with a wage loss of 4.6% if she were to move to the Office and Business Support Services sector, but only a 2.8% loss in the Transportation sector. This heterogeneity in sectoral distances combined with variation in employment opportunities across regions results in different adjustment costs for workers affected by negative shocks. Indeed, we find that import shocks have a much smaller effect on manufacturing workers located in flexible regions relative to those in inflexible regions. Among workers living in inflexible labor markets, the difference between a worker at the 75th percentile of industry import exposure and one at the 25th percentile of exposure amounts to a cumulative earnings loss ranging from 9 to 11% (as a share of initial annual earnings over a 10 year period). The earning losses of workers living in flexible regions is negligible. Workers in flexible regions also experience smaller decreases in employment
and are more likely to transition to non-manufacturing jobs. These results highlight the importance of skill transferability and local labor markets on the incidence of economic shocks.

To the best of our knowledge, we are the first to estimate sectoral distance measures based on observed skill transferability and to analyze the role that these distances play in the context of local labor markets and the incidence of shocks. Our measures of skill transferability build upon a Roy model (A. D. Roy, 1951; Heckman and Sedlacek, 1985) where workers possess heterogeneous skills (both observed and unobserved), skills are priced differently across sectors, and workers select into sectors where they get the highest returns. This framework has been recently adapted to study labor market effects resulting from external shocks (Burstein, Morales, and Vogel, 2015a; Galle, Rodriguez-Clare, and Yi, 2015). In these papers, workers posses a multidimensional vector of unobserved skills drawn from a parameterized distribution that determines the distributional effects of shocks. Related to this literature is work by Artuc, Chaudhuri, and McLaren (2010), Dix-Carneiro (2014), and Caliendo, Dvorkin, and Parro (2015), each of whom incorporate sectoral mobility costs—among other features—in their studies of labor market adjustments and trade. Our work complements this literature by providing skill transferability measures that are based directly on observed wages and skills, require fewer assumptions about the underlying model, and allow distances to vary based on individual characteristics (as opposed to being governed by a few parameters).

Our work also contributes to the broad labor literature on worker adjustments in response to external shocks. This literature includes studies assessing the labor market effects of job displacement (Wachter, Song, and Manchester, 2008; Davis and Von Wachter, 2011), environmental regulations (Walker, 2013), and local demand shocks (Moretti, 2010; Notowidigdo, 2011). More related to this paper are recent studies on the effects of import competition on workers and local labor markets: D. Autor et al. (2014) and D. H. Autor, Dorn, and Hanson (2013) for the U.S., Dauth, Findeisen, and Suedekum (2014) for Germany, and B. K. Kovak (2013) and Dix-Carneiro and B. Kovak (2014) for Brazil. Our work contributes to this literature by indentifying sources of heterogeneity in the adjustment process following an

---

7 Dix-Carneiro (2014) also estimates measures of skill transferability across sectors (in addition to sectoral mobility costs) in his study of labor market adjustments following trade liberalization in Brazil. Our work differs from his in that we emphasize the importance of local labor markets and their industry mix in explaining labor market adjustments. In addition, our methodological approach is less structural and focuses solely on negatively affected workers in the medium run (abstracting for general equilibrium considerations). Dix-Carneiro (2014), on the other hand, estimates a full structural dynamic equilibrium model that is broader in scope and incorporates additional features such as overlapping generations and mobility of physical capital.

8 Sectoral mobility costs have also been studied in the labor literature by Lee and Wolpin (2006).

9 A common strategy in this literature is to impose strong assumptions on the distribution of skills or idiosyncratic shocks (usually governed by a few parameters) and to rely on observed flows of workers across sectors (as opposed to wages) to estimate the relevant parameters. These are partial adaptations of methods popular in the trade literature (Eaton and Kortum, 2002) which rely on similar distributional assumptions, a small number of distributional parameters that govern patterns of trade, and observing the flows of goods across countries to obtain estimates of trade costs.

10 The trade literature also includes a large number of studies on the effects of trade liberalization on sec-
external shock. Specifically, we highlight the important roles of skill-based sectoral distances and local labor markets in determining the magnitude and incidence of negative shocks on workers. Although our study focuses on sector-level shocks, our findings are applicable to any setting that involves labor reallocation across sectors. As such, our work can provide a useful framework to assess the distributional implications of a wide variety of shocks.

A third strand of literature related to our work is the study of human capital specificity. Our measures of sectoral distance and the idea of skill transferability are related to a subfield in the labor literature that studies the importance of different types of human capital on wage growth. Relevant work in this literature includes Neal (1995) and Parent (2000) (whose focus is on industry-specific human capital), Kambourov and Manovskii (2009) who study occupation-specific human capital, and work by P. Sullivan (2010) on both the occupation and industry specificity of human capital. This literature also includes studies relating human capital and the task content of jobs, most notably by Poletaev and C. Robinson (2008) and Gathmann and Schoenberg (2010), that use job-task descriptions to construct vectors of skill-distance between jobs. As a whole, this literature finds that industry, occupation, and task-specific human capital are important determinants of earnings, therefore implying that human capital is not fully transferable across sectors. Our paper expands on this literature by exploring the heterogeneity in degrees of transferability of human capital across different sectors.

Lastly, our work is also related to the literature on skill and spatial mismatch. Among the few empirical studies in this area is Andersson et al. (2011) who use LEHD data to study the role of spatial mismatch on unemployment durations for low-skilled workers. They find that the availability of jobs in a pre-displacement industry reduces unemployment spells. Sahin et al. (2012) study mismatch unemployment (unemployment that arises from workers searching for jobs in the wrong sectors). Using data on vacancies and hires (and stylized model assumptions), they estimate that mismatch across industries accounts for 1/3 of the increase in the unemployment rate in the US in the last decade. A main limitation of their work is that is does not provide any evidence as to what may be the forces behind this mismatch. Our work points to skill distances and local employment structures as potential determinants of the observed mismatch in this literature.11

The rest of the chapter is structured as follows. Section 1.1 presents a simple theoretical framework to motivate our analysis. Section 1.2 describes the data employed in this paper. In Section 1.3, we explain and estimate our measures of sectoral distances. Section 1.4 details the construction of our labor market flexibility index. Section 1.5 presents our main results on the heterogenous effects of shocks and their relation to our labor market flexibility measure. Section 1.6 concludes.

11A related strand of literature explore the role of labor market “thickness” (Bleakley and Lin, 2012), finding that occupational and industry switching rates are higher in more densely populated regions.
1.1 Theoretical Framework

To motivate our empirical analysis, we present a simple model with sectoral distances and local labor markets. In this model, the economy is characterized by $S$ sectors (indexed by $s$) and $R$ regions (indexed by $r$) with population $N_r$. Each region is an open economy, and workers are mobile across sectors but immobile across regions. The number of workers in each region is fixed, and labor supply is inelastic with each worker providing one unit of labor. Workers are endowed with different levels of human capital $X_i$, which includes years of experience working in sector $s$ as well as other measures of skill such as years of education. Importantly, the returns workers get on their skills are sector-specific.

All workers’ initial sector of employment is manufacturing ($s = m$ at time $t = 0$). The initial wage worker $i$ in region $r$ gets in manufacturing is given by the following expression:

$$\ln y_{i0}^r = \alpha_i + X_i' \beta_m$$  \hspace{1cm} (1.1)

where $\alpha_i$ represents worker $i$’s unobserved general ability, and elements of $\beta_m$ are sector-specific returns to human capital $X_i$.

In period $t = 1$, workers choose between different industries—this could be thought of as a decision after being displaced from sector $m$. The potential wage for worker $i$ in sector $k$ is given by:

$$\ln y_{ik}^r = \alpha_i + X_i' \beta_k + \epsilon_{ik}$$  \hspace{1cm} (1.2)

where $\epsilon_{ik}$ is an unobserved sector-specific ability draw which is distributed i.i.d. extreme value type I. Workers sort into the sector that maximizes their utility $V^r_{ik}$, which is determined by the wage they receive as well as non-pecuniary factors and preferences:

$$V^r_{ik} = \ln y_{ik}^r + X_i' \kappa_k + Z_i' \lambda_k + \sigma \theta_{ik}$$

where $\theta_{ik}$ is an i.i.d. preference shock that follows a “Cardell” distribution with parameter $\frac{1}{\sigma}$ (Cardell, 1997), $Z_i$ are non-pecuniary factors that affect worker $i$’s choice, and human capital $X_i$ enters the utility function both through the wage channel and through preferences.

Noting that the individual ability term $\alpha_i$ is constant across choices (and therefore does not affect worker $i$’s decision), and rescaling all utilities by $\frac{1}{\sigma}$, the utility function that characterizes worker $i$’s choice can be simplified to the following expression:

$$V^r_{ik} = X_i' \gamma_k + Z_i' \Gamma_k + \eta_{ik}$$

where $\eta_{ik} \equiv \theta_{ik} + \frac{1}{\sigma} \epsilon_{ik}$. Under our distributional assumptions for $\theta_{ik}$ and $\epsilon_{ik}$, $\eta_{ik}$ is i.i.d. Gumbel distributed (EV1).\(^{13}\)

\(^{12}\)For simplicity, we assume that the initial wage $\ln y_{i0}^r$ does not enter into worker $i$’s sectoral choice.

\(^{13}\)Cardell (1997) shows that if $\theta_{ik} \sim C (\frac{1}{\sigma})$ and $\epsilon_{ik} \sim EV1$, and the two random variables are independent of each other, then $\theta_{ik} + \frac{1}{\sigma} \epsilon_{ik} \sim EV1$.\(\)
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

8

For ease of exposition, let \( Z'_i \Gamma_k = -\tau^r_{m \rightarrow k} \), a non-pecuniary utility cost of moving from sector \( m \) to sector \( k \) that varies across regions. An intuitive way to think of \( \tau^r_{m \rightarrow k} \) is that it captures search costs and information frictions that make it harder for workers in certain regions to find jobs in sector \( k \). In our context, regional variation in \( \tau^r_{m \rightarrow k} \) can be the result of different regional employment structures. For example, workers in regions with few employment opportunities in sector \( k \) may face higher costs as they search for a job in that particular sector.

Given our assumptions, the probability that worker \( i \) in region \( r \) chooses to reallocate from sector \( m \) to sector \( k \) is given by the following expression:

\[
p^r_{i, m \rightarrow k} = \frac{\exp \left( X'_i \gamma_k - \tau^r_{m \rightarrow k} \right)}{\sum_s \exp \left( X'_i \gamma_s - \tau^r_{m \rightarrow s} \right)}
\]

which is a (monotonically) decreasing function of mobility costs \( \tau^r_{m \rightarrow k} \). This means that workers with similar characteristics but living in different regions (i.e. those with different \( \tau^r_{m \rightarrow k} \)) will have different probabilities of choosing sector \( k \)—even when facing the same wage schedule.

From equations 1.1 and 1.2, we can write an expression for the potential wage change related to a move from sector \( m \) to sector \( k \):

\[
\Delta \ln y^r_{i, m \rightarrow k} = X'_i (\beta_k - \beta_m) + \epsilon_{ik}
\]

Defining \( D_{i, m \rightarrow k} \) as an indicator variable for whether worker \( i \) chooses sector \( k \) (i.e. \( D_{i, m \rightarrow k} = 1 \) \( V_{ik} = \max \{ V_{i1}, \ldots, V_{is} \} \)), we can obtain the following expression for the observed wage change for workers who reallocate to sector \( k \):

\[
E \left[ \Delta \ln y^r_{i, m \rightarrow k} \mid X_i, D_{i, m \rightarrow k} = 1 \right] = E \left[ X'_i (\beta_k - \beta_m) + \epsilon_{ik} \mid X_i, D_{i, m \rightarrow k} = 1 \right] = \underbrace{X'_i \beta_{m \rightarrow k}}_{\text{Observed}} + \underbrace{E \left[ \epsilon_{ik} \mid D_{i, m \rightarrow k} = 1 \right]}_{\text{Unobserved}} \tag{1.3}
\]

Equation 1.3 is a standard wage equation relating wages to both observed human capital \( (X_i) \) and unobserved sector-specific components. In this paper, we will focus on how the returns to observed human capital vary across sectors (i.e. estimating \( \beta_{m \rightarrow k}'s \)) while controlling for the unobserved components in the wage equations. Different values of \( \beta \)'s capture different degrees of skill transferability across sectors, which in turn result in varying sectoral reallocation costs. For a given worker \( i \) with human capital \( X_i \), \( X'_i \beta_{m \rightarrow k} \) measures the wage loss (associated with observed human capital) that results from reallocating from sector \( m \) to sector \( k \). We interpret \( X'_i \beta_{m \rightarrow k} \) as a measure of economic distance between sectors \( m \) and \( k \) from worker \( i \)'s perspective.

Aggregating at the regional level, we have that for workers in region \( r \), the expected post-displacement wage loss associated with observed human capital can be written as:

\[
\Delta y^r_m = \frac{1}{N_r} \sum_i \sum_s p^r_{i, m \rightarrow s} X'_i \beta_{m \rightarrow s}
\]
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

This expression highlights the importance of two factors in the reallocation costs of workers. Reallocation costs will vary across regions depending on:

1. The economic distances between \( m \) and other sectors: \( X_i \beta_{m \rightarrow s} \)

2. The reallocation probabilities to each sector \( s \), which are partly determined by the sectoral composition of each region:

\[
p_{i, m \rightarrow k}^r = \frac{\exp(X_i^r \gamma_k - \tau_{m \rightarrow k}^r)}{\sum_s \exp(X_i^r \gamma_s - \tau_{m \rightarrow s}^r)}
\]

The intuition behind these results is simple. In response to a shock, workers will reallocate, and the types of jobs available in each region will determine whether they end up in a “distant” sector or a “close” sector. In this paper, we will estimate measures of sectoral distance based on equation 1.3’s parameters. We will then combine them with the industry mix of regions to determine the losses workers would face in light of a national shock.

1.2 Data

This project makes use of German administrative data collected by the German Social Security System and provided by the Institute of Employment Research (IAB). This rich, linked Employer-Employee data set contains earnings and employment histories for the vast majority of privately-employed German workers from 1975 to 2010. It also contains standard demographic characteristics such as gender, age, nationality, education, and region of residence. Furthermore, the data include an establishment identification number through which it is possible to obtain firm-level figures of the characteristics of fellow employees. Important for this project, the data on employment history is highly detailed and reliable. Employment spells are measured on a daily basis (with the start and end date for each spell), and the industry and occupation of all employment spells are consistently defined and available for each worker throughout the entire time period.

The size and level of detail of the data allow us to observe workers moving across sectors as well as all their relevant characteristics at the time of the move. These include the pre- and post-move daily wages, the exact date of the move, and the length of time between jobs, as well as firm and industry tenure at the time of the job switch. The consistent establishment level ids allow us to reliably identify firm closures as well as learn about the social networks (of coworkers) that workers build over time. For the purposes of our analysis, we divide the economy into 10 big sectors based on standardized NACE Rev2 industry classification codes. The list of sectors is featured in Table 1.1.

The geographic units of observation in this paper are German Labor Market Areas (“Arbeitsmarktkregionen”). These regions are roughly equivalent to US Labor Market Regions constructed by the BLS. Our sample consists of 229 regions, each containing a minimum of 100,000 inhabitants as of December of 2008. The regional identifiers have been modified to be consistent throughout the entire time period.
In all the subsequent analysis, we focus on one particular group: German workers who held manufacturing jobs at any point between 1985 and 2010. For identification purposes, we will employ additional sample restrictions in each estimation procedure. These will be described in detail in the corresponding sections.

There are data limitations worth mentioning. First, as discussed by Dustmann, Ludsteck, and Schoenberg (2009) and Card, Heining, and Kline (2013), the earnings data is censored at the annual Social Security maximum. An additional limitation is the exclusion of some groups from the sample (due to the administrative purposes of the data). In particular, self-employed workers and civil servants are excluded from the data.

1.3 Skill Transferability and Sectoral Distances

Our approach to estimate sectoral distances is grounded in the extensive literature on the importance of human capital and skill accumulation as determinants of wages. This approach aims to measure how skills accumulated in one sector are valued in other sectors. As an illustrative example, think of a worker with 10 years of experience working in a manufacturing firm. If this worker were to be randomly assigned to the Office and Business Support Services sector, she might not find her skills useful and get a low return on her experience. Whereas if such worker were to be (randomly) assigned to a Transportation firm, the returns to her skills would be higher. This differential in returns will form the basis of our sectoral distance measures. Clearly, such a thought experiment is not implementable in reality. Our empirical approach will therefore aim to address the many endogeneity issues arising from observational studies. In particular, we will address the endogenous mobility issue by focusing on exogenously displaced workers and using a selection model to control for endogenous sorting into sectors.

Empirical Approach

Using the notation developed in Section 1.1, the potential wage change for worker $i$ moving from sector $m$ to sector $k$ will be given by:

$$\Delta \ln y_{i,m\rightarrow k} = X_i' \beta_{m\rightarrow k} + \epsilon_{ik}$$

where $\epsilon_{ik}$ is an unobserved sector specific ability and $X_i$ is a vector of standard human capital variables such as experience, education, gender and age.\footnote{Note that $X_i$ is time invariant, which reflects our assumption that worker $i$’s characteristics (e.g. education) do not change during the period in between jobs (the average duration of which is only 2 months in our sample, making this a reasonable assumption). A more subtle point relates to the measurement of experience. We consider $\ln y_{ik}$ to be worker $i$’s initial wage in sector $k$, before she has accumulated experience in sector $k$. Therefore, $X_i$ only includes experience accumulated in the previous sector (manufacturing).}$14$
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

transferability of skills between sector \(m\) and \(k\), which will form the basis for our sectoral distance measures.

OLS estimation of equation 1.4 would result in biased coefficients due to endogenous sorting of workers into sectors. In order to address this problem, we restrict the sample to workers who were exogenously displaced and employ a selection model to correct for post-displacement sorting. The selection correction method we employ is based on the work by Bourguignon, Fournier, and Gurgand (2007) and Dahl (2002). Formally, the model is as follows (we omit the \(m\) subscripts for simplicity):

\[
\begin{align*}
\Delta \ln y_{ik} &= X'_i \beta_k + \epsilon_{ik} \\
V_{ik} &= Z'_i \tau_k + \eta_{ik} \quad (k = 1, \ldots, S) \\
D_{ik} &= \begin{cases} 
1 & \iff V_{ik} = \max(V_{i1}, \ldots, V_{iS}) \\
0 & \text{otherwise}
\end{cases}
\end{align*}
\]

(1.5)

This model tracks very closely the theoretical framework developed in Section 1.1, with \(\Delta \ln y_{ik}\) representing the log change in wages for worker \(i\) moving from sector \(m\) to \(k\), and workers sorting into the sector that maximizes their utility \(V_{ik}\) (which depends on potential wages and non-pecuniary factors associated with each sector). As in the theoretical framework from Section 1.1, we assume the error terms in the selection equation (\(\eta_{ik}\)) are i.i.d extreme value type I.

For the empirical analysis, we impose an additional assumption on the structure of the error terms, which is based on work by Dubin and McFadden (1984) and described in detail in Bourguignon, Fournier, and Gurgand (2007). Specifically, we impose the following linearity assumption:

\[
E[\epsilon_{ik}|\eta_{i1} \ldots \eta_{iS}] = \sigma \frac{\sqrt{6}}{\pi} \sum_s r^s_k (\eta_{is} - E[\eta_{is}])
\]

Under these assumptions, the outcome equation can be written in the following manner:

\[
\Delta \ln y_{ik} = X'_i \beta_k + \lambda_k (p_{i1} \ldots p_{iS}) + \omega_{ik}
\]

(1.6)

Here, \(\lambda_k (\bullet)\) represents the selection correction function with the probabilities \(p_{is}\)'s (that individual \(i\) from sector \(m\) moves to sector \(s\)) as the arguments.\(^{15}\)

This model requires an instrument for the selection equation. The instrument needs to predict worker selection into sectors while at the same time being uncorrelated to the error term in the wage equation. Credible instruments of this sort are difficult to find.\(^{16}\) In this

\(^{15}\)Dubin and McFadden (1984) show that under our assumptions the correction term is \(\lambda_{jk} (\bullet) = \sigma \frac{\sqrt{6}}{\pi} \left[ \sum_{s \neq k} r^s_k \left( \frac{P_{is} \ln P_{is}}{1 - P_{is}} \right) - r^k_k \ln P_{ik} \right] \).

\(^{16}\)In the context of occupational choice, Gathmann and Schoenberg (2010) use a task-based distance measure to other sectors within the same region. Bombardini, Gallipoli, and Pupato (2012) employ state of birth as an instrument for industry choice. In Dix-Carneiro (2014), the selection instrument for sectoral choice is the previous sector of employment (conditional on sectoral tenure).
paper, we propose a novel selection instrument: the number of past co-workers present in each potential target sector $k$ at the time of worker $i$’s displacement. This instrument is based on the growing literature on the importance of social networks in determining labor market outcomes.\footnote{For recent examples, see Saygin, Weber, and Weynandt (2014) and Glitz (2013) on coworker networks, Hellerstein, Kutzbach, and Neumark (2015) on neighborhood networks.}

The reasoning behind our selection instrument is that past co-workers can provide information about job openings in their own firms and industries, increasing the likelihood that a displaced worker will choose a particular industry but without affecting the wage she would get there.

We define our selection instruments $CN_{is}$ (which are included in $Z_i$ in equation 1.5) as the number of worker $i$’s past coworkers who by the time of worker $i$’s displacement had already moved into other firms in sector $s$. Furthermore, we only include a coworker $h$ in worker $i$’s network when the following conditions are satisfied:

1. Worker $i$ and $h$ worked in the same firm for at least 30 days in the 6 years prior to worker $i$’s displacement.
2. Worker $h$ switched firms at least a year before worker $i$ was displaced.
3. Worker $i$ and worker $h$ had different occupations\footnote{Occupations in this case are defined at the 1-digit level.} at the time of their interaction.

We impose restriction 2 in order to address unobserved time-specific demand shocks that could affect both worker $i$ and her coworkers’ moving decisions. Restriction 3 is meant to address the problem of worker $i$ and worker $h$ sharing some unobserved characteristic (e.g. a latent ability in other sectors) that would affect the wage worker $i$ would get in other sectors.\footnote{This would be the case, for example, if worker $i$ and worker $h$ sorted into worker $i$’s pre-displacement firm based on some shared unobserved characteristics.} Appendix A describes in detail the construction of the coworker networks.

**Results**

The results from estimating the separate wage regressions for each target sector (corresponding to 1.6) are discussed in this section. Although our methodology can be generalized to sectoral distances across any number of sectors, in this paper we focus on manufacturing workers and distances from manufacturing into other potential sectors.

We estimate our model for the sample described in section 1.2 (German manufacturing workers). In this section, we impose additional restrictions to ensure our estimates are consistent. First, we exclude workers from East Germany. This ensures that we observe the entire employment histories of workers and avoids potential issues with East German workers possessing different types of skills. Second, we restrict the sample to workers who...
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

Table 1.1: Descriptives for Main Estimation Sample

<table>
<thead>
<tr>
<th>Industry</th>
<th>Age</th>
<th>Secten_manuf</th>
<th>ΔLog(wage)</th>
<th>Nonemp length</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, utilities</td>
<td>27.2</td>
<td>8.4</td>
<td>0.07</td>
<td>3.8</td>
<td>1,839</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>29.1</td>
<td>10.6</td>
<td>0.08</td>
<td>1.5</td>
<td>208,032</td>
</tr>
<tr>
<td>Construction</td>
<td>26.3</td>
<td>7.9</td>
<td>0.12</td>
<td>3.5</td>
<td>10,201</td>
</tr>
<tr>
<td>Retail</td>
<td>27.5</td>
<td>8.8</td>
<td>0.10</td>
<td>2.8</td>
<td>28,242</td>
</tr>
<tr>
<td>Transportation</td>
<td>27.4</td>
<td>8.7</td>
<td>0.06</td>
<td>4.3</td>
<td>3,543</td>
</tr>
<tr>
<td>Hotel, restaurants, low skill svcs</td>
<td>23.9</td>
<td>5.8</td>
<td>0.05</td>
<td>3.9</td>
<td>2,598</td>
</tr>
<tr>
<td>Communication, finance, prof svcs</td>
<td>30.0</td>
<td>10.5</td>
<td>0.03</td>
<td>2.0</td>
<td>14,500</td>
</tr>
<tr>
<td>Office and business support svcs</td>
<td>28.8</td>
<td>9.8</td>
<td>-0.03</td>
<td>5.1</td>
<td>9,274</td>
</tr>
<tr>
<td>Public administration</td>
<td>28.6</td>
<td>9.8</td>
<td>0.01</td>
<td>4.6</td>
<td>1,582</td>
</tr>
<tr>
<td>Education, hospitals, personal svc</td>
<td>28.7</td>
<td>9.8</td>
<td>-0.10</td>
<td>4.4</td>
<td>7,587</td>
</tr>
<tr>
<td>Total</td>
<td>28.8</td>
<td>10.2</td>
<td>0.07</td>
<td>2.0</td>
<td>287,398</td>
</tr>
</tbody>
</table>

Notes: Main estimation sample, displaced manufacturing workers in West Germany 1990-2000

were displaced by firm closures or mass-layoffs. We do this in order to address endogenous mobility. We further restrict our analysis to workers who have not switched sectors before, so that we can focus on workers with one set of skills (and to avoid dealing with workers moving back to their original sectors). Additionally, we exclude workers moving to or from marginal or temporary jobs, as well as workers with incomplete working histories. Imposing these restrictions leaves us with a sample of 287,398 workers who were displaced from a manufacturing firm and eventually found jobs (in any sector, including manufacturing). Table 1.1 shows descriptive statistics for this sample. Column 6 shows that the vast majority of displaced workers in this sample chose to remain in manufacturing after displacement. The figures in column 4 indicate that there is large variation in the wage losses workers experience. Workers moving to Education and other Personal Services experience an unconditional wage loss of 10%, while workers moving to Retail gain on average 10%.

In Appendix A, we show descriptive statistics for our coworker selection instrument, as well as evidence of its predictive power. Table A.1 shows that the workers in our sample had a large coworker network. The average number of coworkers (in any sector) at the time of displacement is 67. Tables A.2 and A.3 (also on Appendix A) present evidence of the predictive power of our instrument. They show the results for the first stage equation of our selection model (a multinomial logit regression of sectoral choice). The results from these regressions clearly show that having coworkers in potential target sectors increases the probability that displaced workers will choose such sector. In Appendix A, we also discuss the potential violations of our exclusion restriction and our planned robustness tests to address

20 For firm closures, we employ the measures developed by Hethey and Schmieder (2010). The construction of our mass-layoff indicator is described in detail in Appendix F.

21 Note that these are the differences between wages in the last job and initial wages in the new job.
**CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS**

Table 1.2: Corrected and Uncorrected Estimates $\beta$

<table>
<thead>
<tr>
<th>Target Industry</th>
<th>$\beta_{OLS}$</th>
<th>$\beta_{DMF1}$</th>
<th>Hausman Test</th>
<th>Wald Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, energy</td>
<td>-0.0382***</td>
<td>0.0020</td>
<td>2.9401</td>
<td>6.1561</td>
</tr>
<tr>
<td></td>
<td>(0.0073)</td>
<td>(0.0138)</td>
<td>[0.0033]</td>
<td>[0.008]</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>-0.0300***</td>
<td>-0.0296***</td>
<td>0.4843</td>
<td>47.3640</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0010)</td>
<td>[0.6282]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Construction</td>
<td>-0.0503***</td>
<td>-0.0450***</td>
<td>1.0158</td>
<td>6.0343</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td>(0.0069)</td>
<td>[0.3097]</td>
<td>[0.074]</td>
</tr>
<tr>
<td>Retail</td>
<td>-0.0445***</td>
<td>-0.0318***</td>
<td>4.3096</td>
<td>14.0879</td>
</tr>
<tr>
<td></td>
<td>(0.0018)</td>
<td>(0.0032)</td>
<td>[0.0000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Transportation</td>
<td>-0.0528***</td>
<td>-0.0281***</td>
<td>3.1270</td>
<td>7.6773</td>
</tr>
<tr>
<td></td>
<td>(0.0059)</td>
<td>(0.0101)</td>
<td>[0.0018]</td>
<td>[0.022]</td>
</tr>
<tr>
<td>Hotel, rest, low skill svcs</td>
<td>-0.0558***</td>
<td>-0.0089</td>
<td>3.5269</td>
<td>5.6963</td>
</tr>
<tr>
<td></td>
<td>(0.0072)</td>
<td>(0.0161)</td>
<td>[0.0004]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>Communication, finance, other prof svcs</td>
<td>-0.0268***</td>
<td>-0.0174***</td>
<td>2.6806</td>
<td>5.0402</td>
</tr>
<tr>
<td></td>
<td>(0.0022)</td>
<td>(0.0040)</td>
<td>[0.0073]</td>
<td>[0.030]</td>
</tr>
<tr>
<td>Office and bus support svcs</td>
<td>-0.0642***</td>
<td>-0.0461***</td>
<td>3.7170</td>
<td>27.5699</td>
</tr>
<tr>
<td></td>
<td>(0.0034)</td>
<td>(0.0065)</td>
<td>[0.0002]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Public administration</td>
<td>-0.0648***</td>
<td>-0.0435***</td>
<td>1.6085</td>
<td>6.2290</td>
</tr>
<tr>
<td></td>
<td>(0.0083)</td>
<td>(0.0157)</td>
<td>[0.1077]</td>
<td>[0.014]</td>
</tr>
<tr>
<td>Education, hosp, personal svcs</td>
<td>-0.0345***</td>
<td>-0.0219***</td>
<td>2.2569</td>
<td>11.5111</td>
</tr>
<tr>
<td></td>
<td>(0.0043)</td>
<td>(0.0078)</td>
<td>[0.0240]</td>
<td>[0.002]</td>
</tr>
</tbody>
</table>

Notes: Estimates of $\beta_k$ for sectoral tenure from equation 1.5. Dependent variable is log difference in daily wages for workers moving from manufacturing into each target sector $k$. Regressors included: sectoral tenure, age group, gender, education, state and year dummies, unemployment duration, and regional employment shares in each industry. Sample of displaced manufacturing workers in West Germany (1990-2010). Column 3 features results from a Hausman test of equality between the corrected and uncorrected coefficients. Column 4 presents test statistics of joint significance of the parameters of the correction function. *** $p<0.01$, ** $p<0.05$, * $p<0.1$, bootstrapped standard errors in parenthesis (250 replications), p-values shown in brackets.

We present a selected set of the estimated coefficients from the full selection model here. Table 1.2 presents the coefficients for sectoral tenure. These coefficients correspond to equation 1.6 with the dependent variable being the log difference in pre-displacement and initial post-displacement wages.\(^{22}\) The set of regressors includes years of manufacturing work experience, age group, education, gender, state and year dummies, unemployment

\(^{22}\)By using initial daily wages, we avoid potential issues with employer learning and differential wage growth across sectors. In the future, we plan to run robustness tests employing changes in monthly and annual earnings.
duration, and regional employment shares in each industry. In all cases, we bootstrap standard errors to account for the two-step estimation procedure. Column 1 in each table shows the uncorrected estimates, while column 2 presents the estimates obtained from our selection model. Column 4 shows a Wald test of joint significance of the correction terms. All of these test statistics are significant at the 5% level, indicating the presence of selection. From the point estimates, it is clear that there is heterogeneity across target sectors. For example, for a manufacturing worker moving into another manufacturing firm, the wage loss associated with one extra year of experience is 2.96%. For a worker moving to Office and Business Support Services, each additional year of experience will result in a (much larger) 4.6% wage loss. Additional results are presented in Appendix B, tables A.4, A.5, and A.6. Although the results are much noisier, there is clear evidence of heterogeneity in returns to human capital across different sectors. Overall, our selection model works as expected. The coworker instrument is highly predictive, and the correction terms enter the wage equations significantly indicating our model is correcting the selection bias as intended.

It is worth comparing this section’s results with those of Dix-Carneiro (2014), who estimates similar measures of imperfect transferability of experience as part of a broader analysis of labor market effects of trade liberalization in Brazil. Conceptually, our approaches are similar in that both allow for selection based on unobserved wage components and idiosyncratic preferences. However, our methodologies differ in important ways. Dix-Carneiro (2014) employs an indirect inference approach to fully estimate a dynamic equilibrium model with several features we abstract from (e.g. capital mobility, overlapping generations, etc.). Our approach imposes less structural assumptions and is narrower in scope. We focus on a restricted sample (designed for identification purposes) of displaced workers making a one-time industry choice. In addition, we rely on a different set of identifying assumptions. Despite these differences, many of our results pertaining skill transferability are qualitatively similar. Like us, Dix-Carneiro (2014) finds large heterogeneity in the degree of transferability of manufacturing experience across sectors. In both cases, the Construction and Retail/Trade sectors provide lower-than-average returns for manufacturing experience, while the opposite is true for the Agriculture, Mining and Transportation sectors.

As in Dix-Carneiro (2014), we study how skill-based sectoral distances affect worker adjustments in response to import shocks. However, we do so by employing a different empirical approach and, more importantly, by incorporating a spatial component to our analysis. Specifically, we study how local labor markets, by virtue of their industrial employment composition and associated sectoral distances, partly determine the adjustment costs of negatively affected workers. In other words, our study focuses on the role of sectoral distances in conjunction with local labor market features. This is another feature differentiating our work from Dix-Carneiro (2014). The next two sections describe in detail our approach and present our main results.

---

23 There is also no distinction between general experience and sectoral experience in our sample.
24 A test of equality of the coefficients rejects the null that they are equal with a bootstrap p-value of 0.000.
Table 1.3: Regional Employment Shares - 1998

<table>
<thead>
<tr>
<th>sector</th>
<th>mean</th>
<th>sd</th>
<th>p25</th>
<th>p75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, energy and utilities</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.34</td>
<td>0.10</td>
<td>0.27</td>
<td>0.41</td>
</tr>
<tr>
<td>Construction</td>
<td>0.10</td>
<td>0.07</td>
<td>0.08</td>
<td>0.12</td>
</tr>
<tr>
<td>Retail</td>
<td>0.16</td>
<td>0.03</td>
<td>0.14</td>
<td>0.18</td>
</tr>
<tr>
<td>Transportation</td>
<td>0.03</td>
<td>0.01</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Hotel, restaurants, low skill svcs</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Communication, finance, and other prof svcs</td>
<td>0.09</td>
<td>0.04</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>Office and business support svcs</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Public administration</td>
<td>0.05</td>
<td>0.02</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>Education, hospitals and other personal svc</td>
<td>0.16</td>
<td>0.04</td>
<td>0.14</td>
<td>0.18</td>
</tr>
<tr>
<td>Total</td>
<td>0.10</td>
<td>0.10</td>
<td>0.03</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Notes: Authors’ own estimates.

1.4 Measures of Labor Market Flexibility

In this section, we employ the estimated sectoral distance parameters of the previous section to construct measures of labor market flexibility for each region $r$. These measures capture how flexible each region is from the perspective of manufacturing workers.

The geographic unit we use to define local labor markets are German Labor Market Areas (“Arbeitsmarktregionen”), described in detail in the data section. We observe 229 of these regions. Table 1.3 shows descriptives for sectoral employment shares across regions for the year 1998. It shows that there is indeed variation in the sectoral composition of regions, both in manufacturing and non-manufacturing employment. As an example, in 1998 the average region had a 10% share of employment in the Construction sector, while regions in the top quartile had shares that were 20% higher (i.e. 12% or more).

We will use this variation in employment shares and our measures of sectoral distances to construct measures of labor market flexibility. The basic intuition is that “Highly Flexible” regions will have large employment shares in sectors close to manufacturing, while inflexible regions will have employment in sectors distant to manufacturing. Formally, we will use the wage regression parameters estimated in Section 1.3 to predict potential wage changes for workers in each region. Then we will aggregate these predicted wage changes at the regional level, using sectoral reallocation probabilities as weights.

We start by obtaining the full sample of workers who held a manufacturing job in the years 1988 and 1998. Using their individual characteristics and the estimated parameters from Section 1.3, we predict the potential wage change related to observed human capital that each worker $i$ would face if she were to move to target sector $s$:

$$\Delta \ln \hat{y}_{i, m \rightarrow s} = X_i' \hat{\delta}_s$$
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

We base this prediction on the human capital characteristics of worker $i$: tenure in manufacturing, gender, age-group, and education.\textsuperscript{25}

We then proceed to compute our index of labor market flexibility by combining the predicted wage changes with sectoral reallocation probabilities ($\hat{p}_{i,m \rightarrow s}$). Let $\Omega (r, t)$ be the set of workers working in manufacturing in region $r$ at time $t$, and let $N_{rt}$ be the size of this set. We define our index as follows:

$$LMF_{rt} = \frac{1}{N_{rt}} \sum_{i \in \Omega (r, t)} \sum_{s} \hat{p}_{i,m \rightarrow s} X_{i}^{t} \hat{\beta}_{s}$$ \hspace{1cm} (1.7)

That is, our measure of labor market flexibility will be the expected reallocation costs (in terms of wages) for workers living in region $r$ at time $t$. This measure depends on sectoral distances faced by workers and their probabilities of reallocation (which vary at the individual and regional level).

We employ two proxies for reallocation probabilities, which results in two flexibility measures. In the first measure, we let $\hat{p}_{i,m \rightarrow s} = \pi_{st}^{r}$ (with $\pi_{st}^{r}$ defined as the employment share in industry $s$ in region $r$ at time $t$):

$$LMF_{1rt} = \frac{1}{N_{rt}} \sum_{i \in \Omega (r, t)} \sum_{s} \pi_{st}^{r} X_{i}^{t} \hat{\beta}_{s}$$

This formulation assumes that reallocation probabilities depend solely on sectoral employment shares (i.e. that workers in regions with a larger number of job opportunities in a particular sector are more likely to switch to such sector). While intuitive, this assumption ignores other factors that might influence sectoral reallocation probabilities. Our second formulation relaxes this assumption by allowing reallocation probabilities to be individual-specific. We do this by allowing reallocation probabilities to depend on individual-level characteristics (in addition to other regional factors). To compute these probabilities, we employ the estimated parameters of our selection model in Section 1.3. That is, we predict each worker’s reallocation probabilities based on the employment shares of her region and her individual characteristics (e.g. experience, gender, network of coworkers, etc). Formally, we let $\hat{p}_{i,m \rightarrow s} = f \left( Z_{i}; \hat{\Gamma}_{s} \right)$ where $Z_{i}$ is the vector of individual and regional characteristics from equation 1.5, and $\hat{\Gamma}_{s}$ represents the vector of corresponding parameters estimated in Section 1.3.\textsuperscript{26}

The result is a modified version of our labor market flexibility index:

\hspace{1cm} \textsuperscript{25}We omit region-specific variables and year dummies from these predictions. We also omit the intercept terms in $\hat{\beta}_{s}$.

\hspace{1cm} \textsuperscript{26}We employ the same list of regressors employed in the wage regressions (equation 1.5): experience, age group, education, gender, state and year dummies, in addition to worker $i$’s coworker networks. All worker $i$ characteristics are measured at the beginning of each period we study. Given the computational difficulties of obtaining the coworker networks for such a large sample, we constructed the coworker network for a random sample of 38\% of the main estimation sample.
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

1.5 Import Shocks and Worker Adjustment

In this section we provide evidence of the importance of labor market flexibility in how workers adjust to external shocks. For this purpose, we study the effect of national industry-level import shocks on worker outcomes. We build on the estimation framework developed by D. Autor et al. (2014), estimating the effects of trade shocks on workers by using an instrumental variable strategy. As in ADHS, we will instrument the increase in trade flows to manufacturing subindustries by the increase in trade flows from China to other “similar”
countries. This type of analysis compares the outcomes of manufacturing workers with similar initial characteristics (e.g. same education, initial tenure on the job, etc.), some of whom worked in manufacturing sub-industries that were greatly affected by import competition against others who initially worked in industries that were not affected by imports.

The baseline estimation equation is:

$$E_{ij\tau} = \gamma_{ij\tau} + \psi \Delta IP_{j\tau} + X_{i\tau}^t \theta + Z_{j\tau}^t \kappa + \epsilon_{ij\tau} \tag{1.8}$$

where $j$ represent the 3-digit manufacturing subindustry where worker $i$ is employed at the beginning of period $\tau$. $E_{ij\tau}$ represents the outcomes of interest such as cumulative earnings or employment. $X_{i\tau}$ is a vector of worker characteristics and $Z_{j\tau}$ represents a vector of initial year industry-level controls. $\Delta IP_{j\tau}$ represents the increase in (normalized) import flows from China and Eastern Europe to Germany in industry $j$ during time period $\tau$.\(^{27}\) As in ADHS, we instrument $\Delta IP_{j\tau}$ with the increase in import competition from China and Eastern Europe to other countries “similar” to Germany. In this setting, $\psi$ represents the causal effect of increases in import competition on worker outcomes. All estimates of $\psi$ shown in this section are from IV regressions.

We expand on ADHS’s strategy by studying how the effect of trade shocks ($\psi$) varies with the degree of flexibility of each labor market. To this end, we employ two different strategies: estimating the baseline equation by quartiles of $LMF_{rt}$ and a Two-Step estimation approach. We discuss each in detail below.

Estimation Sample

We focus on German manufacturing workers during the periods 1988-1998 and 1998-2008 as in Dauth, Findeisen, and Suedekum (2014). Our sample consists of all workers employed in manufacturing at the beginning of each period (i.e. 1988 and 1998). Our main outcome variables $E_{ij\tau}$ will be cumulative employment (measured in days) and normalized cumulative earnings.\(^{28}\) Table 1.4 presents the descriptives for these variables pooling both time periods. On average, workers in our sample experienced an increased in import competition of €14,000 per worker. There is large variation in the trade exposure as well. Workers in industries in the 25th percentile of trade exposure saw a €3,000 increase in import competition while workers in the 75th percentile were affected by a €15,000 shock. Cumulative earnings are on average 9.7 of pre-period earnings, and cumulative employment averages 2,886 days.\(^{29}\)

\(^{27}\)The construction of our trade exposure measures is detailed on Appendix A.1.

\(^{28}\)As in ADHS, we normalize earnings in period $\tau$ by the average annual earnings of the 5 years preceding period $\tau$. Formally, let $E_{ijt} \equiv$ Earnings in year $t$. Then, $E_{ij\tau} = \sum_{t \in \tau} \frac{E_{ijt}}{E_{ij0}}$. As ADHS point out, relative to the approach of taking the logarithm of earnings, this normalization has the benefit of being robust to zero values. Furthermore, this approach benefits from the baseline earnings not being contaminated by post-shock outcomes (since they are constructed using pre-shock years).

\(^{29}\)Note that because we take compute cumulative earnings and employment including both initial and end years, the figures we estimate are for a period of 11 years.
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

Table 1.4: Descriptives - Full Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>sd</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Imports per worker</td>
<td>14</td>
<td>26</td>
<td>3</td>
<td>9</td>
<td>15</td>
<td>8,023,968</td>
</tr>
<tr>
<td>Cumulative Earnings</td>
<td>9.7</td>
<td>5.4</td>
<td>6.3</td>
<td>10.38</td>
<td>11.98</td>
<td>8,023,968</td>
</tr>
<tr>
<td>Cumulative Employment</td>
<td>2,886</td>
<td>1,085</td>
<td>2,192</td>
<td>3,532</td>
<td>3,653</td>
<td>8,023,968</td>
</tr>
<tr>
<td>Age</td>
<td>41</td>
<td>11</td>
<td>32</td>
<td>41</td>
<td>50</td>
<td>8,023,968</td>
</tr>
<tr>
<td>Experience</td>
<td>14.0</td>
<td>5.5</td>
<td>10.5</td>
<td>13.0</td>
<td>18.3</td>
<td>8,023,968</td>
</tr>
</tbody>
</table>

Notes: Sample of workers in manufacturing jobs in the years 1988 and 1998. Earnings and employment measured for 10-year period following initial year. Cumulative earnings measured in multiples of avg annual earnings 5 years before start of period. Cumulative employment measured in days.

Regressions by Quartile of $LMF_{r\tau}$

In this section, we show the results of estimating the baseline estimation equation (1.8) and allowing the estimated effects to vary with our measures of labor market flexibility. We split regions into four quartiles based on their computed $LMF_{r\tau}$ index (Q=4 being the highest, most flexible group) and then interact the main regressor $\Delta IP_{j\tau}$ with dummies for each of these quartiles. Thus, we estimate the following specification using the IV approach described above:

$$E_{ij\tau} = \gamma_{\tau} + \mu_Q + \psi_Q \Delta IP_{j\tau} + X_{i\tau}'\theta + Z_{j\tau}'\kappa + \epsilon_{ij\tau}$$  (1.9)

Our vector of individual level controls $X_{i\tau}$ includes: age, gender, education, initial year firm tenure and labor market experience, state of residence dummies, and region-level trade shocks.\(^{30}\) The industry-level control vector $Z_{j\tau}$ includes industry level export growth during time period $\tau$ (at the 3-digit sub-industry level), the Herfindahl Index, the Ellison-Glaeser agglomeration index, and 1-digit industry dummies. In all estimations, we also include period and $LMF_{r\tau}$-quartile fixed effects.

Table 1.5 presents the main results of this chapter. Columns 1 and 3 show the results for our regressions at the national level. Consistent we previous findings, exposure to import competition leads to a reduction in cumulative employment.\(^{31}\) Columns 2 and 4 show how these effects vary with the degree of labor market flexibility of each region. In terms of earnings, import shocks seem to have a significantly larger negative effects on workers in the least flexible regions (those in the first quartile of the $LMF_{r\tau}$ distribution). The estimated $\psi_{Q1}$ is negative and statistically significant. The estimates for regions in the other three

\(^{30}\)We follow D. H. Autor, Dorn, and Hanson (2013) in constructing region-level measures of trade exposure by apportioning the national changes in industry imports to each region based on its initial employment structure. The construction of this variable is detailed in data appendix A.1.

\(^{31}\)Dauth, Findeisen, and Suedekum (2014) estimate that a €1,000 import shocks leads to a reduction in employment of 1.4 days.
Table 1.5: Regressions by Quartile of $LMF_{rt}$

<table>
<thead>
<tr>
<th></th>
<th>(1) Earnings</th>
<th>(2) Earnings</th>
<th>(3) Employment</th>
<th>(4) Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta IP_{j,t}$</td>
<td>-0.381***</td>
<td>-0.762***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.128)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q1} = 1)$</td>
<td>-0.978***</td>
<td>-1.966**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.297)</td>
<td>(0.637)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q2} = 1)$</td>
<td>-0.552***</td>
<td>-0.857**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
<td>(0.277)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q3} = 1)$</td>
<td>-0.388**</td>
<td>-0.736***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.178)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q4} = 1)$</td>
<td>-0.248**</td>
<td>-0.641***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
<td>(0.115)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>8,023,968</td>
<td>8,023,968</td>
<td>8,023,968</td>
<td>8,023,968</td>
</tr>
<tr>
<td>$\chi^2_3$</td>
<td>22.074</td>
<td>40.779</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.000]</td>
<td>[0.000]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Cumulative earnings normalized by the average annual earnings of the 5 years preceding period $\tau$. Cumulative employment measured in days. $\chi^2$ statistics test for equality of estimated effect of import exposure across quartiles of $LMF_{rt}$. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, p-values in brackets.

Quartiles are smaller in magnitude and become smaller with higher labor market flexibility. A test of equality for the four coefficients is rejected at the 0.0001% level. In terms of economic significance, the -0.978 coefficient means that moving a worker from the 25th to the 75th percentile of import competition exposure would result in a loss of 11% of initial annual earnings (over a 10 year period). The effect of import shocks on workers in more flexible regions is much smaller at 3%. In terms of employment, the results largely follow a similar pattern, with inflexible regions experiencing a much larger decline in total employment than regions in the upper end of the flexibility distribution. Again, a test of equality for the four coefficients is rejected at the 0.0001% confidence level.

In Table 1.6, we conduct several robustness tests to our main specification (both for earnings and employment). Columns 1 and 4 restrict our estimation sample to workers below age 50. Columns 2 and 5 exclude from the estimation sample all large labor market areas (defined as having more than one million workers at the beginning of period $\tau$). Columns 3 and 6 exclude Eastern Germany. All the results are qualitatively similar and follow the same pattern of larger losses for workers in inflexible regions. Overall, the results obtained
### Table 1.6: Regressions by Quartile of $LMF_{tt}$ - Robustness Tests

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_1} = 1)$</td>
<td>-0.908**</td>
<td>-0.873**</td>
<td>-0.723**</td>
<td>-1.850***</td>
<td>-1.719**</td>
<td>-1.391**</td>
</tr>
<tr>
<td></td>
<td>(0.242)</td>
<td>(0.262)</td>
<td>(0.226)</td>
<td>(0.525)</td>
<td>(0.554)</td>
<td>(0.516)</td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_2} = 1)$</td>
<td>-0.510***</td>
<td>-0.522**</td>
<td>-0.468***</td>
<td>-0.670**</td>
<td>-0.775**</td>
<td>-0.667**</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
<td>(0.160)</td>
<td>(0.139)</td>
<td>(0.242)</td>
<td>(0.268)</td>
<td>(0.242)</td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_3} = 1)$</td>
<td>-0.345**</td>
<td>-0.332*</td>
<td>-0.315**</td>
<td>-0.609***</td>
<td>-0.637***</td>
<td>-0.604***</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.139)</td>
<td>(0.109)</td>
<td>(0.140)</td>
<td>(0.181)</td>
<td>(0.152)</td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_4} = 1)$</td>
<td>-0.227**</td>
<td>-0.359**</td>
<td>-0.248***</td>
<td>-0.498***</td>
<td>-0.773***</td>
<td>-0.595***</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.126)</td>
<td>(0.068)</td>
<td>(0.116)</td>
<td>(0.224)</td>
<td>(0.121)</td>
</tr>
<tr>
<td>Excluding age 50 over</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Excluding large LMAs</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Excluding East Germany</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>$N$</td>
<td>5,887,698</td>
<td>5,514,732</td>
<td>7,137,718</td>
<td>5,887,698</td>
<td>5,514,732</td>
<td>7,137,718</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>25.094</td>
<td>19.617</td>
<td>23.235</td>
<td>35.141</td>
<td>25.588</td>
<td>33.630</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

**Notes:** Cumulative earnings normalized by the average annual earnings of the 5 years preceding period $\tau$. Cumulative employment measured in days. Large LMAs defined as those with employment size over 1,000,000 at the beginning of period $\tau$. $\chi^2$ statistics test for equality of estimated effect of import exposure across quartiles of $LMF_{tt}$. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, p-values in brackets.

so far are consistent with an important role of skill transferability and sectoral composition of labor markets in the effects of trade shocks on employment and earnings.

In Figure ??, we expand our analysis to the dynamic effects of import exposure. Panel A shows the estimated effects on earnings over time. Each point in the graph represents an estimate $\hat{\psi}_Q$ that relates the 10-year import penetration shock to cumulative earnings from the initial year through the year shown on the x-axis. Panel B shows a similar graph but with the outcome variable being the probability of transitioning to a non-manufacturing sector job (scaled by 100). Consistent with the findings of ADHS for the US, the effects of import exposure on earnings only become apparent a few years after the initial period. The results shown on the right panel indicate that import competition makes it more likely that workers will transition to jobs in non-manufacturing sectors. This trade-induced sectoral reallocation towards non-manufacturing jobs occurs in all types of regions and is larger in flexible regions.

In appendix D, table A.8, we further analyze the effect of import exposure on reallocation of employment across sectors. We estimate the same regression (equation 1.9) but use cumulative employment by industry as the dependent variable. Our findings indicate that import competition led to reallocation to sectors outside of manufacturing. The magnitude of the shift to non-manufacturing sectors (as a whole) varies across types of regions. The
Notes: Each panel plots the regression coefficients $\psi_q$ and 90% confidence intervals obtained from 10 separate regressions that relate the outcome variable on the y-axis to the 10-yr import exposure measures employed in the main estimation. The outcome variable on the left panel is cumulative earnings from the initial year through the year shown on the x-axis. The outcome variable on the right panel is the probability of transitioning to a non-manufacturing sector, multiplied by 100.

The largest employment shift to non-manufacturing industries occurs in regions in the highest quartile of labor market flexibility; however, the second largest shift to non-manufacturing occurs in regions in the lowest quartile. There is also large heterogeneity in the particular industries to which workers reallocate, but there is no discernible pattern related to labor market flexibility. One clear pattern is that workers in flexible regions are more likely to move to the Communication and Professional Services sector. In the most flexible regions (highest quartile), the employment shift to this industry accounts for more than 50% of the total employment shift outside of manufacturing, while in the most inflexible regions the share is much smaller at 31%.

Two-Step Estimation Approach

Our results in the previous section point to the important role that labor market flexibility plays in the effect of trade shocks on workers. To address concerns that our findings could result from our $LMF_{rt}$ index being correlated with unobserved region characteristics, in this section we present results from a two-step estimation approach that allows us to control for region-level characteristics that could affect the how workers are affected by shocks.

The methodology we employ is a two-step procedure. In the first step, we estimate our baseline IV regression (equation 1.8) but at the regional level, obtaining a set of $r_{ij}$ parameters for each region. In the second step, we regress $\psi_{ij}$ on our $LMF_{rt}$ index and a host of region-level controls. Formally, we have:

$$E_{ijrt} = \gamma_r + \psi_{ij} \cdot \Delta IP_{jrt} + X'_{it} \theta + Z'_{jt} \kappa + \epsilon_{ijrt}$$

(1.10)
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

Table 1.7: Two-Step Estimation Descriptives (First Step)

<table>
<thead>
<tr>
<th></th>
<th>Cumulative Earnings</th>
<th>Cumulative Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi_{r}^\tau$</td>
<td>-1.2778</td>
<td>-2.6691</td>
</tr>
<tr>
<td></td>
<td>(2.8383)</td>
<td>(5.7361)</td>
</tr>
</tbody>
</table>

Observations 458

Notes: Estimated $\psi_{r}^\tau$’s from equation 1.10. Mean of estimated coefficients ($\hat{\psi}_{r}^\tau$) reported (standard deviation in parenthesis). Cumulative earnings normalized by the average annual earnings of the 5 years preceding period $\tau$. Cumulative employment measured in days.

$$\psi_{r}^\tau = \eta_{r} + \delta LMF_{r}^\tau + W_{r}^\tau \theta + \omega_{r}$$ \tag{1.11}

where $W_{r}^\tau$ is a vector of region characteristics that includes: initial region employment size, initial share of manufacturing employment, total employment growth during period $\tau$, regional trade exposure during period $\tau$,\(^{32}\) as well as region level pre-trends in employment and wages.

We estimate each step separately and weight the second step by the inverse of variance of $\psi_{r}^\tau$. For the second step, we normalize all the region level regressors so that their coefficients are comparable. The results from the first step are presented in table 1.7. The point estimates indicate that the effects of import exposure on earnings and employment are negative in the average region. These effects, however, vary substantially across regions, as can be appreciated by the large standard deviation.

The results from the second-step estimation are presented in table 1.8. They show that labor market flexibility is important in determining the effect of shocks on workers, even after controlling for a host of region level characteristics, including overall employment growth. Column 1 shows the coefficient of $LMF_{r}^\tau$ without any controls, column 2 adds the region level controls listed above, and column 3 adds region-level pre-trends in employment and wages. In all cases, the coefficient for $LMF_{r}^\tau$ is highly significant and a strong predictor of the effects of import exposure on workers. Not surprisingly, the regional share of manufacturing jobs also plays an important role as does the region-level trade exposure. Qualitatively, these results are similar and consistent with those in the previous section. Labor market flexibility ameliorates the negative effects of import competition on workers’ earnings.

To sum up, the results from this exercise validate the findings from the previous section. Workers living in flexible labor markets are less affected by import shocks, irrespective of the overall conditions in their local labor markets. In addition, the results show that labor market flexibility is one of the most important determinants of the adjustment costs faced by negatively affected workers.

\(^{32}\)The construction of region-level trade exposure is detailed in footnote 30 and data appendix A.1.
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

Table 1.8: Two-Step Estimation (Second Step)

<table>
<thead>
<tr>
<th></th>
<th>Cumulative Earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>$LMF_{rr}$</td>
<td>0.102**</td>
</tr>
<tr>
<td></td>
<td>(0.0348)</td>
</tr>
<tr>
<td>Manufacturing Share$_{rr0}$</td>
<td>0.170***</td>
</tr>
<tr>
<td></td>
<td>(0.0490)</td>
</tr>
<tr>
<td>Regional Trade Exposure$_{rr}$</td>
<td>0.0470**</td>
</tr>
<tr>
<td></td>
<td>(0.0169)</td>
</tr>
<tr>
<td>Net Employment Growth$_{rr}$</td>
<td>-0.0021</td>
</tr>
<tr>
<td></td>
<td>(0.0414)</td>
</tr>
<tr>
<td>Initial Employment Size$_{rr0}$</td>
<td>0.0162</td>
</tr>
<tr>
<td></td>
<td>(0.0187)</td>
</tr>
</tbody>
</table>

Region Level Controls: No Yes Yes
Pre-trends (wage/emp): No No Yes
Observations: 458 458 458
Adjusted $R^2$: 0.012 0.039 0.069

Notes: Estimates from equation 1.11. Region level controls (in SD units) include: initial year employment size and employment share in manufacturing, initial year educational structure, net employment growth during period $\tau$, region-level trade exposure during period $\tau$ (see footnote 30 for details on this variable). Pre-trends include 3yr pretrend growth rates in overall employment, overall wage, manufacturing employment, and manufacturing wages.

1.6 Conclusion

The findings in this chapter highlight the important role that skill transferability and local labor markets have on the adjustment costs of workers. Using rich administrative data, we estimate new measures of skill transferability and show that there is indeed large heterogeneity in how workers can transfer theirs skills when they move across industries. We then show that this heterogeneity and the variation in employment opportunities across regions results in differing adjustment costs for workers affected by negative shocks. To capture this idea, we introduce the concept of Labor Market Flexibility and show that import shocks have a much smaller effect on manufacturing workers located in flexible regions than on those located in inflexible regions.

Our first contribution is the estimation of skill transferability measures and showing there is significant heterogeneity in skill transferability across sectors. Our second contribution is to show that skill transferability and the industry mix of local labor markets play a large role in the adjustment costs workers face in response to a national shock. Both of these findings have important implications for many areas of active research. These include the
CHAPTER 1. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

literature on job mobility and displacement costs, the skills and spatial mismatch literature, as well as the growing literature on local labor markets. More importantly, our findings are of particular relevance to the recent and growing literature on trade and labor market adjustments. Given that trade liberalization leads to sectoral reallocation, our findings suggests that sectoral distances and local labor markets should be an important component of any distributional analysis of the gains of trade.
Chapter 2

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

with Simon Galle and Andres Rodriguez-Clare

---

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. Roman Zarate provided excellent research assistance.
CHAPTER 2. SLICING THE PIE

While existing gravity models of international trade provide a transparent approach to quantify the aggregate welfare effects of trade (Arkolakis, Costinot, and Rodriguez-Clare, 2012; Costinot and Rodriguez-Clare, 2014), they remain silent on the associated distributional effects due to the standard representative-agent assumption.¹ Yet, a growing empirical literature shows that trade has sharply different effects on real incomes across different groups of agents (e.g. D. H. Autor, Dorn, and Hanson (2013), D. Autor et al. (2014), Dix-Carneiro and B. Kovak (2014), and 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 chapter 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 an Andrew Donald 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 \( i \),

\[
W_{ig} = \prod_{s} \text{Multi-sector ACR} \bigg( \frac{\hat{\lambda}_{iis}^{-\beta_{is}/\theta}}{\hat{\pi}_{igs}^{-\beta_{is}/\kappa}} \bigg),
\]

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, Costinot, and Rodriguez-Clare (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, \( \hat{\lambda}_{iis}^{-1/\theta} \). 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, \( \hat{\pi}_{igs}^{-1/\kappa} \). 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 2.1, 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, Donaldson, and Komunjer (2012) - henceforth CDK - to incorporate an upward sloping labor-supply curve to each sector.² In fact, as \( \kappa \to \infty \), our model collapses to

¹Notable 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.

²CDK extend the seminal Eaton and Kortum (2002) framework to a multi-sector environment. As shown
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 2.1, given changes in sectoral employment shares, $\hat{\pi}_{igs}$, a lower $\kappa$ implies a higher between-group variance in the welfare effects of trade shocks. The case $\kappa \to 1$ 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 2.1 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 ($\hat{\pi}_{igs}, s = 1, \ldots, S$) from the expenditure shares ($\beta_{is}, s = 1, \ldots, S$). 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

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.

This chapter 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.

For the specific-factors model (i.e., the model in which labor is sector specific), the formula in Equation 2.1 is valid for $\kappa = 1$ if we define $\pi_{igs}$ 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.

Formally, $S_{ig} \equiv \exp D_{KL}(\pi_{ig} \parallel \beta_i) \equiv \exp \sum_s \beta_{is} \ln(\beta_{is}/\pi_{igs})$. 

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 (D. H. Autor, Dorn, and Hanson, 2013; Dauth, Findeisen, and Suedekum, 2014; Dix-Carneiro and B. Kovak, 2014; B. K. 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 chapter 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

---

6B. K. Kovak (2013) proposes a small-economy model to understand, up to a first-order approximation, the differential effect of tariff changes across regions. Compared to that, ours is a general equilibrium model for the world economy that connects to the gravity literature and yields tractable expressions for aggregate and group-level welfare effects in terms of changes in trade and employment shares, which in turn can be computed for counterfactual shocks using the techniques in Dekle, Eaton and Kortum (2008).

7In future work we plan to allow $\theta$ to vary across sectors. We can also allow $\kappa$ to vary across groups of workers, but doing so would require estimating $\kappa$ separately for each group, which is a significant challenge. We have developed extensions of our methodology to allow for intermediate goods, non-tradables or home production, and mobility of workers across regions, but at the time of writing we have not implemented these extensions in the data.

8As in ACR, the gains from trade are computed as the negative of the proportional welfare change caused by the country moving to autarky.
compared to autarky, the rise of China is pro-rich in our simulations.

Our work is related to several research areas in trade. In addition to the above-mentioned research on trade and local-labor markets, there is a large theoretical and empirical literature on the unequal effects of trade on labor-market outcomes – see for example D. Autor et al. (2014), Costinot and Vogel (2010), Burstein and Vogel (2012), Helpman, Itskhoki, Muendler, et al. (2012), and Krishna, Poole, and Senses (2012). A literature focusing specifically on the effect of trade shocks on the reallocation of workers across sectors finds significant effects for developed countries (Artuç, Chaudhuri, and McLaren, 2010; Revenga, 1992), which is the focus of our analysis.\footnote{See also Gourinchas (1999) and Kline (2008) for evidence of substantial reallocation in response to sectoral (but not trade) price shocks.}

Artuç, Chaudhuri, and McLaren (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 A Kerem Coşar (2010), A. Kerem Coşar, Guner, and Tybout (2013), Kam-bourov (2009) and Ritter (2012).\footnote{In 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 Muendler (2011)), and Dix-Carneiro (2014).} While all these papers focus on the differential impact of trade through the earnings channel, another set of papers focuses on the expenditure channel, as in Atkin and Donaldson (2014), Faber (2014), Fajgelbaum and Khandelwal (2014) and Porto (2006).

Our work 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, Hurst, et al. (2013) for the productivity literature. Closer to our work, Burstein, Morales, and Vogel (2015b) 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 D. H. Autor, Dorn, and Hanson (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

\footnote{There 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, Decaluwe, and Robichaud (2008) integrate multiple chapters on methodology and empirical findings of the CGE approach into a book-length discussion.}
are the same for all groups. Instead, 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 chapter is structured as follows. In Section 2.1 we start out with a short empirical overview of the relation between trade and sectoral reallocation in Germany. Section 2.2 provides the baseline model and its extensions. The data is described in Section 2.3, while Section 2.4 presents our counterfactual analysis of a German return to autarky and of a Chinese technology shock for different values of \( \kappa \). Section 2.5 discusses estimation approach for the parameter \( \kappa \), presents our main results, and finally uses a Bartik-style methodology as in D. H. Autor, Dorn, and Hanson (2013) to compare the distributional implications of the China trade shock in our model with those in the data. Section 2.6 concludes.

### 2.1 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 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.

### 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

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

\[
\frac{y_t - y_{t-1}}{E_t} = (\beta_{ts} - \beta_{t-1}) \lambda_{ts} + (\lambda_{ts} - \lambda_{t-1}) \beta_{ts} - \frac{X_t}{E_t} + \frac{X_{t-1}}{E_{t-1}}.
\]

"Output-share" reallocation
"Home-induced" reallocation
"Trade-induced" reallocation

Figure 2.1: Decomposition of Changes in Output Shares

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 2.1, 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.”

We now quantify the share of trade-induced and home-induced reallocation in the output-share reallocation. Define \( G_{ts} \equiv y_{ts} - y_{t-1} \), \( H_{ts} \equiv (\beta_{ts} - \beta_{t-1}) \lambda_{ts} \), \( T_{ts} \equiv (\lambda_{ts} - \lambda_{t-1}) \beta_{ts} - \frac{X_t}{E_t} + \frac{X_{t-1}}{E_{t-1}} \), such that \( G_{ts} = H_{ts} + T_{ts} \). We want to know what share of the variance of changes in output shares \( (G_{ts}) \) is home-induced (related to \( H_{ts} \)), and what share is trade-induced (related to \( T_{ts} \)). We can answer this question by running two separate regressions where we either regress \( H_{ts} \) on \( G_{ts} \), or \( T_{ts} \) on \( G_{ts} \).\(^{13}\) The results are shown in Table 2.1. Around 64%
Table 2.1: 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>0.643***</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

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

Figure 2.2: Relation between Sectoral Output and Employment Shares

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.

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 $\pi_{ts}^t \equiv L_{ts}^t / L_t$. 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 2.2.

**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, Findeisen, and Suedekum (2014). Specifically, for each sector $s$, we construct an
CHAPTER 2. SLICING THE PIE

Table 2.2: Output and Labor Reallocation in Response to Trade Shock

<table>
<thead>
<tr>
<th></th>
<th>Output Shares (%)</th>
<th>Employment Share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Difference</td>
<td>(2) Growth Rate</td>
</tr>
<tr>
<td>(\Delta IP_{East\rightarrow Other}^{st})</td>
<td>-0.0128</td>
<td>-0.00304</td>
</tr>
<tr>
<td></td>
<td>(0.0156)</td>
<td>(0.00184)</td>
</tr>
<tr>
<td>Observations</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>((R^2))</td>
<td>0.046</td>
<td>0.164</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.

\* \(p < 0.05\), \** \(p < 0.01\), \*** \(p < 0.001\)

import penetration measure \(\Delta M_{East\rightarrow Other}^{st}\) 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 \(t\).\(^{14}\)

Formally,

\[
\Delta IP_{st}^{East\rightarrow Other} = \frac{\Delta M_{st}^{East\rightarrow Other}}{L_{st}^{Germany}},
\]

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

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

with dependent variable \(v_{st} \equiv z_{st} - z_{st-1}\) or \(v_{st} \equiv \frac{z_{st}}{z_{st-1}} - 1\) 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.

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.

\(^{14}\)The instrument group employed by Dauth, Findeisen, and Suedekum (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, 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, Findeisen, and Suedekum (2014).
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.

2.2 Theory: Baseline Model

We present a multi-sector, multi-country, Ricardian model of trade with heterogeneous workers. There are \( N \) countries and \( S \) sectors. Each sector is modeled as in Eaton and Kortum (2002 – henceforth EK): there is a continuum of goods, preferences across goods within a sector are CES with elasticity of substitution \( \sigma \), and technologies have constant returns to scale with 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 \( \tau_{ij} \geq 1 \) 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. 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 \( g \).\(^{15}\) Thus, workers within each group are ex-ante identical but ex-post heterogeneous due to different ability draws across sectors, as in Roy (1951), while workers across groups also differ in that they draw their abilities from different distributions. The number of workers in a group is fixed and denoted by \( L_{ig} \). In the baseline model labor supply is inelastic – workers simply choose the sector to which they supply their entire labor endowment.

If \( \kappa \rightarrow \infty \) 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 \( \tau_{ij} \rightarrow \infty \) 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, Hurst, et al. (2013)).\(^{16}\)

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

---

\(^{15}\)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.

\(^{16}\)There 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 \( L/L_i \) 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.
technologies are national, wages cannot differ across groups. Let wages per efficiency unit in sector \( s \) of country \( i \) be denoted by \( w_{is} \). From EK we know that the demand for efficiency units in sector \( s \) in country \( i \) is

\[
\frac{1}{w_{is}} \sum_j \lambda_{ij} \beta_{js} Y_j,
\]

where \( Y_j \) is the total income for country \( j \) and \( \lambda_{ij} \) are sectoral trade shares given by

\[
\lambda_{ij} = \frac{T_{is} (\tau_{ij} w_{is})^{-\theta}}{\sum_l T_{ls} (\tau_{is} w_{is})^{-\theta}}.
\]

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

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

where \( \gamma \equiv \Gamma(1 - \frac{1}{\theta})^{1/(1-\sigma)} \).

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

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

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

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

where \( \eta \equiv \Gamma(1 - 1/\kappa) \).

One implication of this lemma is that income levels per worker are equalized across sectors. That is, for group \( g \), we have

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

\(^{17}\)Lemma 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 by \( \kappa/(1 - \rho) \).
CHAPTER 2. SLICING THE PIE

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., $w_{is}E_{igs}/\sum w_{ik}E_{igk}$) is also given by $\pi_{igs}$. Note also that total income of group $g$ in country $i$ is $Y_{ig} \equiv \sum_s w_{is}E_{igs} = \eta L_{ig} \Phi_{ig}$. 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

$$E LD_{is} \equiv \frac{1}{w_{is}} \sum_j \lambda_{ijs} \beta_{js} Y_j - \sum_g E_{igs}. \quad (2.4)$$

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

Comparative Statics

Consider some change in trade costs or technology parameters. We proceed as in Dekle, Eaton, and Kortum (2008) and solve for the proportional change in the endogenous variables. Formally, using notation $\hat{x} \equiv x'/x$, we consider shocks $\hat{\tau}_{ijs}$ 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 $E LD'_{is} = 0$ for all $i, s$. Noting that $w'_{is}E'_{igs} = \hat{\pi}_{igs} \hat{\Phi}_{ig} \hat{\pi}_{igs} Y_{ig}$, equation $E LD'_{is} = 0$ can be written as

$$\sum_g \hat{\pi}_{igs} \hat{\Phi}_{ig} \hat{\pi}_{igs} Y_{ig} = \sum_j \hat{\lambda}_{ijs} \lambda_{ijs} \beta_{js} \sum_g \hat{\Phi}_{jg} Y_{jg} \quad (2.5)$$

with

$$\hat{\Phi}_{ig} = \left( \sum_k \pi_{igk} \hat{w}_{ik}^\kappa \right)^{1/\kappa}, \quad (2.6)$$

$$\hat{\lambda}_{ijs} = \frac{\hat{T}_{is} (\hat{\tau}_{ijs} \hat{w}_{is})^{-\theta}}{\sum_k \lambda_{kjs} \hat{T}_{ks} (\hat{\tau}_{kjs} \hat{w}_{ks})^{-\theta}}, \quad (2.7)$$

and

$$\hat{\pi}_{igs} = \frac{\hat{w}_{is}^\kappa}{\sum_k \pi_{igk} \hat{w}_{ik}^\kappa}. \quad (2.8)$$

This equation can be solved for $\hat{w}_{is}$ given data on income levels, $Y_{ig}$, trade shares, $\lambda_{ijs}$, expenditure shares, $\beta_{is}$, labor allocation shares $\pi_{igs}$, and labor endowments, $L_{ig}$, and the trade-cost shocks, $\hat{\tau}_{ijs}$. From the $\hat{w}_{is}$ we can then solve for all other relevant changes, including changes in trade shares using (2.7) and changes in employment shares using (2.8).
Welfare Effects

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

\[
\frac{\hat{W}_{ig}}{\hat{P}_{ig}} = \hat{\Phi}_{ig} \prod_s \hat{P}_{is}^{-\beta_{is}}. \tag{2.9}
\]

From (2.3) and (2.7) and given \( \hat{T}_{is} = 1 \) for all \( s \) we have \( \hat{P}_{is} = \hat{w}_{is} \hat{\lambda}_{is}^{1/\theta} \) while from (2.6) and (2.8) we have \( \hat{w}_{is}/\hat{\Phi}_{ig} = \pi_{igs}^{1/\kappa} \). Combining these two results with (2.9) 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

\[
\hat{W}_{ig} = \prod_s \hat{\lambda}_{is}^{-\beta_{is}/\theta} \cdot \prod_s \hat{\pi}_{igs}^{-\beta_{is}/\kappa}. \tag{2.10}
\]

The RHS of the expression in (2.10) has two components: the term \( \prod_s \hat{\lambda}_{is}^{-\beta_{is}/\theta} \) 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 \( \prod_s \hat{\lambda}_{is}^{-\beta_{is}/\theta} \), 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 \( \prod_s \hat{\lambda}_{is}^{-\beta_{is}/\theta} \) 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 \( s = 1, \ldots, S \).

An alternative way to derive the result in Proposition 1 is to start from the trade and labor supply elasticities implied by our model and proceed as in ACR to infer changes in prices from trade shares and changes in wages from labor shares. Using notation \( p_{ij} \equiv w_{is} \tau_{ij} \), the trade side of the model implies

\[
\frac{d \ln (\lambda_{ij}/\lambda_{jj})}{d \ln (p_{ij}/p_{jj})} = -\theta, \tag{2.11}
\]

while on the labor side we have

\[
\frac{d \ln (\pi_{ij}/\pi_{jk})}{d \ln (w_{ij}/w_{jk})} = -\kappa. \tag{2.12}
\]

Envelope conditions for the consumption and work choices of agents imply

\[
d \ln P_{js} = \sum_i \lambda_{ij} d \ln p_{ij}s
\]
CHAPTER 2. SLICING THE PIE

and

\[ d \ln Y_{jg} = \sum_s \pi_{jgs} d \ln w_{ij{s}}, \]

respectively. Using \( d \ln p_{j{s}} = w_{js} \), solving for \( d \ln p_{j{s}} \) from Equation 2.11, and plugging into the expression for \( d \ln P_{j{s}} \) yields \( d \ln P_{j{s}} = d \ln w_{js} + (1/\theta) d \ln \lambda_{j{s}} \). Similarly, we can get \( d \ln Y_{jg} = d \ln w_{js} -(1/\kappa) d \ln \pi_{jgs} \) for any \( s \). Integrating these expressions yields \( \dot{P}_{j{s}} = \dot{w}_{j{s}} \hat{\lambda}_{j{s}}^{1/\theta} \)

and \( \dot{Y}_{jg} = \dot{w}_{j{s}} \hat{\pi}_{jgs}^{-1/\kappa} \) for any \( s \), and hence \( \dot{Y}_{jg}/\dot{P}_{j{s}} = \hat{\lambda}_{j{s}}^{-1/\theta} \hat{\pi}_{jgs}^{-1/\kappa} \). Cobb-Douglas preferences with expenditure shares \( \beta_{j{s}} \) then lead to the expression in (2.10).

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

\[ \hat{W}_i = \prod_s \hat{\lambda}_{tis}^{-\beta_{tis}/\theta} \cdot \sum_g \left( \frac{Y_{ig}}{Y_i} \right) \prod_s \hat{\pi}_{tis}^{-\beta_{tis}/\kappa}. \]

The aggregate welfare effect of a trade shock is no longer given by the multi-sector ACR term (i.e., \( \hat{W}_i \neq \prod_s \hat{\lambda}_{tis}^{-\beta_{tis}/\theta} \)). 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

\[ \frac{\hat{Y}_{ig}}{\hat{Y}_i} = \frac{\prod_s \hat{\pi}_{tis}^{-\beta_{tis}/\kappa}}{\sum_h \left( \frac{Y_{ih}}{Y_i} \right) \prod_s \hat{\pi}_{ths}^{-\beta_{tis}/\kappa}}. \tag{2.13} \]

The term \( \prod_s \hat{\pi}_{tis}^{-\beta_{tis}/\kappa} \) 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 \( \pi_{ig} \equiv \{\pi_{i{g}1}, \pi_{i{g}2}, ..., \pi_{i{g}S}\} \) from \( \beta_{i} \equiv \{\beta_{i1}, \beta_{i2}, ..., \beta_{iS}\} \) is given by \( D_{KL}(\pi_{ig} \parallel \beta_{i}) \equiv \sum_s \beta_{is} \ln(\beta_{is}/\pi_{tis}) \). Note that if group \( g \) in country \( i \) was in full autarky (i.e., not trading with any other group or country) then \( \pi_{tis} = \beta_{tis} \). 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

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

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 \( \prod_s \hat{\lambda}_{tis}^{-\beta_{tis}/\theta} \)). Consider a group \( g \) in country \( i \) that happens to have efficiency parameters \( (A_{i{g}1}, ..., A_{i{g}S}) \) 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.

**Gains from Trade**

Following ACR, we define the gains from trade as the negative of the proportional change in real income for a shock that takes the economy back to autarky: $GT_i \equiv 1 - \hat{W}^A_i$ and $GT_{ig} \equiv 1 - \hat{W}^A_{ig}$. 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 (2.5) only requires knowing the values of trade and employment shares for country $i$, namely $\lambda_{iis}$ for all $s$ and $\pi_{i gs}$ for all $g, s$. This can be seen by letting $\hat{\tau}_{ijs} \to \infty$ in Equation (2.5), which yields

$$\sum_g \hat{\pi}_{igs} \Phi_{ig} \pi_{i gs} Y_{ig} = \beta_{is} \sum_g \Phi_{ig} Y_{ig},$$

(2.14)

**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

$$\hat{W}^A_i = \prod_s \lambda_{iis}^{\beta_{is}/\theta} \cdot \exp \left[ -\frac{1}{\kappa} D_{KL}(\pi_i \| \beta_i) \right].$$

Since $D_{KL}(\pi_i \| \beta_i) > 0$, 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 Rodriguez-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

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

The term $D_{KL}(\pi_{ig}^A \| \beta_i) - D_{KL}(\pi_{ig} \| \beta_i)$ 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 $D_{KL}(\pi_{ig} \| \beta_i) < D_{KL}(\pi_{ig}^A \| \beta_i)$, and hence lower gains from trade.
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

\[
\lim_{\kappa \to 1} \hat{Y}_{ig} = \sum_s \pi_{igs} \hat{w}_{is}. \tag{2.15}
\]

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

\[
\lim_{\kappa \to 1} \hat{r}_{is} = \frac{\hat{w}_{is}}{\sum_k r_{ik} \hat{w}_{ik}}.
\]

Combined with \( \lim_{\kappa \to 1} \hat{Y}_i = \sum_k r_{ik} \hat{w}_{ik} \) we finally get

\[
\lim_{\kappa \to 1} \frac{\hat{Y}_{ig}}{\hat{Y}_i} = \sum_s \pi_{igs} \hat{r}_{is}. \tag{2.16}
\]

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 D. H. Autor, Dorn, and Hanson (2013), we can instrument the group-level Bartik-style variable \( \sum_s \pi_{igs} \hat{r}_{is} \) with \( \sum_s \pi_{iga} \Delta \Pi_{i East \to \text{Other}} \) 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.\(^{18}\) 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 (2.14) combined with (2.8) we get

\[
\hat{w}_{is} \sum_g \hat{F}_{ig}^{1-\kappa} \pi_{igs} Y_{ig} = \beta_{is} \hat{Y}_i Y_i.
\]

Setting \( \hat{Y}_i = 1 \) by choice of numeraire and setting \( \kappa = 1 \) yields \( \hat{w}_{is} = \beta_{is}/r_{is}. \)

\(^{19}\) Plugging into (2.15) yields

\[
\lim_{\kappa \to 1} \frac{\hat{Y}_{ig}}{\hat{Y}_i} = I_{ig} \equiv \sum_s \pi_{igs} \frac{\beta_{is}}{r_{is}}. \tag{2.17}
\]

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

\(^{18}\) 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.

\(^{19}\) 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 \( \hat{w}_{is} = \beta_{is}/r_{is} = 1 - FCT_{is}/L_{is} \).
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 \( \tilde{Y}_{ig}^A / \tilde{Y}_i^A \geq 1 \) and that
the variance of \( \tilde{Y}_{ig}^A / \tilde{Y}_i^A \) across \( g \) falls with \( \kappa \). Of course, one can also use the result in (2.17)
to rewrite the result in (2.16) and get an expression for any foreign shock as
\[
\lim_{\kappa \to 1} \frac{\tilde{Y}_{ig}}{\tilde{Y}_i} = \frac{1}{I_{ig}}.
\]

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 \( \rho \to \infty \).\(^{20}\)

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.\(^{21}\)

We will compare these effects with the standard ones, \( \bar{W}_i \) and \( GT_i = 1 - \bar{W}_i^A \). Given our
definition of \( V_i \), we have \( \hat{U}_i = \bar{W}_i / \bar{V}_i \) \( IGT_i = 1 - \frac{1 - GT_i}{V_i^A} \). If the foreign shock increases
inequality (\( \hat{V}_i > 1 \)) then \( \hat{U}_i < \bar{W}_i \) while if inequality falls (\( \hat{V}_i < 1 \)) then \( \hat{U}_i > \bar{W}_i \). Similarly,
if inequality is higher in the observed equilibrium than in autarky then \( IGT_i < GT_i \), while
in the opposite case \( IGT_i > GT_i \).

Alternative Models and Extensions

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

\(^{20}\) Related welfare measures are examined by Cordoba and Verdier (2008) and Heathcote, Storesletten,
and Violante (2008) and Jones and Klenow (2016), who incorporate income risk into the analysis of aggregate
welfare in macro models without trade.

\(^{21}\) 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 \( Pr(q \leq Q) = e^{-\Phi_{\tilde{q}} Q^{\rho}} \). Hence, inequality
measures which are invariant to the scale of the Fréchet are unaffected by the trade shocks.
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

\[
ELD_{is} = \frac{1}{w_{is}} \sum_{j,g} \lambda_{ij}s \beta_{js} \xi_{jg} Y_{jg} - \sum_{g} E_{igs},
\]

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

\[
ELD_{i0} = \frac{1}{w_{i0}} (1 - \xi_{ig}) Y_{ig} - E_{i0gs}.
\]

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

\[
\xi_{ig} = \frac{\left( \prod_{s \geq 1} P_{is}^{\beta_{is}} \right)^{1-\chi}}{\left( \prod_{s \geq 1} P_{is}^{\beta_{is}} \right)^{1-\chi} + P_{i0}^{1-\chi}},
\]

with \( P_{is} \) for \( s \geq 1 \) still given \( 2.3 \) and \( P_{i0} = \eta^{-1} T_{i0}^{-1/\theta} w_{i0} \). Without loss of generality we assume henceforth that \( T_{i0} = \eta^{-\theta} \) for all \( i \), so that \( P_{i0} = w_{i0} \).

Noting that \( \lambda_{ij}, \xi_{ig}, Y_{jg} \) and \( E_{igs} \) are all functions of the matrix of wages \( \boldsymbol{w}^T \equiv \{w_{is}\} \) for all \( i \) and \( s = 1, ..., S \) and the vector \( \boldsymbol{w}^{NT} \equiv \{w_{i0}\} \) for all \( ig \), the system \( ELD_{is} = 0 \) for all \( i, s \) and \( ELD_{i0} \) for all \( ig \) is a system of equations in \( \boldsymbol{w}^T \) and \( \boldsymbol{w}^{NT} \) 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.

\[
^{22}\text{Using notation } w_{igs} \text{ for wages for convenience (in equilibrium we still have } w_{igs} = w_{is} \text{ for all } s \geq 1), \text{ employment shares are now } \pi_{igs} = A_{igs} w_{igs}/\Phi_{ig} \text{ while the supply of efficiency units is } E_{igs} = \frac{\gamma_{igs}}{w_{igs}} \pi_{igs} L_{ig}, \text{ with } \Phi_{ig} = \sum_s A_{igs} w_{igs}.\]
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 $w_{igM} \equiv (\sum_{s \geq 1} A_{igs} w_{is}^{\kappa})^{1/\kappa}$, this can be rewritten as

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

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 $w_{igM}/\prod_{s \geq 1} P_{is}^\beta_{is}$ 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 Karabourbounis (2013). In the quantitative analysis below we will show results with the model extended to allow for home production using this value of $\chi$.

**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 (2.2) and (2.3), except that instead of $w_{is}$ we now have $c_{is}$, where $c_{is}$ is given by

$$c_{is} = w_{is}^{1-\alpha_{is}} \prod_{k} P_{ik}^{\alpha_{iks}}.$$

(2.18)

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 (2.3) (but with $w_{is}$ replaced by $c_{is}$) yields

$$P_{js} = \eta^{-1} \left(\sum_{i} T_{is} r_{js} w_{is}^{-(1-\alpha_{is})}\prod_{k} (P_{ik}^{-\theta})^{\alpha_{iks}}\right)^{-1/\theta}.$$


CHAPTER 2. SLICING THE PIE

Given wages, this equation represents a system of $N \times S$ equations in $P_{js}$ for all $j$ and $s$, which can be used to solve for $P_{js}$ and hence $c_{is}$ and $\lambda_{ijs}$. 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 $R_{is} = \sum_{j=1}^{n} \lambda_{ijs} X_{js}$ 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,

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

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

$$ELD_{is} \equiv R_{is} - \sum_{g} E_{igs}.$$  

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

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

where $\hat{\Phi}_{ig}$ is as in (2.6) and

$$\hat{\lambda}_{ijs} = \frac{\left( \hat{\pi}_{ijs} W_{is}^{1-\alpha_{is}} \prod_{k} \hat{P}_{ik}^{\alpha_{iks}} \right)^{-\theta}}{\sum_{l} \lambda_{iljs} \left( \hat{\pi}_{iljs} W_{ls}^{1-\alpha_{is}} \prod_{k} \hat{P}_{ik}^{\alpha_{iks}} \right)^{-\theta}},$$

$$\hat{P}_{js}^{-\theta} = \sum_{i} \lambda_{ijs} \hat{\pi}_{ijs} W_{is}^{-(1-\alpha_{is})\theta} \prod_{k} \left( \hat{P}_{ik}^{-\theta} \right)^{\alpha_{iks}},$$

and

$$\hat{R}_{is} R_{is} = \sum_{j} \lambda_{ijs} \hat{\lambda}_{ijs} \left( \beta_{js} \sum_{g} \hat{\Phi}_{ig} Y_{jg} + \sum_{k=1}^{S} \alpha_{jsk} \hat{R}_{jk} R_{jk} \right).$$

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

$$\tilde{W}_{ig} = \prod_{s,k} \lambda_{iik}^{-\beta_{is}\tilde{a}_{is}\kappa}/\theta \prod_{s,k} n_{igk}^{-\beta_{is}\tilde{a}_{is}\kappa(1-\alpha_{ik})/\kappa}$$

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

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.\(^{23}\) 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.\(^{24}\)

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 Frechet distribution with parameters $\kappa$ and $A_{ish}$. Workers are fully described by a matrix $z = \{z_{hs}\}$ and an origin region $g$. A worker from region $g$ in country $i$ that wants to work in region $h$ of country $i$ has a proportional adjustment to income determined by $\zeta_{igh}$, with $\zeta_{igg} = 1$ and $\zeta_{igh} \leq 1$ for all $i, g, h$. Thus, a worker from $g$ that works in region $h$ in sector $s$ has income of $w_{is}\zeta_{igh}z_{hs}$.

We now let

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

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

\(^{23}\)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 Frechet distribution with parameters 1 and $\kappa$, and that their efficiency units if they work in $(g, s)$ are $A_{ig}^{1/\kappa}x_s$ (note that this is isomorphic to our current specification because $\Pr(z \leq a) = \Pr(A_{ig}^{1/\kappa}x \leq a)$). In this interpretation, $A_{ig}^{1/\kappa}$ 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. D. H. Autor, Dorn, and Hanson (2013), Dauth, Findeisen, and Suedekum (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.
CHAPTER 2. SLICING THE PIE

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

\[
\pi_{igfs} \equiv \int_{\Omega_{gfs}} dF(z) = \frac{A_{fs}(\zeta_{gfw})^\kappa}{\Phi_{ig}^\kappa},
\]

where \( \Phi_{ig}^\kappa \equiv \sum_{h,k} A_{hk} (\zeta_{gfw})^\kappa \). The efficiency units supplied by this group in sector \((f, s)\) are given by

\[
E_{igfs} \equiv L_{ig} \int_{\Omega_{gfs}} z_{fs} dF_i(z) = \pi_{igfs} \gamma L_{ig} \frac{\Phi_{ig}}{w_{is} \zeta_{igf}}.
\]

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

Let \( \mu_{ihs} \equiv \sum_s \pi_{ihs} \) be the share of workers from \( g \) that work in \( h \). It is easy to verify that \( \pi_{ihs}/\mu_{ihs} = \pi_{ihs}/\mu_{ihs} \) for all \( i, g, h, s \). Thus, conditional on locating in region \( h \), all workers irrespective of their origin have sector employment shares given by \( \pi_{ihs} = \pi_{ihs}/\mu_{ihs} \). The shares \( \pi_{ihs} \) and \( \mu_{ihs} \) 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

\[
ELD_{is} \equiv \frac{1}{w_{is}} \sum_j \lambda_{ij}s \beta_{js} Y_j - \sum_{g,h} E_{ighs}.
\]

Noting that \( \lambda_{ij}s, Y_j \) 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

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

with \( \hat{\Phi}_{ig}^\kappa = \sum_{h,s} \mu_{ihs} \pi_{ihs} \hat{w}_{is}^\kappa \), (2.7) and \( \hat{\pi}_{ihs} = \hat{\pi}_{ihs}/\hat{\mu}_{ihs}, \hat{\pi}_{ihs} = \hat{w}_{is}/\hat{\Phi}_{ig}^\kappa \), and \( \hat{\mu}_{ihs} = \sum_s \pi_{ihs} \hat{\pi}_{ihs} \). Equation (2.5) can be solved for \( \hat{w}_{is} \) given data on income levels, \( Y_{ig} \), trade shares, \( \lambda_{ij}s \), migration shares \( \mu_{ihs} \), employment shares \( \pi_{ihs} \), and the shocks, \( \hat{\pi}_{ihs} \) and \( \hat{T}_{js} \). In turn, given \( \hat{w}_{is} \), changes in trade shares can be obtained from (2.7), while changes in migration and employment shares can be obtained from the expressions for \( \hat{\pi}_{ihs} \) and \( \hat{\mu}_{ihs} \) above.

Given \( \hat{w}_{ik} \), the following proposition analogous to Proposition 1 characterizes the impact of a trade shock on ex-ante real wages for different groups of workers.
Table 2.3: 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>

Proposition 4. Given some trade shock, the ex-ante percentage change in the real wage of group \( g \) in country \( i \) is given by

\[
\hat{W}_{ig} = \prod_s \hat{\lambda}_{is}^{-\beta_s/\theta} \cdot \prod_s (\hat{\mu}_{igg} \hat{\pi}_{igs})^{-\beta_s/\kappa}
\]

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

2.3 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 \( (\pi_{ig}) \) 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

\(^{25}\)We are in the process of reproducing the simulations for other years.
inhabitants as of December of 2008. In the current version of the data, we observe 265 of these regions (all located in West Germany).\footnote{The employment counts are based on the job in which workers spent the longest spell during 2003.} \footnote{In cases where $\pi_{ig}=0$, we imputed a small value to make the data consistent with our model.}

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

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

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

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

In our estimations in Section 2.5, 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, Findeisen, and Suedekum (2014).

### 2.4 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, $\hat{W}_{ig}$, $\hat{W}_i$ and $\hat{U}_i$, respectively, for $i =$ Germany and $g = 1, ..., 265$. In all the ensuing exercises, we follow Costinot and Rodriguez-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).

#### A move to autarky

Table 2.4 summarizes the results for $\hat{W}_{ig}$ and $\hat{W}_i$. 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
CHAPTER 2. SLICING THE PIE

Table 2.4: 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>$\bar{w}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regional income change:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<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</td>
<td>0.920</td>
<td>0.920</td>
<td>0.920</td>
</tr>
<tr>
<td>N</td>
<td>265</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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.

Figure 2.3 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, $r_{is}^e = \beta_{is}$, 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 2.5 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 2.4 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 2.2, $I_{ig} \equiv \sum_g \pi_{igs} \beta_{ris}$ (in logs, horizontal axis). In Section 2.2 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

$^{29}$The table displays both $\bar{w}$ and the mean value for $\hat{W}_{ig}$. 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 $\kappa \to 1$. 


one, indicating that the $I_{1y}$ 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 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”.
### Table 2.5: Index of sectoral import competition

<table>
<thead>
<tr>
<th>$\beta_{is}/r_{is}$</th>
<th>Industry</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.224 s = C15T16</td>
<td>Food products, beverages and tobacco</td>
</tr>
<tr>
<td>1.26 s = C17T19</td>
<td>Textiles, textile products, leather and footwear</td>
</tr>
<tr>
<td>0.865 s = C20</td>
<td>Wood and products of wood and cork</td>
</tr>
<tr>
<td>0.838 s = C21T22</td>
<td>Pulp, paper, paper products, printing and publishing</td>
</tr>
<tr>
<td>9.159 s = C23</td>
<td>Coke, refined petroleum products and nuclear fuel</td>
</tr>
<tr>
<td>1.342 s = C24</td>
<td>Chemicals and chemical products</td>
</tr>
<tr>
<td>0.715 s = C25</td>
<td>Rubber and plastics products</td>
</tr>
<tr>
<td>0.989 s = C26</td>
<td>Other non-metallic mineral products</td>
</tr>
<tr>
<td>1.11 s = C27</td>
<td>Basic metals</td>
</tr>
<tr>
<td>0.706 s = C28</td>
<td>Fabricated metal products, except mach. and equip.</td>
</tr>
<tr>
<td>0.647 s = C29</td>
<td>Machinery and equipment, n.e.c.</td>
</tr>
<tr>
<td>0.93 s = C30</td>
<td>Electrical and optical equipment</td>
</tr>
<tr>
<td>1.408 s = C34</td>
<td>Motor vehicles, trailers and semi-trailers</td>
</tr>
<tr>
<td>1.162 s = C35</td>
<td>Other transport equipment</td>
</tr>
<tr>
<td>0.826 s = C36</td>
<td>Manufacturing n.e.c. and recycling</td>
</tr>
</tbody>
</table>

### Figure 2.4: Distribution of Gains by Region

![Graph showing distribution of gains by region](image)
CHAPTER 2. SLICING THE PIE

Given the distribution of group-level gains from trade, we can compute the inequality-adjusted gains from trade (IGT), as described in Section 2.2. Figure 2.5 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 2.6 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 pre-dominantly feature export-oriented regions, and these regions gain more from trade than the average region. This means that certainly for high \( \rho \), IGT > GT.\(^{30}\)

\(^{30}\)We are in the process of exploring the robustness of these data patterns.
Figure 2.5: Inequality-adjusted gains from trade

Figure 2.6: Relation between import-competition and earnings per worker
Productivity increase in China

Motivated by recent research on the rise of China and its distributional impact on US D. H. Autor, Dorn, and Hanson (2013) or German Dauth, Findeisen, and Suedekum (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 $T_i^{1/\theta} = 5$ for $i = \text{China}$ and all $s$.\footnote{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 $T_i^{1/\theta} = 5$ is on the high side of these estimates.} 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.\footnote{The WIOD dataset is discussed in Timmer et al. (2015).}

As shown in Table 2.6, 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 2.7.

Figure 2.7: Distribution of Gains by Region

\[\text{Proportional change in real income} \quad \kappa = 1, 3, 7, 15\]
Table 2.6: $\tilde{W}_{ig}$ in Germany - $\forall s : \hat{T}_{1}^{1/\theta_{China,s}} = 5$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>$\hat{W}_{i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{W}_{ig}, \kappa \to 1$ (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>$\tilde{W}_{ig}, \kappa = 3$</td>
<td>1.009</td>
<td>0.008</td>
<td>0.965</td>
<td>1.046</td>
<td>1.011</td>
</tr>
<tr>
<td>$\tilde{W}_{ig}, \kappa = 7$</td>
<td>1.005</td>
<td>0.002</td>
<td>0.995</td>
<td>1.013</td>
<td>1.006</td>
</tr>
<tr>
<td>$\tilde{W}_{ig}, \kappa = 15$</td>
<td>1.005</td>
<td>0.001</td>
<td>1.002</td>
<td>1.006</td>
<td>1.005</td>
</tr>
<tr>
<td>$\tilde{W}_{ig}, \kappa \to \infty$ (CDK)</td>
<td>1.004</td>
<td>0</td>
<td>1.004</td>
<td>1.004</td>
<td>1.004</td>
</tr>
<tr>
<td>$N$</td>
<td>265</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 2.2. Based on equation 2.16 and $\tilde{W}_{ig} = \tilde{W}_{i} \tilde{Y}_{ig} / \hat{Y}_{i}$, in the limit as $\kappa \to 1$ we have

$$\ln \tilde{W}_{ig} = \ln \tilde{W}_{i} + \ln \sum_{s} \pi_{igs} \hat{r}_{is}. \tag{2.21}$$

In Figure 2.8, we display this relationship between $\ln \tilde{W}_{ig}$ and $\ln \sum_{s} \pi_{igs} \hat{r}_{is}$, the regional exposure to the national output response.$^{33}$ 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 2.21. Figure 2.8 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 $\kappa$:

$$\ln \tilde{W}_{ig} = \ln \tilde{W}_{i} + \beta \ln \sum_{s} \pi_{igs} \hat{r}_{is}. \tag{2.22}$$

Figure 2.9 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 2.9 when we compare the model and data using a Bartik approach in section 2.5.

$^{33}$It is easy to show that if $\kappa \to 1$ then $\sum_{s} \pi_{igs} \hat{r}_{is} = 1 / \hat{T}_{ig}$ (see Section 2.2). Here we use the expression $\sum_{s} \pi_{igs} \hat{r}_{is}$ because of its Bartik structure, which we will use to relate the model implications to those we see in the data.
Figure 2.8: Welfare-effects and changes in import-competition

![Figure 2.8]

Figure 2.9: Relation between $\ln \sum_{i} \pi_{igs} \hat{r}_{is}$ and $\kappa$

![Figure 2.9]

The coefficient $\beta$, on the vertical axis, is estimated in the following regressions: $\ln \hat{W}_{ig} = \ln \hat{W}_{i} + \beta \ln \sum_{i} \pi_{igs} \hat{r}_{is}$, 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 2.10 we plot the inequality-adjusted welfare effect, $\hat{U}_i$ for $i = \text{Germany}$. 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 2.11, there is a negative covariance between the change in the degree of import competition ($\hat{I}_{ig}$) and the initial income level ($Y_{ig}$). This implies that the cross-region distributional impact of the China shock is pro-rich.

Figure 2.10: Inequality-Adjusted welfare-effects from the China shock

---

34 As mentioned in the previous footnote, in the limit $\kappa \to 1$ we have $\sum_s \pi_{igs} \hat{r}_{is} = 1/\hat{I}_{ig}$, hence $\ln \hat{W}_{ig} = \ln \hat{W}_i - \ln \hat{I}_{ig}$. 
2.5 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.\textsuperscript{35} In this section, we present our strategy for structurally estimating $\kappa$. This approach combines clean identification with solid structural foundations.\textsuperscript{36} As in section 2.4, our empirical analysis focuses on Germany and defines groups in terms of geographical units.

Our approach is based on the estimation approach in Burstein, Morales, and Vogel (2015b), 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 $\hat{w}_{is}$, 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 $\kappa$.

\textsuperscript{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) and Head and Mayer (2014).

\textsuperscript{36}In the existing literature, Hsieh, Hurst, et al. (2013) and Burstein, Morales, and Vogel (2015b) obtain values of $\kappa$ for a Roy-framework applying to worker allocation across occupations rather than sectors. Our second estimation approach is based on the strategy in Burstein, Morales, and Vogel (2015b).
CHAPTER 2. SLICING THE PIE

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

$$\frac{\hat{w}_{is}^\kappa}{\hat{w}_{i1}^\kappa} = \frac{\hat{\pi}_{igs}}{\hat{\pi}_{ig1}} \quad (2.23)$$

Combining these expressions we obtain the following equation

$$\ln \hat{Y}_{ig} = \frac{1}{\kappa} \ln \left( \sum_s \pi_{igs} \frac{\hat{\pi}_{igs}}{\hat{\pi}_{ig1}} \hat{w}_{i1}^\kappa \right) \quad (2.24)$$

Before we take this equation to the data\textsuperscript{37}, we reduce sensitivity to group-level noise by observing that equation 2.23 holds for all $g$ in state/country $i$ such that we can define $\nu_{is}(k) \equiv \exp \left( \frac{1}{\kappa} \sum_k \log \frac{\hat{w}_{ik}^\kappa}{\hat{w}_{i1}^\kappa} \right)$ and then update equation 2.24 to

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

In order to eliminate the sensitivity of this relation to the choice of reference sector, we can use the fact that $\forall k : \hat{w}_{is}^\kappa = \hat{w}_{ik}^\kappa \nu_{is}(k)$, to write $\hat{w}_{is}^\kappa = \left( \exp \left( \frac{1}{\kappa} \sum_k \log \hat{w}_{ik}^\kappa \right) \right) \nu_{is}$, where $\nu_{is} \equiv \exp \left( \frac{1}{\kappa} \sum_k \log \nu_{is}(k) \right)$. This way, we arrive at the following equation

$$\sum_s \pi_{igs} \hat{w}_{is}^\kappa = \left( \exp \left( \frac{1}{\kappa} \sum_k \log \hat{w}_{ik}^\kappa \right) \right) \sum_s \pi_{igs} \nu_{is} \quad (2.25)$$

Estimating equation

We can substitute equation 2.25 into 2.24 and obtain our estimating equation,

$$\ln \hat{Y}_{ig} = b_i + \frac{1}{\kappa} \ln \sum_s \pi_{igs} \nu_{is} + \varepsilon_{ig} \quad (2.26)$$

where $b_i \equiv \frac{1}{\kappa} \left( \frac{1}{S} \sum_k \log \hat{w}_{ik}^\kappa \right)$. Finally, we require exogenous variation in $\sum_s \pi_{igs} \nu_{is}$. To this end, we use the Bartik-type instrument $\sum_s \pi_{igs} \Delta IP_{st \rightarrow Other}^{East}$, which turns the sectoral trade shock $\Delta IP_{st \rightarrow Other}^{East}$, defined in section 2.1, into a regional trade-shock. In fact, this instrument is closely related to the region-level trade-shocks in D. H. Autor, Dorn, and Hanson (2013).

\textsuperscript{37}Note that it simplifies to $\ln \hat{Y}_{ig} = a_i - \frac{1}{\kappa} \ln \hat{\pi}_{ig1}$, 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.
### Table 2.7: Labor Reallocation in Response to Trade Shock

<table>
<thead>
<tr>
<th>$\Delta \ln \hat{\pi}_{igst}$</th>
<th>Lag = 3</th>
<th>Lag = 4</th>
<th>Lag = 5</th>
<th>Lag = 6</th>
<th>Lag = 7</th>
<th>Lag = 8</th>
<th>Lag = 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta IP_{st}^{East\rightarrow Other}$</td>
<td>-0.0063***</td>
<td>-0.0053***</td>
<td>-0.0038*</td>
<td>-0.0039*</td>
<td>-0.0042**</td>
<td>-0.0041**</td>
<td>-0.0042**</td>
</tr>
<tr>
<td></td>
<td>[0.0090]</td>
<td>[0.0220]</td>
<td>[0.0749]</td>
<td>[0.0519]</td>
<td>[0.0120]</td>
<td>[0.0340]</td>
<td>[0.0440]</td>
</tr>
<tr>
<td>Observations</td>
<td>4018</td>
<td>4009</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. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Data from 1999-2008; $\Delta IP_{st}^{East\rightarrow Other} = \frac{\Delta M_{st}^{East\rightarrow Other}}{\Delta M_{st}^{East\rightarrow Other}}$ with $\Delta M_{st}^{East\rightarrow Other}$ in 1000 EURO.

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

## 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 $\hat{\pi}_{igst} \equiv \frac{\pi_{igst}}{\pi_{igst}}$. Table 2.7 presents the estimation results for this regression. For each of the specifications, we find a negative impact of import-competition on the relative growth of a sector, and except for lags 5 and 6, this impact is significant at the 5% level. This confirms that our trade-shock variable $\Delta IP_{st}^{East\rightarrow Other}$ induces sectoral reallocation in the expected direction.

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 2.8 presents our results for this estimation approach. The point estimates for $\kappa$ range from 2.9 to 5, with a 95% confidence interval for the most precise $\kappa$ estimate (specification 5) of 1.1-4.7. For these values of $\kappa$, the distributional impacts of trade are substantial compared to their aggregate impact (see Section 2.4). For convenience, in the remainder of this section we focus on $\kappa = 3$.

---

38 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 $\pi_{igst}$. 

39 Appendix Figure B.1 plots the scatters for the first stage.

40 It is possible that there is a downward bias on $\kappa$ (i.e. an upward bias on the regression coefficient of interest), since in the derivation of the structural estimation equation, we are holding constant the share of the labor force employed in manufacturing. If instead we allow for elastic labor supply to manufacturing, as discussed in section 2.2, then given $\kappa$, the same level of within-manufacturing reallocation is associated with a higher magnitude in the change of average manufacturing earnings $\hat{Y}_{ig}$. We extend the baseline estimation approach to allow for reallocation into “home production” in appendix Section ??.. This exercise requires additional data, and we are looking into the options for obtaining data-access.
Table 2.8: Reallocation and regional income per worker

<table>
<thead>
<tr>
<th></th>
<th>First Stage</th>
<th>Second Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5)</td>
<td>(6) (7) (8) (9)</td>
</tr>
<tr>
<td></td>
<td>Lag = 3</td>
<td>Lag = 4</td>
</tr>
<tr>
<td></td>
<td>Lag = 5</td>
<td>Lag = 6</td>
</tr>
<tr>
<td></td>
<td>Lag = 7</td>
<td>Lag = 8</td>
</tr>
<tr>
<td></td>
<td>Lag = 9</td>
<td></td>
</tr>
<tr>
<td>(\sum_s \pi_{igs} \Delta P_{s}^{\text{East-\text{Other}}})</td>
<td>-0.004***</td>
<td>-0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>(\sum_s \pi_{igs} \nu_{is})</td>
<td>0.299***</td>
<td>0.224***</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Implied (\kappa)</td>
<td>3.346***</td>
<td>4.463***</td>
</tr>
<tr>
<td></td>
<td>(0.958)</td>
<td>(1.659)</td>
</tr>
<tr>
<td>Observations</td>
<td>795</td>
<td>530</td>
</tr>
</tbody>
</table>

Standard errors, clustered at the group-level, in parentheses; * \(p < 0.1\), ** \(p < 0.05\), *** \(p < 0.01\).

Standard errors for the implied \(\kappa\) computed using the Delta method.

Data from 1999-2008, with \(\Delta P_{s}^{\text{East-\text{Other}}}\) denoted in 1000 EURO with base year 2005.

The lag after 1999 indicates the construction of the time-period. Lags 3 and 4 allow for multiple time-periods. \(\hat{Y}_{ig}\) is average income per manufacturing worker.

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 2.4 we showed that the China shock, as captured by the impact of the Bartik-style variable \(\sum_s \pi_{igs} \hat{r}_{is}\), 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 3 to 9 years, we run the empirical counterpart of equation 2.22.

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

with \(\sum_s \pi_{igs} \Delta P_{s}^{\text{East-\text{Other}}}\) as an instrument for \(\ln \sum_s \pi_{igs} \hat{r}_{is}\), in the style of D. H. Autor, Dorn, and Hanson (2013) and Dauth, Findeisen, and Suedekum (2014).

Table 2.9 presents the results. The coefficient is positive and significantly different from zero at the 5% level for specifications 2 and 4-7. This positive and significant relationship in the data is consistent with the theoretical prediction that regional welfare is strongly correlated with \(\sum_s \pi_{igs} \hat{r}_{is}\). Moreover, based on Figure 2.9, the point estimates in specifications 2 and 4-7, imply values for \(\kappa\) between 2 and 4. These values are in line with the estimates in Table 2.8. Finally, the confidence intervals for the coefficients in the more precisely estimated

---

\[41\] Appendix Figure B.2 plots the scatters for the first stage.
### Table 2.9: Changes in import-competition and regional income per worker

<table>
<thead>
<tr>
<th>Lag = 3</th>
<th>Lag = 4</th>
<th>Lag = 5</th>
<th>Lag = 6</th>
<th>Lag = 7</th>
<th>Lag = 8</th>
<th>Lag = 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sum_{s} \pi_{igs} \Delta IP_{g}^{East\rightarrow Other}$</td>
<td>-0.001***</td>
<td>-0.002***</td>
<td>-0.005***</td>
<td>-0.005***</td>
<td>-0.004***</td>
<td>-0.004***</td>
</tr>
<tr>
<td>$R^2$</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>F-stat</td>
<td>8.26</td>
<td>87.37</td>
<td>135.56</td>
<td>174.69</td>
<td>152.07</td>
<td>178.67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lag = 3</th>
<th>Lag = 4</th>
<th>Lag = 5</th>
<th>Lag = 6</th>
<th>Lag = 7</th>
<th>Lag = 8</th>
<th>Lag = 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sum_{s} \pi_{igs} \hat{r}_{ts}$</td>
<td>1.220*</td>
<td>0.440**</td>
<td>0.206</td>
<td>0.267***</td>
<td>0.398***</td>
<td>0.344***</td>
</tr>
<tr>
<td>ln$\hat{Y}_{ig}$</td>
<td>(0.662)</td>
<td>(0.181)</td>
<td>(0.137)</td>
<td>(0.114)</td>
<td>(0.130)</td>
<td>(0.136)</td>
</tr>
<tr>
<td>Observations</td>
<td>795</td>
<td>530</td>
<td>265</td>
<td>265</td>
<td>265</td>
<td>265</td>
</tr>
</tbody>
</table>

Standard errors, clustered at the group-level, in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

The lag after 1999 indicates the construction of the time-period. Lags 3 and 4 allow for multiple time-periods.

Specifications are contained within zero and one, as required by the theory (see discussion in Section 2.2 and illustration in Section 2.4).

### 2.6 Conclusion

In this chapter, we develop and apply a framework to quantify the aggregate and distributional effects arising from trade liberalization. Our 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. In our empirical analysis, we employ trade and labor data from Germany and classify workers into groups based on their region of residence. In order to quantify the impact of trade liberalization, we propose a new notion of “inequality-adjusted” welfare effects. This measure captures the full cross-region distribution of welfare changes in a single measure, as the counterfactual scenario is evaluated by a risk-averse agent behind the veil of ignorance regarding the region to which she will be assigned.

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, as between-region inequality falls with trade relative to autarky, but the opposite happens for the shock in which China expands in the world economy.
Chapter 3

Productivity Spillovers: Evidence from Inside a Firm

with Torsten Walter
CHAPTER 3. PRODUCTIVITY SPILLOVERS

Understanding how productivity is shaped at the micro-level is key to understanding economic growth and development. Endogenous growth models have long suggested diverse mechanisms such as diffusion of technology, productivity spillovers and learning-by-doing that may foster productivity growth.\(^1\) Empirical evidence on these topics, however, has been limited until recently. In recent years, the empirical literature has come a long way painting a clearer picture of the determinants of productivity. The growing availability of detailed productivity data has allowed researchers to learn a lot about firm productivity. An area in which the evidence is particularly scarce is the determinants of productivity within large firms. Although large firms are known to be major drivers of economic development,\(^2\) little is understood about how innovations and productivity growth arise inside these firms.

To shed new light on this topic, we investigate a particular mechanism of productivity growth inside a large firm: the role of technology adoption and resulting productivity spillovers. We refer to technology in a broad sense, including traditionally unobserved and hard-to-measure factors of production such as the organization and management of production processes. Understanding technology adoption in firms is crucial for understanding how technological innovation translates into productivity growth. At the same time, productivity spillovers are likely to be important for our understanding of productivity dispersion between firms, as within-firm spillovers may amplify idiosyncratic productivity shocks that affect only a subset of units within a firm. For example, productivity-increasing changes in work practices in a certain unit of a firm may quickly be adopted by other units, thus increasing the overall productivity of the firm significantly. Indeed, within-firm productivity spillovers of this kind could contribute to explain widely observed persistent productivity differences across plants within narrowly defined industries (Syverson, 2004).\(^3\)

In this chapter, we examine productivity gains due to changes in technology and how these spill over within a firm. To do so, we conduct a case study of a large Latin American garment manufacturer. Production in this firm takes places in small teams that work independently but alongside each other. Data on the productivity of each team, as well as its location, is recorded on a daily basis. We exploit this setting and the gradual introduction of modern manufacturing techniques across teams to estimate the overall productivity-enhancing effect of this change in technology. Furthermore, we decompose this effect into a direct effect and a spillover effect across neighboring teams. We also provide suggestive evidence on the

\(^1\)See Romer (1986), Lucas (1988), Aghion and Howitt (1998), and Acemoglu (2009) for examples of endogenous growth models featuring technology diffusion and productivity spillovers. The learning-by-doing literature originated from the seminal work by Arrow (1962) and has been part of the growth literature ever since.

\(^2\)See Gabaix (2011).

\(^3\)Syverson (2011) provides an extensive survey on the topic of persistent productivity differences and potential explanations for this stylized fact. Several explanations have been suggested, among others unmeasured differences in inputs such as management practices and the quality of labor and capital, differences in the ease of technology adoption due to distinct organizational structures, and organizational learning-by-doing. The explanation we propose here is closely related to the latter. Variation in organizational learning rates could explain persistent productivity dispersion (Thompson, 2012) and differences in the size of within firm spillovers are one potential origin of differential organizational learning rates.
mechanisms driving the productivity spillovers.

Our empirical approach is twofold. First, we provide graphical evidence of the impact of modern manufacturing techniques on the level and the dispersion of productivity. Second, we pursue a difference-in-difference strategy to separately identify the direct effect of modern manufacturing techniques and spillover effects from the change in technology. To do so, we exploit the variation in technology across teams over time and space. Our main regression estimates the effect of a team’s treatment status - whether or not the team is working with modern manufacturing techniques - and its neighbors’ treatment status on the team’s own productivity. In order to capture the dynamics of these effects, we include leads and lags. We argue that, conditional on a set of controls, the order in which modern manufacturing is introduced is plausibly exogenous to team productivity.

Our analysis results in two main findings. First, the introduction of modern manufacturing techniques led to a substantial increase in productivity. Treated teams experienced an increase in productivity of 30%, which was gradually achieved over the course of ten weeks after the treatment date. A natural interpretation of this finding is that it takes time to learn how to use a new technology. Second, there were significant spillovers from treated teams to adjacent untreated teams. We find that untreated teams located next to treated teams experienced a 25% increase in productivity. As with the direct effect, these spillover effects took about ten weeks to materialize. Once again, the timing of effects is consistent with learning, both from own experimentation and from others.

We also gather suggestive evidence that spillovers are caused by knowledge diffusion as opposed to peer pressure. We find that the timing of the spillover effects is more consistent with the idea of untreated teams learning about modern manufacturing from their neighbors. This is because the dynamics of the spillover effects do not track closely those of the direct treatment effects (which would be the case in most scenarios involving peer pressure). In addition, we have qualitative evidence from conversations with plant workers and observations made on-site (during plant visits), which are consistent with untreated teams adopting certain aspects of modern manufacturing in their production processes. A limitation of our study, however, is the fact that our data does not allow us to observe this technology adoption directly.

The remainder of this chapter is structured as follows. Section 3.1 discusses the relevant literature. Section 3.2 describes the setting of our study in detail, while section 3.3 presents the data employed in our analysis. In section 3.4, we outline our empirical strategy and section 3.5 presents the results. Section 3.6 concludes and describes potential paths for further research.

### 3.1 Literature Review

Our work in this chapter is related to three broad strands in the economic literature. First, it is related to the literature on the determinants of productivity, and in particular to research on productivity spillovers, learning-by-doing, and management practices.
CHAPTER 3. PRODUCTIVITY SPILLOVERS

The idea that on-the-job interaction yields positive externalities across workers is an old one. It has been around at least since Marshall (1890). In recent years, empirical studies have found productivity spillovers in different contexts and attributed them to different underlying mechanisms, predominantly to peer pressure and learning. Mas and Moretti (2009) find productivity spillovers among supermarket cashiers and suggest that these spillovers are due to peer pressure. Bandiera, Barankay, and Rasul (2010) identify spillovers among socially connected workers on a fruit farm. They propose that these effects are due to the desire of workers to socialize with their friends.\(^4\) The evidence on knowledge spillovers is scarce and mixed. Jackson and Bruegmann (2009) provide suggestive evidence of peer learning among elementary school teachers. Azoulay, Graff Zivin, and Wang (2010) find productivity spillovers among medical researchers in the US while Waldinger (2012) fails to find evidence of productivity spillovers between researchers in Nazi Germany. In a recent paper, Chan, Li, and Pierce (2013) detect productivity spillovers among salesmen in a department store and argue that these are due to peer-based learning.

The roots of the learning-by-doing literature also go far back. While the interpretation of the negative empirical relationship between unit costs and cumulative produced quantity as an organizational learning curve was introduced into economics by Arrow (1962), “economists continue to have remarkably little understanding of the processes by which production experiences translate into organizational learning-by-doing” (Thompson, 2012)\(^5\). Two recent papers have made progress at this frontier. Hendel and Spiegel (2014) propose that tweaking and micro-innovations drive organizational learning-by-doing and provide suggestive evidence from a steel mill in favor of their hypothesis. The presence of within-firm productivity spillovers as we find them may help explain the size of the productivity-enhancing effects of micro-innovations which the authors document because such spillovers would imply magnification effects. Levitt, List, and Syverson (2013) present another mechanism through which organizational learning operates. Using detailed production data from an automobile plant, they show that knowledge is passed on from workers to managers who then institutionalize this knowledge. This way the gained knowledge becomes part of the organizational capital and spreads quickly across all workers - even when workers do not have any direct contact.

The literature investigating how and why management practices affect productivity has been growing rapidly since the path-breaking work on the measurement of management practices by Bloom and Reenen (2007). The idea that at least to a certain extent management is a technology rather than entirely context-specific has gained ground. One implication of this idea is that management practices should spill over (Bloom, Sadun, and Van Reenen, 2013). Bloom, Eifert, et al. (2013) provide suggestive evidence along these lines. Some firms in their experiment owned both plants that participated in the experiment and plants that did not. If the participating plants of a firm were assigned to the treatment group and provided with consulting, the authors did not only observe an adoption of the management

\(^4\)Other papers that focus on productivity spillovers due to social pressure are Falk and Ichino (2006) and Kaur, Kremer, and Mullainathan (2010).

\(^5\)Thompson (2012) provides a good survey of this literature.
practices suggested by the consultants in the treatment plants, but also - to a lesser degree - in the non-experimental plants owned by the same firm. Even though our focus is not on management practices themselves, our work is related to this literature because it shares the described view of organizational practices akin to technologies. As outlined before, the introduction of modern manufacturing techniques is comprised of a significant change in organizational practices next to a minor purely technological change.

Second, while focusing on within-firm spillovers and learning, we view our work as complementary to several empirical literatures that concentrate on between-firm spillovers, among others the literature on agglomeration and a stream of papers on technology adoption in developing countries.

In the agglomeration literature, it has been a long-standing presumption that manufacturing exhibits substantial agglomeration economies. Indeed, Kline and Moretti (2014) find “strong evidence of localized agglomeration economies in the manufacturing sector” in the US. By convincingly documenting productivity spillovers in manufacturing, our work illustrates how positive technological externalities may be at the root of these agglomeration economies.\(^6\)

The technology adoption literature is focused on the concept of learning about the returns of a technology. While it largely explores barriers to the diffusion of technology in a setting where adoption is voluntary and focuses on the adoption decision as the outcome of social learning,\(^7\) Foster and Rosenzweig (1995) is a notable exception. In their seminal work, the authors consider both how farmers decide to adopt a new kind of seeds and how they learn how to use it. Similar to our context, farmers learn the proper use of the new technology from their own experimentation and their neighbors’ experimentation with it.

Third, a literature which is methodologically closely related to our study is often referred to as insider econometrics. Ichniowski and Shaw (2009) summarize this approach as “combining insights from industry insiders with rigorous econometric tests about the adoption and productivity effects of new management practices using rich industry-specific data”.

Our work is particularly linked to a series of insider-econometric papers which study the impact of competition on productivity. The transition to modern manufacturing techniques we focus on was initially caused by the market entry of global competitors. Like Schmitz (2005) who studies US iron ore mines, we observe a change in work practices in response to heightened competition. As in the case of the mines, this change results in a substantial increase in productivity. Similarly, Bridgman, Gomes, and Teixeira (2011) and Das et al. (2013) report large increases in productivity without any substantial capital investment or hiring in state-owned companies in response to threat of entry. While Bridgman, Gomes, and Teixeira (2011) attribute the increase to corporate restructuring measures in general,\(^6\)

\(^6\)For other related work in this area see for example Moretti (2004) and Greenstone, Hornbeck, and Moretti (2010). The literature on R&D spillovers is also closely related, see for example Lychagin et al. (2010) or Bloom, Schankerman, and Reenen (2013).

\(^7\)See for example Besley and Case (1993), Kremer and Miguel (2007), Conley and Udry (2010), and Duflo, Kremer, and J. Robinson (2011).
Das et al. (2013) put it down to specific training of workers.\textsuperscript{8}

### 3.2 Context

#### The setting

We study a single factory of a large garment manufacturer in Latin America. The factory is divided into three production halls which are located in three different buildings. In each production hall, a large number of production teams sews garments. Each team is essentially a production line. In this chapter we focus exclusively on one production hall which contains 137 teams.

The organizational structure of the production is as follows. Each production hall is managed by a production manager. Within each hall, the layer below the manager is composed of several supervisors each responsible for about 17 teams. Finally, team-leaders are responsible for 1 to 3 teams and report to their supervisors.\textsuperscript{9} See figure 3.1 for a graphical illustration of the hierarchy.

A team consists of about 16 workers on average.\textsuperscript{10} Accordingly, the hall is the workplace of approximately 2200 workers. Figure 3.2 presents the layout of the production hall. Thick grey lines indicate divisions, each of which is overseen by one of the eight different supervisors in the production hall. Teams produce a variety of polo-shirts, t-shirts, tops, and underwear. 99\% of the products produced belong to 10 out of 25 product categories. A product category contains a group of very similar products such as simple uni-colored polo-shirts, for example. A team produces on average seven different products per month. Teams within a division are specialized in the production of garments from only a few categories. Each team is equipped with a set of machines. The use of those depends on the specific product being produced. Workers vary in their skill level regarding the use of the different machines.

Initially, the production process is organized as follows. When a team starts the production of a new product, all the necessary material will brought up to the team. Then the team leader distributes the production steps and operations across workers. Each worker will receive the inputs for their step. They will conduct their operation repeatedly piling up their output by their side. When the pile has reached a certain size, the output will be carried over to another worker who is responsible for the subsequent step. Importantly, each worker’s desk (including machine) is fixed in a given position within the squared area

\textsuperscript{8}Hamilton, Nickerson, and Owan (2003) is the only insider-study known to us which is also based on data from a garment manufacturer. The topic of this paper is only remotely related to ours. The authors study a change in the payment scheme from an individual piece rate to a group based incentive pay at a US garment manufacturer.

\textsuperscript{9}While the number of production teams is stable throughout our sample period, the number of team-leaders is sharply reduced from above 70 to below 50, thus leaving each remaining team leader responsible for a larger number of teams. This sharp reduction largely occurred at the beginning of January 2013 and will be subject to future research.

\textsuperscript{10}The number of workers per team falls from roughly 18 to roughly 13 throughout our sample period.
CHAPTER 3. PRODUCTIVITY SPILLOVERS

Figure 3.1: Hierarchical organization of production.
Production is organized hierarchically in four layers. It is headed by a production hall manager. The responsibility is then subdivided among supervisors, each of them supervising a number of teams. Each team is led by a team leader. Team leaders are frequently in charge of more than a single team, often leading 2 or 3 teams at a time. The bottom layer of the hierarchy consists of the production teams, the workers. The encircled numbers on the left indicate the number of units in each layer of the hierarchy in the production hall.

in which the team works. Figure 3.3 (top panel) illustrates the typical spatial arrangement of workers within team. It is not rare for workers conducting subsequent production steps to sit far apart from each other. This results in workers having to interrupt their main tasks to carry the intermediate input piles to the next step in the production process.

The intervention: Introduction of modern manufacturing techniques

As foreign global players entered the national market for garments, the manufacturer reacted to increased competition in two ways. First, it recognized the need to improve efficiency and second, it decided to increasingly focus on fast fashion. The latter change in strategy implied that teams would produce a larger variety of products while producing a lower quantity of each. As a consequence, the rigid and rather inefficient production process had to be adapted. In order to meet the new challenges modern manufacturing techniques were introduced.

Modern manufacturing allows for more flexibility in the production. Desks are equipped with wheels and therefore become mobile. They can be arranged in any convenient way and are set up as a production line. Each worker receives their input from the preceding worker in the line, completes their production step and hands their output on to the next worker
Figure 3.2: Layout of the production hall.

Bird’s eye view of the production hall. Each small box represents a production a team. All production teams within a larger grey framed area - also referred to as division - have the same supervisor at any given point in time during our sample period. Thick dotted lines indicate wide alleyways.

immediately - thus creating a constant flow. There is no need to get up from the desk and carry output to another worker’s desk any more because desks are located sufficiently close to each other and workers in charge of the subsequent production step are always seated next to their predecessors. The arrangement of desks is product and team-specific. Team leaders decide individually upon the arrangement given a product. While team leaders’ primary tasks were matching workers with production steps and machines, monitoring, and problem solving before modern manufacturing was introduced, now team leaders are also in charge of the arrangement of desks. Key to a good setup is the avoidance of bottle-necks because any bottle neck in a production line will affect the output of the entire team negatively. Whenever bottle-necks arise, they need to be recognized and removed quickly in order to allow for high performance. The newly gained responsibility regarding both the setup of desks and the detection and removal of bottle-necks represent an increase in the autonomy of team leaders. Modern manufacturing also alters the way in which workers interdepend on each other’s work. In a production line which is characterized by constantly flowing production such interdependencies are stronger than they were under the old production process.

The implementation of modern manufacturing is carried out by a team of two consultants. When modern manufacturing is implemented in a given team, the team leader is initially briefed on the new production process. Then the entire team including the leader has an
(a) Old production process

(b) New production process

Figure 3.3: Production process before and after the introduction of modern manufacturing techniques.

Bird’s-eye view of a production team. White rectangles represent workers’ desks. The black and grey rectangle indicate the team-leader’s and the quality controller’s desk, respectively. In the top panel, the spatial arrangement of workers in a production team before the introduction of modern manufacturing is illustrated. Worker desks are fixed and arranged in a standardized way. In the bottom panel, an exemplary arrangement of worker desks after the introduction of modern manufacturing is shown. Desks are mobile and arranged as a production line. Each worker receives their input from the preceding worker in the line, completes their production step and hands their output on to the next worker immediately - thus creating a constant flow. The arrangement of desks is product- and team-specific under modern manufacturing. Team leaders decide individually upon the arrangement given the product.
introductionsary session which lasts about an hour. This session is designed to diminish workers’ potential aversion to the upcoming change as well as to explain the key ideas driving the new production process. The former is addressed by videos showing interviews with workers from another factory of the firm which has already made the transition to the new process. Interviewed workers speak positively about the change, pointing among other things at the gains in earnings implied by the increases in productivity. These accrue because workers are paid a productivity-dependent monthly bonus. The new production process itself is also explained in a short video clip. One of the concepts which is key to the successful realization of the new production process is bottle-necks. Therefore, several games in which workers pass around chips are used to illustrate how bottle-necks in a production line slow down overall production. Thereafter, teams are trained on the job and the switch to the new process is accompanied by consultants for several weeks.

The introduction of modern manufacturing - henceforth also referred to as treatment - is an intervention which is composed of several components:

1. Technological change (in the narrower sense): Workers’ desks are equipped with wheels.

2. Organizational change (also technological in the broader sense): Workers form a production line and the production process is characterized by a constant flow. The new design of the production process implies an increase in the autonomy of the team leader - through his additional responsibility for the setup of desks and the detection of bottlenecks - and an increase in the interdependence of workers’ output.

3. Training: Team leaders receive a briefing, teams have an introductory session and the implementation process is initially accompanied by consultants.

Modern manufacturing was introduced gradually across teams and began on November 30th 2012. Figure 3.4 illustrates this. The top panel shows how the number of treated teams - teams for which modern manufacturing is implemented - increases steadily over time from late November 2012 on. By the end of June 2013, 80 teams are treated. The bottom panel plots the number of teams with at least one treated neighbor over time. All teams surrounding a given team are coded as neighbors and thus, a team can have up to eight neighbors. The number of teams with at least one treated neighbor likewise increases over time. Figure 3.5 illustrates the phase-in across teams in the production hall spatially.

3.3 Data

Measuring productivity

The company we study records each team’s productivity using an internal measure called utilization. We use daily utilization as the main measure of productivity throughout the

\footnote{Different definitions of neighboring teams are feasible and we address this issue in our robustness checks.}
Figure 3.4: Timing of the introduction of modern manufacturing techniques
The top graph shows how the number of teams with modern manufacturing develops over time. The bottom graph describes the number of teams with at least one treated neighbor. All teams surrounding a certain team are coded as neighbors. A team can have 8 neighbors at maximum.
Figure 3.5: Phase-in of modern manufacturing techniques in the production hall

Bird’s eye view of the production hall at different points in time throughout our sample period. Each small box represents a production a team. White boxes represent untreated teams, i.e. teams which do not have modern manufacturing, yet. Black boxes represent teams with modern manufacturing - also referred to as treated teams.
chapter. Daily utilization of team \( i \) producing products \( p \in P \) on day \( t \) is computed as follows:

\[
u_{it} = \frac{\sum_{p \in P} q_{ipt} \cdot b_{pt}}{n_{it} \cdot h_{it}}\]

where \( q_{ipt} \) is the quantity of product \( p \) produced by team \( i \) on day \( t \), \( b_{it} \) is the benchmark time given to team \( i \) to produce product \( p \) on day \( t \), \( n_{it} \) is the number of workers present in team \( i \) on day \( t \) and \( h_{it} \) is the working time available per worker in minutes in team \( i \) on day \( t \). In essence, utilization is a classic measure of labor productivity, the ratio of output (in time units) to labor input measured in time units.

Benchmark times \( b_{it} \) make productivity comparable across the different manufactured products. They are determined by the production engineering department. Every production step involved in the production of product \( p \) is timed repeatedly.\(^{12}\) The measured times are averaged and summed up over the production steps in order to obtain the benchmark time to produce product \( p \). Occasionally, benchmark times for a given product are adjusted. These benchmark times do not provide a perfect normalization of output quantities across different products. They may vary in their precision and be affected by measurement error. Furthermore, they may be biased because workers who are timed during their work have an incentive to work slowly in order to achieve a high benchmark time. At the same time, benchmark times for each specific process are an average over times it took several different workers to complete the process and hence, the influence of an individual on the final benchmark is limited. Moreover, workers being timed may not want to present themselves as particularly slow workers because they are concerned about their reputation, for example. It is not clear in which way benchmark times may be distorted. But there is no reason to expect them to be distorted differentially across teams, either.\(^{13}\)

Workers are paid a base salary and a monthly bonus based on their team’s average productivity in the preceding month. Team leaders are also paid a base salary. In addition, they receive a monthly bonus which amounts to twice the team members’ bonus.\(^{14}\) This implies that both team members and team leaders have a financial incentive to learn quickly how to perform well using modern manufacturing techniques. A measure of each team’s productivity is openly displayed for each team on a scoreboard located next to the team on one of the alleys in the plant. On any day the scoreboard displays the present day’s productivity (updated roughly every two hours), the preceding day’s productivity and the average monthly productivity. This means that teams can easily observe how well neighbors are performing and link performance to the techniques used.

\(^{12}\)The timing process is carried out for a small sample of workers, with each worker timed several times.
\(^{13}\)In robustness checks we show that our results are not driven by differential changes in benchmark times.
\(^{14}\)Team leaders frequently lead more than one team. In this case their bonus is based on the average of the efficiencies of their teams in the last month.
CHAPTER 3. PRODUCTIVITY SPILLOVERS

Current Sample
The data on which this chapter is based is daily productivity data (i.e. recorded utilization) from all the teams in the production hall from January 9th 2012 to June 28th 2013. This time period contains 341 working days on which we observe production. In addition to the produced quantities, benchmark times, numbers of workers, and available working times, we also observe which products are produced and which product category they belong to. Moreover, we exploit the information we have on the location of teams and the identity of their team leaders and supervisors. Finally, we have the dates in which modern manufacturing was introduced to each team.\footnote{Due to a clerical error, we are currently missing the treatment dates for teams in division 8. For this reason, we currently exclude all observations for the teams in this division from our analysis. Since this division is isolated from the other divisions (see figure 3.2), this does not affect the analysis of spillover effects across teams.}

Table 3.1 provides an overview of the data sample we analyze in subsequent sections. In the time period of our sample 80 out of 137 teams are treated, i.e. start to operate under modern manufacturing. While in divisions 1 and 7 all teams were treated, none were treated in division 2. In the remaining divisions the share of treated teams varies from below 50\% to above 90\%. divisions produce products from different categories. Some divisions are highly specialized and produce products from a single category more than 85\% of working days. The production time of teams in other divisions is more evenly distributed among products from two or three different categories. Note that teams from divisions 2, 3 and 4 produce roughly the same mix of products. While average utilization varies across divisions, it is very similar in divisions 2, 3 and 4 suggesting that differences in utilization may be linked to product categories. It is important that within divisions all teams produce products from all the categories their division is specialized in. It is not the fact that there is further specialization of teams within divisions. Within divisions it is largely coincidence determining which team will produce which exact product. A team finishing the demanded quantity of a given product will simply start producing the next product in line.\footnote{Two entries of Table 3.1 should be noted. First, the number of treated teams in division 5 is 2. Nonetheless, the number of treated neighbors in this division is zero. This is due to the fact that the two teams which are treated in division 5 are treated in June 2013, the month for which we do not have production data for the remaining 5 teams in division 5. Second, the average number of workers per team in division 5 is much higher than in the other divisions. This is because in early 2012, teams in division 5 were much larger (consisted of 42 workers). After the first quarter of 2012, teams were restructured and their size was adjusted to the size of the other teams in the hall.}

3.4 Empirical strategy

Graphical evidence
In a first step, we assess the effect of the intervention on the level and on the dispersion of productivity graphically. In order to visualize the effect on productivity levels, we plot the
### Table 3.1: Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of teams ever treated</td>
<td>125</td>
<td>22</td>
<td>22</td>
<td>22</td>
<td>22</td>
<td>22</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>Number of teams treated daily</td>
<td>20</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>Product categories by frequency</td>
<td>30</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1)</td>
<td>2)</td>
<td>3)</td>
<td>1)</td>
<td>2)</td>
<td>3)</td>
<td>1)</td>
</tr>
<tr>
<td></td>
<td>Utilization</td>
<td>0.0530</td>
<td>0.0575</td>
<td>0.0575</td>
<td>0.0530</td>
<td>0.0575</td>
<td>0.0575</td>
<td>0.0530</td>
</tr>
<tr>
<td></td>
<td>Benchmark time</td>
<td>2.3551</td>
<td>2.7071</td>
<td>2.7071</td>
<td>2.3551</td>
<td>2.7071</td>
<td>2.7071</td>
<td>2.3551</td>
</tr>
<tr>
<td></td>
<td>Match factor</td>
<td>0.0764</td>
<td>0.0764</td>
<td>0.0764</td>
<td>0.0764</td>
<td>0.0764</td>
<td>0.0764</td>
<td>0.0764</td>
</tr>
<tr>
<td></td>
<td>Scale factor</td>
<td>0.7882</td>
<td>0.7882</td>
<td>0.7882</td>
<td>0.7882</td>
<td>0.7882</td>
<td>0.7882</td>
<td>0.7882</td>
</tr>
<tr>
<td></td>
<td>Number of treated neighbors</td>
<td>0.6151</td>
<td>0.6151</td>
<td>0.6151</td>
<td>0.6151</td>
<td>0.6151</td>
<td>0.6151</td>
<td>0.6151</td>
</tr>
<tr>
<td></td>
<td>Number of workers</td>
<td>10.6499</td>
<td>10.6499</td>
<td>10.6499</td>
<td>10.6499</td>
<td>10.6499</td>
<td>10.6499</td>
<td>10.6499</td>
</tr>
<tr>
<td>Observations</td>
<td>42071</td>
<td>66229</td>
<td>66229</td>
<td>66229</td>
<td>66229</td>
<td>66229</td>
<td>66229</td>
<td>66229</td>
</tr>
</tbody>
</table>

Table 3.1: Summary statistics
time series of utilization for the different divisions and compare them based on the dates at which modern manufacturing techniques were first introduced within the divisions. We then plot the distribution of daily productivity in the months of June 2012 (when no teams had been treated) and June 2013 (when 80 teams had been treated). In order to examine how the distribution of productivity shifted with increasing treatment duration, we further divide teams into four groups: teams treated for 50 days or more by the end of June 2013, teams treated for less than 50 days by the end of June 2013, teams treated by the end of June 2013, and teams not treated by the end of June 2013.

Difference-in-difference approach

Due to the non-random nature of the introduction of modern manufacturing, the separate identification of the direct effect of modern manufacturing and spillover effects across neighboring teams is challenging. We take a difference-in-difference approach where untreated teams serve as a control group for treated teams at any point in time, but selection is an obvious concern. Therefore, all our regressions include team fixed effects (to address static selection) and leads and lags (to address dynamic selection). We estimate the following specification:

\[
\ln (P_{it}) = \alpha_i + \tau_t + \delta X_{it} + \sum_{s \in [S, \bar{S}]} \psi_s \Delta D_{it-s} + \psi_{\bar{S}} D_{it-\bar{S}} \\
+ \sum_{s \in [S, \bar{S}]} \kappa_s \Delta N_{it-s} (1 - D_{it-s}) + \kappa_{\bar{S}} N_{it-\bar{S}} (1 - D_{it-\bar{S}}) + \epsilon_{it}
\]  

(3.1)

where \(P_{it}\) is productivity of team \(i\) on day \(t\), measured as utilization. \(D_{it}\) is an indicator variable for team \(i\)’s treatment status on day \(t\), and \(N_{it}\) is an indicator variable for whether any of team \(i\)’s neighbors operates under modern manufacturing on day \(t\). \(\Delta D_{it-s}\) is an indicator which takes value one if at time \(t\) team \(i\) was treated \(s\) days ago. \(\Delta N_{it-s}\) is an indicator which takes value one if team \(i\) was first exposed to modern manufacturing through its neighbors \(s\) days ago (i.e. \(\Delta N_{it-s}\) will be one if the first of team \(i\)’s neighbors to be treated received treatment \(s\) days ago). \(X_{it}\) is a set of control variables, \(\alpha_i\) is a set of team fixed effects and \(\tau_t\) includes day of the week, month of the year and week fixed effects. We also run robustness checks in which we vary the set of control variables and the set of time fixed effects.

The regression coefficient \(\psi_s\) can be interpreted as the direct effect on productivity of having been introduced to modern manufacturing \(s\) days ago. The coefficient \(\kappa_s\) captures the effect of having had at least one neighboring team introduced to modern manufacturing \(s\) days ago (conditional on team \(i\) being untreated at the time).

The identifying assumption for \(\kappa_s\) is that controlling for team fixed effects, time fixed effects, other control variables, leads and lags of the treatment status and the remaining leads and lags of \(\Delta N\) as well as \(N_{it-\bar{S}}\), the error term \(\epsilon_{it}\) is uncorrelated with \(\Delta N_{it-s}\).
Figure 3.6: Daily average utilization in production hall 1 over time

The graph plots daily average utilization throughout the sample period of 341 working days, differentiating between three groups of teams: teams never treated in the sample period (57 teams), teams treated for 0-50 days within the sample period (treated late: 39 teams), and teams treated for more than 50 days in the sample period (treated early: 41 teams). The vertical line indicates the day on which the first team was treated.

This assumption is violated if there exists a time-varying factor which is correlated with the timing of the treatment of neighbors and the team’s productivity in a way which is not captured by the other regressors. The identifying assumption for $\psi_s$ is analogous. There are two particular concerns regarding the identifying assumptions. The first concern is that there is selection into treatment conditional on the included controls. The second concern is that the introduction of modern manufacturing techniques is correlated with changes in the determination of benchmark times or product variety. While we cannot entirely rule these cases out, we address them as detailed below.

According to the management of the firm and consultants, the determination of the order in which teams were treated was a complex process as different managers (head of production engineering, production hall managers, supervisors, and others) and consultants held different stakes in this decision, thus representing different positions in negotiations about the treatment order. In addition, capacity constraints, worker vacations, and many other factors had to be taken into account. Therefore, we believe it is unlikely that the roll-out order was systematically linked to unobserved determinants of team productivity.

Figure 3.7 provides additional evidence supporting our identifying assumptions. It plots the daily average utilization of teams treated early, late and never over time. The daily
average utilization of these three groups evolves very similarly in the period before modern manufacturing is introduced for the first time and trends are roughly parallel.\(^\text{17}\) Hence, it seems like untreated teams may serve as a good counterfactual of treated teams. After the beginning of the introduction of modern manufacturing techniques, trends are no longer parallel. Daily average utilization of teams treated early increases disproportionately soon after the beginning of the roll-out. With some delay daily average utilization of teams treated late increases relative to the one of never treated teams as well.

Next, we take a closer look at observable differences among treated teams. We plot team average utilization in the months July to October 2012 against the introduction dates of modern manufacturing. It can be seen from figure 3.8 that the correlation is essentially zero.\(^\text{18}\) This speaks against static selection based on fixed team characteristics that affect productivity.

Regarding the second set of concerns, note that the determination of benchmark times would have to differ systematically between treated and untreated teams at a given point in time in order to bias our estimates. As the same production engineers were in charge of

\(^{17}\)Note that in the first 80 days of the sample period some internal restructuring took place at the firm. Therefore, we do not place much emphasis on these early observations.

\(^{18}\)This result is independent of the chosen time window prior to modern manufacturing. We have varied the months prior to modern manufacturing over which team utilization is averaged and always found a zero correlation.
measuring process times in teams with and without modern manufacturing techniques, and modern manufacturing was phased in over a long time horizon, this seems unlikely. A change in the variety and types of products produced which is correlated with treatment status is equally unlikely. Within division, sometimes even across divisions, products are assigned to teams on a first-come-first-serve basis. This is to say whenever a team finishes producing an order, i.e. a determined quantity of a given product, the team leader reports to the stock manager who hands out the raw materials for the next product. Most raw materials only arrive at the depot shortly before. As a result, the stock manager usually hands out raw materials for products in the same order as they came in and is not able to target products systematically to teams. Given that each team usually produces several products per week and the exact production time each team will need to finish their order is hard to predict, it seems unlikely that the arrival of raw materials at the depot is planned and actually occurs in a way such that after all certain products are intentionally produced by certain teams.\footnote{In future work, we will address both the concern regarding a potential change in the determination of benchmark times and the concern regarding a potential change in the product mix formally.}

\section{Results}

\subsection*{Graphical evidence}

Before turning to the regression results on direct effects and spillover effects of modern manufacturing on productivity, we present graphical evidence of the overall impact of the treatment. Figure 3.8 documents the impact of modern manufacturing techniques on average productivity. It shows how daily average utilization evolves over time in 6 out of the 8 divisions we have data for. In each plot the vertical line indicates the day the first team within the division is treated. In all divisions, daily average utilization increases after the introduction of modern manufacturing. This increase is not immediate, however. It takes time until the productivity-enhancing effect of modern manufacturing kicks in.

Next, we provide some distributional evidence on the effect of modern manufacturing. Figure 3.9 shows the cross-sectional distribution of daily utilization for June 2012 and June 2013. Notice that in June 2012 the introduction of modern manufacturing had not started yet. By the end of June 2013, however, 80 teams had been treated, 41 for more than 50 days. The distribution plot on the top of figure 3.9 shows four separate distributions: the distribution in June 2012 for teams which are eventually treated, the June 2012 distribution for teams which are never treated, and the two corresponding distributions for June 2013.

In the bottom plot, we split teams by whether they have been treated for at least 50 days or not. We make three observations. First, there is substantial dispersion in productivity across teams. It can easily be seen that the least productive teams are less than half as productive as the most productive teams. Second, comparing the top and the bottom plot, we see that the effect of modern manufacturing is concentrated on teams that have been treated for a significant amount of time (in this case more than 50 days). Third, as teams
Figure 3.8: Daily mean utilization in production hall 1 by division
The vertical line indicates the day on which the first team from the corresponding division was treated. Plots are ordered by the date on which the first team within a division was treated. In divisions 2 and 8, no team was ever treated in our sample period. In divisions 1 and 7 all teams were treated while in the remaining divisions 3, 4, and 6 only some were treated. Teams in division 5 were only treated in June 2013. Since we lack production data for 5 out of 7 teams in this month, we do not present the corresponding graph for division 5 here.
gain experience with modern manufacturing techniques, the dispersion in productivity across these teams shrinks remarkably.\textsuperscript{20}

To sum up, the results from this section illustrate two points regarding the effects of modern manufacturing techniques on productivity. First, the introduction of modern manufacturing resulted in big increases in productivity, but this productivity-enhancing effect is lagged. This is not surprising and consistent with the fact that it takes time to learn a new technology, an insight which was prominently pointed out to economists by David (1990). Second, modern manufacturing techniques led to a reduction in the dispersion of productivity across teams. It seems like a priori highly productive teams gain less from the change in the production process than a priori less productive ones.

Regression results

The results shown below are based on the regression model (equation 3.1) presented in the preceding section. Apart from the fixed effects explicitly specified in the regression formulation, our baseline specification includes the following regressors: team leader fixed effects and product family fixed effects. We restrict the sample to observations from the beginning of July 2012 onwards. \( S \) and \( \overline{S} \) are set to \(-25\) and \(75\), respectively. Standard errors are clustered at the team level.

Figure 3.10 plots the estimated regression coefficients \( \psi_s \) for \( s \in [-25, 75] \). The dashed lines indicate the 95\% confidence interval. We see that the direct effect of modern manufacturing is lagged and positive. From the sixth week after treatment (i.e. 30 working days after treatment), the direct effect is significantly larger than zero and remains so. The effect rises slowly but continuously for about ten weeks after treatment. Then it stabilizes at an effect size of about 30\%. The estimates for the later lags are noisier because we do not observe enough teams that are treated for 50 and more working days. The fact that none of the leads is significantly different from zero is reassuring. It does not seem like there is dynamic selection of teams into treatment based on unobservables which are strongly correlated with productivity.

Figure 3.11 plots the estimated regression coefficients \( \kappa_s \) for \( s \in [-25, 75] \), analogous to figure 3.11. As was the case with the direct effects, the estimated spillover effects are lagged. Only after about eight weeks the effect of having a treated neighboring team is consistently larger than zero. Even though the estimates are fairly imprecise, there is a clear positive trend starting eight weeks into the treatment of team \( i \)'s neighbors. Spillovers reach a size of about 25\% after ten weeks and remain of around this size from there on. This means that being exposed to modern manufacturing through a treated neighbor leads to a lasting 25\% increase in own productivity about ten weeks later (conditional on being untreated).

The presented results show that introducing modern manufacturing to the firm affected productivity through two channels. There is a direct effect from the treatment and a spillover effect from treated to untreated neighboring teams. Both of these effect are lagged. Ten

\textsuperscript{20}The reduction in dispersion is a finding we plan to explore more closely and to quantify in future work.
Figure 3.9: Distribution of daily productivity

This figure plots the distribution of daily productivity across production teams for the months of June 2012 and June 2013. In June 2012, no team was treated. By the end of June 2013, 80 out of 125 teams had been treated, 41 of them for more than 50 days. The plot on the top separates teams according to whether they are treated at some point in the sample period or not. The plot on the bottom separates teams according to whether are treated for at least 50 days in the sample period or not.
 CHAPTER 3. PRODUCTIVITY SPILLOVERS

Figure 3.10: Direct effect
Leads and lags of $\psi$, the direct effect of modern manufacturing on team productivity. Dashed lines indicate 95% confidence interval. Estimates based on the regression specification presented in section 3.4. Sample restricted to observations from July 2012 onwards. $S$ and $\bar{S}$ set to $-25$ and $75$, respectively. Standard errors clustered at the team level.

Figure 3.11: Spillover effects
Leads and lags of $\kappa$, the productivity spillovers. Dashed lines indicate 95% confidence interval. Estimates based on the regression specification presented in section 3.4. Sample restricted to observations from July 2012 onwards. $S$ and $\bar{S}$ set to $-25$ and $75$, respectively. Standard errors clustered at the team level.
weeks after being introduced to modern manufacturing, treated teams increase their own productivity by about 30%, while spillover effects to untreated teams result in a productivity increase of about 25%.

The question that arises at this point is why the observed productivity spillovers occur. The two leading explanations of productivity spillovers in the literature are peer pressure and knowledge diffusion. While our data does not allow us to directly test which mechanism is at play, several pieces of evidence suggest that the observed spillovers are the result of knowledge diffusion and learning. First, there is the timing of the estimated effects. The evolution of the estimated effects (both direct and through spillovers) is more consistent with knowledge diffusion than peer pressure. To illustrate this point, in figure 3.12 we plot the estimated parameters for direct effects and spillover effects, but aggregating our units of observation at the weekly level. The results are qualitatively similar to those in our baseline specification, but the aggregation results in smaller standard errors and provides a clearer picture on the dynamics of the two effects. The direct effect trends upwards from the fifth to the tenth week, after which it stabilizes at around 30 percent. The spillover effects, on the other hand, only becomes significantly positive after the ninth week. If peer pressure was driving spillovers, we would expect the spillover effects to partially track the direct effect over time. A more plausible story is that teams only begin to pay close attention to the new production process at their neighbor’s once they observe that their neighbor is more productive using the new technology. That is when teams engage in learning from their neighbors. This process of learning takes a few weeks before it pays off in terms of productivity. In fact, anecdotal evidence from observations made at the manufacturing plant is consistent with this explanation. Untreated teams close to treated ones were observed to deviate from the old arrangement of worker desks. In many cases, the set up chosen by these teams partially resembled that of their treated neighbors, and aimed to achieve a (partially) continuous production flow. In addition, in informal conversations team leaders also revealed to us that over time many untreated teams noticed the new manufacturing techniques and started to partially imitate their neighbors, especially with regards to the constant production flow.

3.6 Conclusion

We study the introduction of modern manufacturing at a large garment manufacturing plant in Latin America. This introduction is a multi-faceted change in the production process which implies the transition from a fairly rigid and standardized production method to a flexible and product-specific one. While initially workers sew garments at fixed desks and complete their production task in bundles, modern manufacturing leads to a constant flow of production from worker to worker like in a production line. First, we present graphical evidence of the productivity-increasing effect of this change in the production process. Modern manufacturing increased productivity substantially and decreased the dispersion in productivity across teams. However, this effect is lagged by several business weeks. In a sec-
CHAPTER 3. PRODUCTIVITY SPILLOVERS

Figure 3.12: Spillover effects

Leads and lags of $\kappa$, the productivity spillovers. Dashed lines indicate 95% confidence interval. Estimates based on the regression specification presented in section 3.4. Sample restricted to observations from July 2012 onwards. $S$ and $\overline{S}$ set to −25 and 75, respectively. Standard errors clustered at the team level.

In the second step, we exploit the gradual introduction of modern manufacturing across production teams to decompose the effect of modern manufacturing into a direct and a spillover effect across neighboring teams. For this purpose, we take a difference-in-difference approach. The identification of the direct effect as well as productivity spillovers is driven by variation in the production technology across teams over time. We find that the direct effect of modern manufacturing increases slowly over time. It reaches a size of about 30% after 10 weeks and remains stable thereafter. We also find evidence of substantial productivity spillovers from treated to untreated teams. These spillover effects on productivity take longer to materialize, but after 10 weeks they amount to a 25% increase in productivity. They are essentially zero during the first eight weeks after a neighbor has been treated and only then they increase slowly and reach their full size after about ten weeks. The timing of these effects and anecdotal evidence suggest that these effects are the result of knowledge diffusion and learning. Our analysis, however, is limited by the fact that we do not directly observe the adoption of modern manufacturing features in untreated teams. All we observe is an increase in productivity based on which we argue that it is likely that neighbors learn from each other, but we cannot rule out alternative explanations entirely.

In the future, we intend to extend our analysis by employing additional data on the composition of production teams as well as data from production halls 2 and 3. In addition to complementary robustness tests, we plan to further explore the potential mechanisms underlying the observed spillovers. As we argued above, the evidence we have gathered so far
points to knowledge diffusion and learning as the main mechanism driving the productivity spillovers. An interesting extension of this idea is exploring whether the organizational structure of the firm facilitates or deters this type of spillovers. For example, we plan to explore the importance of team leaders and the number of teams under their purview on the size of spillover effects and the speed of learning.

Finally, we intend to elaborate on the role of within-firm productivity spillovers and their potential to explain persistent productivity differences across firms within narrowly defined industries. We plan to approach this aspect by developing a theoretical model which can explain such persistent productivity differences based on idiosyncratic productivity shocks within firms which are amplified by spillover effects within a firm. A subsequent calibration of the model using our estimated spillovers will allow us to assess how much dispersion the proposed forces could explain.
Bibliography


— (2015b). “Accounting for changes in between-group inequality”. In: unpublished manuscript, UCLA, Princeton and NYU.

Burstein, Ariel and Jonathan Vogel (2012). “International trade, technology, and the skill premium”. In: Manuscript, Columbia University and UCLA.


Cöşar, A Kerem (2010). “Adjusting to trade liberalization: Reallocation and labor market policies”. In: *University of Chicago Booth School of Business, unpublished manuscript*.


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

Fajgelbaum, Pablo D and Amit K Khandelwal (2014). “Measuring the unequal gains from trade”. In: unpublished manuscript, Colombia and UCLA.


Appendix A

Industry Mix, Local Labor Markets, and the Incidence of Trade Shocks

A.1 Data Appendix

Measures of Exogenous Displacement

We currently employ three sources to identify exogenous displacements of workers: plant exits identified through administrative data and worker flows, small-firm exits identified through bankruptcies, and mass layoffs.

Plant exit is associated with a plant ID vanishing from the data. The disappearance of a plant ID, however, can be due to very different reasons including takeovers, spin-offs, or ownership changes. To better proxy true closures, we use the extension files based on the work of Hethey-Maier and Schmieder (2013). Hethey-Maier and Schmieder (2013) use worker flows and consider only those vanishing plant ID’s as true closures where, after the ID vanished, workers are dispersed over many different plants. In the current version of the paper, we employ the following plant closure categories from Hethey-Maier and Schmieder (2013): small death, atomized death, and chunky death (codes 4-6).

Bankruptcies are mainly identified using administrative data routinely collected by the BA’s local branches. This data results from the administrative process of the Insolvenzgeld, which is a compensation scheme each employee who has not received his wage due to employer bankruptcy is eligible to. We define bankruptcy as a vanishing plant ID for plants with a bankruptcy spell. One advantage of using bankruptcies is that it does not rely on worker flows and that it is therefore possible to identify failure of very small firms. Detailed information about the data on exits and bankruptcies is given in Mueller and Stegmaier (2015). In the current version of the paper, we employ bankruptcy related closures for the years 2008–2010.

Another approach to identify displacements relies on mass layoffs. We define a mass-

---

1To be more precise, they require that the largest cluster of workers moving from the vanishing ID to the same new plant ID makes up less than a certain percentage of the source plant’s employment.
APPENDIX A. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHOCKS

layoff (similar to Schmieder et al. 2009) as a reduction in plant-level total employment by 30 percent or more within one calendar year and require that, at the most, 20 percent of the worker outflow is clustered in one successor plant to avoid takeovers etc. again. To avoid capturing plants with volatile employment, we further require that employment has not been increased by more than 30 percent in the years prior and after the mass layoff. To make this approximation meaningful, we consider only plants that had 50 or more employees at June 30 prior to the event. All displacement events take place at some point between June 30th of a given year and June 29th of a given year + 1. In the current version of the paper, we employ mass- layoffs that occur in the time period 1998–2010.

Measures of Import Exposure

Following D. Autor et al., 2014, we construct measures of exogenous trade shocks arising from import competition from China and Eastern Europe. These measures have been adapted to the German context in a recent paper by Dauth, Findeisen, and Suedekum, 2014. As in the two aforementioned papers, we obtained trade flow figures at the commodity level (HS6 codes) from the UNComtrade database. We then proceeded to map these trade flows to 3-digit industries (NACE Rev3 codes) using the same correspondence tables employed by Dauth, Findeisen, and Suedekum, 2014.

Our import penetration measures are constructed at the 3-digit industry level and at the national level. For each industry \( j \), we create a measure of the change in import penetration per worker \( (\Delta IP_{j\tau}) \) in time period \( \tau \). Each measure is constructed as follows:

\[
\Delta IP_{j\tau} = \frac{\Delta IM_{j\tau}^{East\rightarrow Germany}}{E_{j\tau0}}
\]

Where \( \Delta IM_{j\tau}^{East\rightarrow Germany} \) is the change in industry \( j \) imports to Germany from China and Eastern Europe during time period \( \tau \), and \( E_{j\tau0} \) is the number of workers in Germany employed in industry \( j \) at the beginning of time period \( \tau \). We construct these trade measures for two time periods: 1988–1998 and 1998–2008. To control for possible unobserved industry shocks, we employ the same IV strategy as ADHS: we instrument \( \Delta IP_{j\tau} \) with \( \Delta IP_{j\tau}^{East\rightarrow Other} \), the increase in industry level import competition from China and Eastern Europe to a group of countries “similar” to Germany. Formally,

\[
\Delta IP_{j\tau}^{East\rightarrow Other} = \frac{\Delta IM_{j\tau}^{East\rightarrow Other}}{E_{j\tau0}}
\]

\(^2\)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.

\(^3\)Following Dauth, Findeisen, and Suedekum, 2014, we focus on manufacturing sub-industries only (NACE codes 150-380). This excludes agriculture and mining industries.
APPENDIX A. INDUSTRY MIX, LOCAL LABOR MARKETS, AND THE INCIDENCE OF TRADE SHocks

We follow Dauth, Findeisen, and Suedekum, 2014 and define this group of similar countries to include Australia, Canada, Japan, Norway, New Zealand, Sweden, Singapore, and the United Kingdom. The intuition behind the instrument is that the “rise of the East” is an exogenous event, and as such should have similar effects on countries with similar income levels to Germany. For a discussion on the robustness of this instrument, see Dauth, Findeisen, and Suedekum, 2014.

Measures of Region-Level Import Exposure

We also construct region-level measures of trade exposure which are included as controls in all of our specifications. As in D. H. Autor, Dorn, and Hanson, 2013 and Dauth, Findeisen, and Suedekum, 2014, these measures capture the import exposure of all manufacturing workers initially located in a given region. They are constructed by combining the national changes in imports for each 3-digit manufacturing industry and the industry composition of each region. Formally, our measure of region-level trade exposure for region \( r \) during time period \( \tau \) can be written as:

\[
\Delta IP_{r\tau} = \sum_j \frac{E_{rj0} \Delta IM_{j\tau}^{East\rightarrow Germany}}{E_{r\tau0} E_{j0}}
\]

where \( \Delta IM_{j\tau}^{East\rightarrow Germany} \) and \( E_{j0} \) are defined as in the previous section, \( \frac{E_{rj0}}{E_{r\tau0}} \) is the share of manufacturing workers in region \( r \) who work in industry \( j \) at the beginning of period \( \tau \).

A.2 Selection Model - First Stage

In this section, we describe the construction of our coworker network instrument. We then present descriptives of the coworker instrument employed in section 1.3 and show results of the first stage of our selection model (equation 1.5).

Details of coworker network construction

In the current version of the paper, we construct the networks of past coworkers as follows:

First, for each worker \( i \) who was displaced at time \( t_0 \) and started a new job at time \( t_1 \), we define a “window” of time for possible interactions. Currently, the window is set at \([t_1 - 6\text{yrs.}, t_1 - 1\text{yr}]\).

Second, we identify all workers with whom worker \( i \) had a relevant interaction during the time window. We define a relevant interaction as having worked in the same firm for a period of at least 30 days. If there are multiple interactions (in different firms), we only keep the last interaction.

Third, for each coworker \( j \) identified as having their (last) interaction with \( i \) in our specified window, we identify their job information at time \( t_1 \). We drop any coworker \( j \) who
at time $t_1$ is working in the same firm where the last interaction took place. This restriction effectively rules out counting coworkers from the same firm from which $i$ was displaced. It also excludes from our network coworkers who remained working in firms in which worker $i$ previously worked, even if $i$ was displaced from a different firm. In other words, our network only includes coworkers in “new” potential firms for $i$. For coworkers who had multiple jobs at time $t_1$, we only count the job with the highest wage.

Lastly, we add up all of the unique workers in each sector to construct the variables $CN_{is}$.

**Descriptives of coworker networks**

Table A.1 shows features of the coworker networks of our main estimation sample (with all the restrictions described in Section 1.3). We present these figures separately by the target industry $k$ workers chose after displacement. Column 1 shows the average number of coworkers (in any sector) that workers in our sample had at the time of their displacement (i.e. the size of their coworker network). Column 2 shows the average numbers of coworkers in the manufacturing sector (but in other firms) for our main estimation sample. Column 3 presents the average number of coworkers in the chosen sector $k$.

**Table A.1: Descriptives - Coworker Networks**

<table>
<thead>
<tr>
<th>Sector</th>
<th>$CN_{all}$</th>
<th>$CN_{manuf}$</th>
<th>$CN_k$</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, energy</td>
<td>37.5</td>
<td>22.6</td>
<td>0.9</td>
<td>1839</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>71.7</td>
<td>39.0</td>
<td>39.0</td>
<td>208032</td>
</tr>
<tr>
<td>Construction</td>
<td>29.1</td>
<td>14.9</td>
<td>2.2</td>
<td>10201</td>
</tr>
<tr>
<td>Retail</td>
<td>38.0</td>
<td>18.9</td>
<td>6.7</td>
<td>28242</td>
</tr>
<tr>
<td>Transportation</td>
<td>49.8</td>
<td>24.6</td>
<td>5.5</td>
<td>3543</td>
</tr>
<tr>
<td>Hotel, rest, low skill svcs</td>
<td>15.8</td>
<td>8.5</td>
<td>0.4</td>
<td>2598</td>
</tr>
<tr>
<td>Communication, other prof svcs</td>
<td>141.0</td>
<td>72.7</td>
<td>37.6</td>
<td>14500</td>
</tr>
<tr>
<td>Office and bus support svcs</td>
<td>55.2</td>
<td>29.2</td>
<td>3.9</td>
<td>9274</td>
</tr>
<tr>
<td>Public Administration</td>
<td>44.7</td>
<td>25.4</td>
<td>0.7</td>
<td>1582</td>
</tr>
<tr>
<td>Education, hosp, personal svcs</td>
<td>41.0</td>
<td>20.9</td>
<td>2.8</td>
<td>7587</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>67.9</strong></td>
<td><strong>36.4</strong></td>
<td><strong>31.1</strong></td>
<td><strong>287398</strong></td>
</tr>
</tbody>
</table>

Notes: Main estimation sample.
Predictive power of coworker networks

From equation 1.5, we have that each worker $i$ (displaced from sector $m$) chooses a new sector by maximizing her utility $V_{ik}$, defined as:

$$V_{ik} = X_i'\Gamma_k + \sum_{s=1}^{10} \gamma_{iks}CN_{is} + \sum_{s=1}^{10} \kappa_{ks}EmpShare_{rs} + \eta_{ik} \quad (A.1)$$

Given our assumption of $\eta_{ik} \sim EV$, this first stage can be estimated using a multinomial logit regression. The results of this estimation are presented in Table 1.5 (for networks without the occupation restriction) and Table A.3 (for networks with the occupation restriction). Each column contains the coefficients for the choice of target sector $k$. The entries in each column contain the estimated coefficient $\gamma_{iks}$ for a fixed sector $k$. Hence, the entries on the diagonal indicate that having coworkers in sector $k$ increases the probability that worker $i$ moves to $k$. The last column presents the estimate for an alternative specification in which we allow the coworker instrument to enter as an alternative specific variable. Formally, this specification takes the form:

$$V_{ik} = X_i'\Gamma_k + \gamma CN_{ik} + \kappa EmpShare_{rk} + \eta_{ik} \quad (A.2)$$

where $\gamma$ is our parameter of interest.

In all cases, the coworker variables have the expected sign and enter the selection model significantly, as shown by the large $\chi^2$ statistics. We take this as strong evidence of our instrument’s predictive power.
### Table A.2: Multinomial Logit Model

<table>
<thead>
<tr>
<th>Outcome $k$</th>
<th>Agriculture, mining</th>
<th>Construction</th>
<th>Retail</th>
<th>Transportation</th>
<th>Low skill svcs</th>
<th>Finance, prof svcs</th>
<th>Office, support svcs</th>
<th>Public Admin.</th>
<th>Personal svcs</th>
<th>ASCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{N1}$</td>
<td>0.0129***</td>
<td>0.0129**</td>
<td>0.000171</td>
<td>-0.000532</td>
<td>-0.0251</td>
<td>-0.0116**</td>
<td>-0.00146</td>
<td>0.0127**</td>
<td>-0.0171</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00424)</td>
<td>(0.00402)</td>
<td>(0.00596)</td>
<td>(0.00535)</td>
<td>(0.0364)</td>
<td>(0.00433)</td>
<td>(0.00491)</td>
<td>(0.00407)</td>
<td>(0.0139)</td>
<td></td>
</tr>
<tr>
<td>$C_{N2}$</td>
<td>-0.00236*</td>
<td>-0.00108**</td>
<td>-0.000867</td>
<td>0.0000109</td>
<td>-</td>
<td>0.000520***</td>
<td>0.00128</td>
<td>-0.00133***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00000263)</td>
<td>(0.000971)**</td>
<td>(0.000374)</td>
<td>(0.0000820)</td>
<td>(0.00000570)</td>
<td>(0.0000140)</td>
<td>(0.000355)</td>
<td>(0.000233)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_{N3}$</td>
<td>0.00272</td>
<td>0.0306***</td>
<td>0.0000757</td>
<td>-0.000553</td>
<td>-0.0344</td>
<td>0.00101</td>
<td>0.00410</td>
<td>-0.00863</td>
<td>0.000140</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00671)</td>
<td>(0.00297)</td>
<td>(0.00441)</td>
<td>(0.0200)</td>
<td>(0.00195)</td>
<td>(0.00259)</td>
<td>(0.00653)</td>
<td>(0.00431)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_{N4}$</td>
<td>-0.00405</td>
<td>-0.00506***</td>
<td>0.0105***</td>
<td>-0.000546</td>
<td>0.00413</td>
<td>-0.00243***</td>
<td>0.000565</td>
<td>-0.00246</td>
<td>-0.00234*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00449)</td>
<td>(0.00281)</td>
<td>(0.00712)</td>
<td>(0.00130)</td>
<td>(0.00819)</td>
<td>(0.000610)</td>
<td>(0.00100)</td>
<td>(0.00257)</td>
<td>(0.00117)</td>
<td></td>
</tr>
<tr>
<td>$C_{N5}$</td>
<td>-0.0127</td>
<td>0.00119</td>
<td>-0.00300</td>
<td>0.00131***</td>
<td>-0.000620</td>
<td>-0.00166*</td>
<td>-0.00509</td>
<td>-0.000762</td>
<td>-0.00501</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00940)</td>
<td>(0.00738)</td>
<td>(0.00921)</td>
<td>(0.00317)</td>
<td>(0.00244)</td>
<td>(0.000737)</td>
<td>(0.00340)</td>
<td>(0.000665)</td>
<td>(0.000390)</td>
<td></td>
</tr>
<tr>
<td>$C_{N6}$</td>
<td>-0.0594</td>
<td>-0.0521</td>
<td>-0.0138</td>
<td>-0.000156</td>
<td>0.102***</td>
<td>-0.0144**</td>
<td>-0.0294**</td>
<td>-0.0498</td>
<td>-0.0588***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0362)</td>
<td>(0.0268)</td>
<td>(0.00913)</td>
<td>(0.0124)</td>
<td>(0.0257)</td>
<td>(0.00461)</td>
<td>(0.00976)</td>
<td>(0.0328)</td>
<td>(0.00983)</td>
<td></td>
</tr>
<tr>
<td>$C_{N7}$</td>
<td>-0.00114</td>
<td>0.00259***</td>
<td>0.000563</td>
<td>-0.00510***</td>
<td>0.000631</td>
<td>-</td>
<td>0.000524***</td>
<td>0.000770**</td>
<td>-0.000427</td>
<td>0.0000920</td>
</tr>
<tr>
<td></td>
<td>(0.00180)</td>
<td>(0.000558)</td>
<td>(0.000289)</td>
<td>(0.00133)</td>
<td>(0.000638)</td>
<td>(0.0000734)</td>
<td>(0.000120)</td>
<td>(0.000292)</td>
<td>(0.000617)</td>
<td></td>
</tr>
<tr>
<td>$C_{N8}$</td>
<td>0.0108</td>
<td>-0.0150</td>
<td>-0.0154***</td>
<td>0.0311***</td>
<td>-0.0517*</td>
<td>0.00304</td>
<td>0.0283***</td>
<td>-0.0253*</td>
<td>0.0166***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0150)</td>
<td>(0.00943)</td>
<td>(0.00294)</td>
<td>(0.00327)</td>
<td>(0.0223)</td>
<td>(0.00180)</td>
<td>(0.00304)</td>
<td>(0.0108)</td>
<td>(0.00367)</td>
<td></td>
</tr>
<tr>
<td>$C_{N9}$</td>
<td>0.0396*</td>
<td>0.00251</td>
<td>-0.0417***</td>
<td>0.0266**</td>
<td>-0.00393</td>
<td>0.0428***</td>
<td>0.0353***</td>
<td>0.0553***</td>
<td>0.0406***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0166)</td>
<td>(0.0126)</td>
<td>(0.0101)</td>
<td>(0.0103)</td>
<td>(0.0360)</td>
<td>(0.00587)</td>
<td>(0.00763)</td>
<td>(0.0129)</td>
<td>(0.00857)</td>
<td></td>
</tr>
<tr>
<td>$C_{N10}$</td>
<td>-0.00759</td>
<td>-0.0338***</td>
<td>-0.00990*</td>
<td>-0.0128**</td>
<td>-0.0273*</td>
<td>0.00384*</td>
<td>0.000282</td>
<td>-0.00374</td>
<td>0.0123***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0151)</td>
<td>(0.00991)</td>
<td>(0.00344)</td>
<td>(0.00497)</td>
<td>(0.0130)</td>
<td>(0.00169)</td>
<td>(0.00352)</td>
<td>(0.00671)</td>
<td>(0.00227)</td>
<td></td>
</tr>
<tr>
<td>$C_{Nik}$</td>
<td>0.00482***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000377)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>22.167</td>
<td>282.791</td>
<td>369.001</td>
<td>149.839</td>
<td>45.601</td>
<td>178.881</td>
<td>236.604</td>
<td>47.360</td>
<td>155.256</td>
<td>163.590</td>
</tr>
<tr>
<td></td>
<td>[0.0143]</td>
<td>[0.0000]</td>
<td>[0.0000]</td>
<td>[0.0000]</td>
<td>[0.0000]</td>
<td>[0.0000]</td>
<td>[0.0000]</td>
<td>[0.0000]</td>
<td>[0.0000]</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>287.298</td>
<td>2,872,980</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.872,980</td>
</tr>
</tbody>
</table>

Notes: Estimates from equation A.1. Each column represents a potential target sector $k$. Each cell contains the estimated coefficient $\gamma_k$ for $C_{Nik}$ (the number of coworkers with jobs in sector $s$ at the time of worker $i$’s switch). $\chi^2$ statistics test for joint significance of coefficients $\gamma_k$ (for $s = 1, \ldots, 10$). Robust standard errors in parenthesis, p-values in brackets. Base outcome=manufacturing. The last column presents the estimate $\gamma$ for the alternative specific conditional logit specification (equation A.2).
Table A.3: Multinomial Logit Model - Occupation Restriction

<table>
<thead>
<tr>
<th>Outcome k</th>
<th>Agriculture, mining</th>
<th>Construction</th>
<th>Retail</th>
<th>Transportation Low skill svcs</th>
<th>Finance, prof svcs</th>
<th>Office, support svcs</th>
<th>Public Admin.</th>
<th>Personal svcs</th>
<th>ASCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN_{i1}</td>
<td>0.0204***</td>
<td>0.0228***</td>
<td>0.00834</td>
<td>0.00723</td>
<td>-0.0440</td>
<td>-0.0122**</td>
<td>-0.00348</td>
<td>0.0106</td>
<td>-0.00794</td>
</tr>
<tr>
<td></td>
<td>(0.00590)</td>
<td>(0.00417)</td>
<td>(0.00479)</td>
<td>(0.00595)</td>
<td>(0.0457)</td>
<td>(0.00438)</td>
<td>(0.00560)</td>
<td>(0.00540)</td>
<td>(0.0138)</td>
</tr>
<tr>
<td>CN_{i2}</td>
<td>0.000159</td>
<td>-0.00149</td>
<td>-0.000989*</td>
<td>-0.000478</td>
<td>0.000215**</td>
<td>-0.000842**</td>
<td>0.000492</td>
<td>-0.00169***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000386)</td>
<td>(0.000809)</td>
<td>(0.000443)</td>
<td>(0.00101)</td>
<td>(0.0000797)</td>
<td>(0.000271)</td>
<td>(0.000356)</td>
<td>(0.000375)</td>
<td></td>
</tr>
<tr>
<td>CN_{i3}</td>
<td>-0.00516</td>
<td>0.0335***</td>
<td>-0.000792</td>
<td>0.00169</td>
<td>-0.0542*</td>
<td>0.00498*</td>
<td>-0.00231</td>
<td>-0.00119</td>
<td>0.00130</td>
</tr>
<tr>
<td></td>
<td>(0.00076)</td>
<td>(0.00304)</td>
<td>(0.00311)</td>
<td>(0.00599)</td>
<td>(0.0265)</td>
<td>(0.00199)</td>
<td>(0.00357)</td>
<td>(0.00738)</td>
<td>(0.00629)</td>
</tr>
<tr>
<td>CN_{i4}</td>
<td>-0.00147</td>
<td>-0.00336</td>
<td>0.00996***</td>
<td>-0.00378</td>
<td>0.0108*</td>
<td>-0.00255**</td>
<td>0.000197</td>
<td>-0.00549</td>
<td>-0.00230</td>
</tr>
<tr>
<td></td>
<td>(0.00566)</td>
<td>(0.00293)</td>
<td>(0.000755)</td>
<td>(0.00849)</td>
<td>(0.000755)</td>
<td>(0.00129)</td>
<td>(0.00357)</td>
<td>(0.00165)</td>
<td></td>
</tr>
<tr>
<td>CN_{i5}</td>
<td>-0.00309</td>
<td>0.0000345</td>
<td>-0.00183</td>
<td>-0.000715</td>
<td>-0.00218*</td>
<td>-0.00196*</td>
<td>-0.00160</td>
<td>-0.00799</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00265)</td>
<td>(0.000724)</td>
<td>(0.000145)</td>
<td>(0.000344)</td>
<td>(0.000120)</td>
<td>(0.000873)</td>
<td>(0.000625)</td>
<td>(0.000966)</td>
<td>(0.00576)</td>
</tr>
<tr>
<td>CN_{i6}</td>
<td>-0.0211</td>
<td>-0.0495*</td>
<td>-0.0511***</td>
<td>-0.0175</td>
<td>0.0725</td>
<td>-0.0180**</td>
<td>-0.0461**</td>
<td>-0.0453</td>
<td>-0.0565***</td>
</tr>
<tr>
<td></td>
<td>(0.0327)</td>
<td>(0.0212)</td>
<td>(0.0123)</td>
<td>(0.0183)</td>
<td>(0.0397)</td>
<td>(0.00631)</td>
<td>(0.0156)</td>
<td>(0.0367)</td>
<td>(0.0161)</td>
</tr>
<tr>
<td>CN_{i7}</td>
<td>-0.000534</td>
<td>0.00218***</td>
<td>0.00112***</td>
<td>-0.00537*</td>
<td>0.00113*</td>
<td>-0.00387**</td>
<td>0.000730</td>
<td>-0.000127</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00138)</td>
<td>(0.000661)</td>
<td>(0.000214)</td>
<td>(0.000225)</td>
<td>(0.000565)</td>
<td>(0.0000835)</td>
<td>(0.000109)</td>
<td>(0.000339)</td>
<td>(0.000702)</td>
</tr>
<tr>
<td>CN_{i8}</td>
<td>0.0102</td>
<td>0.00244</td>
<td>-0.00574</td>
<td>0.0351***</td>
<td>-0.0698*</td>
<td>0.00380</td>
<td>0.0305***</td>
<td>-0.0226</td>
<td>0.0178***</td>
</tr>
<tr>
<td></td>
<td>(0.0201)</td>
<td>(0.0111)</td>
<td>(0.00389)</td>
<td>(0.00481)</td>
<td>(0.0289)</td>
<td>(0.00259)</td>
<td>(0.00396)</td>
<td>(0.0142)</td>
<td>(0.00469)</td>
</tr>
<tr>
<td>CN_{i9}</td>
<td>0.0469*</td>
<td>-0.0526***</td>
<td>0.0203</td>
<td>-0.0287</td>
<td>0.0305***</td>
<td>0.0489***</td>
<td>0.0312</td>
<td>0.0340***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0205)</td>
<td>(0.0157)</td>
<td>(0.0113)</td>
<td>(0.0131)</td>
<td>(0.0399)</td>
<td>(0.00631)</td>
<td>(0.00907)</td>
<td>(0.0187)</td>
<td>(0.0100)</td>
</tr>
<tr>
<td>CN_{i10}</td>
<td>-0.0394*</td>
<td>-0.0599***</td>
<td>-0.0202***</td>
<td>-0.00928</td>
<td>-0.0296</td>
<td>0.00694*</td>
<td>-0.00318</td>
<td>0.00627</td>
<td>0.0128**</td>
</tr>
<tr>
<td></td>
<td>(0.0164)</td>
<td>(0.0116)</td>
<td>(0.00529)</td>
<td>(0.00726)</td>
<td>(0.0191)</td>
<td>(0.00245)</td>
<td>(0.00476)</td>
<td>(0.00787)</td>
<td>(0.00403)</td>
</tr>
<tr>
<td>CN_{ik}</td>
<td>0.000276***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000534)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[ \chi^2 = 33.32 \quad N = 287,298 \quad 2^{10.5} \]

Notes: Estimates from equation A.1. Each column represents a potential target sector \( k \). Each cell contains the estimated coefficient \( \gamma_k^s \) for \( CN_{is} \) (the number of coworkers with jobs in sector \( s \) at the time of worker \( i \)’s switch, restricted to coworkers in different occupations at the time of last interaction). \( \chi^2 \) statistics test for joint significance of coefficients \( \gamma_k^s \) (for \( s = 1, \ldots, 10 \)). Robust standard errors in parenthesis, p-values in brackets. Base outcome=manufacturing. The last column presents the estimate \( \gamma \) for the alternative specific conditional logit specification (equation A.2).
Potential violations of the exclusion restriction

Formally, the exclusion restriction in our setting requires $CN_{ik}$ and $\epsilon_{ik}$ to be independent of each other (see selection model 1.5). That is, that the number of past coworkers in a particular sector $k$ is uncorrelated to the wage worker $i$ gets in such sector (after controlling for observed characteristics). We already impose the restriction on the coworkers switch date to avoid problems with unobserved time specific shocks, and the occupation restriction to (partially) address pre-displacement sorting.

Even then, the exclusion restriction will fail if past coworkers share other unobserved characteristics with worker $i$ (despite being in different occupations), and these characteristics enter the error term in the wage equation. Such would be the case if workers sort into firms (within manufacturing) based on unobserved characteristics such as absolute ability or by comparative advantage regardless of their occupation.

In the future we plan conduct additional robustness tests by imposing additional restrictions of the coworkers we include in our estimation. Specifically, we plan to restrict $CN_{is}$ to include only coworkers in different within-firm wage quartiles (relative to worker $i$) and education levels.
## A.3 Selection Model - Second Stage

Table A.4: Corrected and Uncorrected Estimates \( \beta \) - Gender

<table>
<thead>
<tr>
<th>Target Industry</th>
<th>( \beta_{OLS} )</th>
<th>( \beta_{DMF1} )</th>
<th>Hausman Test</th>
<th>Wald Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, energy</td>
<td>-0.1213***</td>
<td>-0.2406**</td>
<td>-1.1524</td>
<td>6.1561</td>
</tr>
<tr>
<td></td>
<td>(0.0363)</td>
<td>(0.1097)</td>
<td>[0.2491]</td>
<td>[0.008]</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.0078***</td>
<td>0.0715***</td>
<td>9.4877</td>
<td>47.3640</td>
</tr>
<tr>
<td></td>
<td>(0.0019)</td>
<td>(0.0070)</td>
<td>[0.0000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Construction</td>
<td>-0.1202***</td>
<td>-0.0534</td>
<td>1.2208</td>
<td>6.0343</td>
</tr>
<tr>
<td></td>
<td>(0.0190)</td>
<td>(0.0579)</td>
<td>[0.2222]</td>
<td>[0.074]</td>
</tr>
<tr>
<td>Retail</td>
<td>0.0089</td>
<td>0.0249</td>
<td>0.8574</td>
<td>14.0879</td>
</tr>
<tr>
<td></td>
<td>(0.0060)</td>
<td>(0.0196)</td>
<td>[0.3912]</td>
<td>[0.022]</td>
</tr>
<tr>
<td>Transportation</td>
<td>-0.0325</td>
<td>0.0898</td>
<td>2.3474</td>
<td>7.6773</td>
</tr>
<tr>
<td></td>
<td>(0.0221)</td>
<td>(0.0566)</td>
<td>[0.0189]</td>
<td>[0.022]</td>
</tr>
<tr>
<td>Hotel, rest, low skill svs</td>
<td>0.0801***</td>
<td>-0.2221**</td>
<td>-3.0380</td>
<td>5.6963</td>
</tr>
<tr>
<td></td>
<td>(0.0218)</td>
<td>(0.1018)</td>
<td>[0.0024]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>Communication, finance, other prof svs</td>
<td>0.0045</td>
<td>0.0369*</td>
<td>1.6393</td>
<td>5.0402</td>
</tr>
<tr>
<td></td>
<td>(0.0086)</td>
<td>(0.0216)</td>
<td>[0.1012]</td>
<td>[0.030]</td>
</tr>
<tr>
<td>Office and bus support svs</td>
<td>-0.0277*</td>
<td>0.0225</td>
<td>1.2469</td>
<td>27.5699</td>
</tr>
<tr>
<td></td>
<td>(0.0151)</td>
<td>(0.0430)</td>
<td>[0.2124]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Public administration</td>
<td>0.0004</td>
<td>0.0757</td>
<td>0.8275</td>
<td>6.2290</td>
</tr>
<tr>
<td></td>
<td>(0.0315)</td>
<td>(0.0963)</td>
<td>[0.4079]</td>
<td>[0.014]</td>
</tr>
<tr>
<td>Education, hosp, personal svs</td>
<td>0.0304**</td>
<td>0.1354***</td>
<td>2.3396</td>
<td>11.5111</td>
</tr>
<tr>
<td></td>
<td>(0.0147)</td>
<td>(0.0472)</td>
<td>[0.0193]</td>
<td>[0.002]</td>
</tr>
</tbody>
</table>

Notes: Estimates of \( \beta_k \) for a female indicator variable from equation 1.5. Dependent variable is log difference in daily wages for workers moving from manufacturing into each target sector \( k \). Regressors included: sectoral tenure, age group, gender, education, state and year dummies, unemployment duration, and regional employment shares in each industry. Sample of displaced manufacturing workers in West Germany (1990-2010). Column 3 features results from a Hausman test of equality between the corrected and uncorrected coefficients. Column 4 presents test statistics of joint significance of the parameters of the correction function. *** \( p<0.01 \), ** \( p<0.05 \), * \( p<0.1 \), bootstrapped standard errors in parenthesis (250 replications), p-values shown in brackets.
Table A.5: Corrected and Uncorrected Estimates $\beta$ - Apprenticeship

<table>
<thead>
<tr>
<th>Target Industry</th>
<th>$\beta_{OLS}$</th>
<th>$\beta_{DMF}$</th>
<th>Hausman Test</th>
<th>Wald Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, energy</td>
<td>0.0276</td>
<td>0.1509</td>
<td>1.1907</td>
<td>6.1561</td>
</tr>
<tr>
<td></td>
<td>(0.0362)</td>
<td>(0.1097)</td>
<td>[0.2338]</td>
<td>[0.008]</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.0377***</td>
<td>0.0685***</td>
<td>2.9447</td>
<td>47.3640</td>
</tr>
<tr>
<td></td>
<td>(0.0033)</td>
<td>(0.0110)</td>
<td>[0.0032]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Construction</td>
<td>0.0133</td>
<td>0.0949*</td>
<td>1.5768</td>
<td>6.0343</td>
</tr>
<tr>
<td></td>
<td>(0.0140)</td>
<td>(0.0536)</td>
<td>[0.1148]</td>
<td>[0.074]</td>
</tr>
<tr>
<td>Retail</td>
<td>0.0744***</td>
<td>0.2009***</td>
<td>5.3249</td>
<td>14.0879</td>
</tr>
<tr>
<td></td>
<td>(0.0088)</td>
<td>(0.0253)</td>
<td>[0.0000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Transportation</td>
<td>0.0548**</td>
<td>0.2465***</td>
<td>2.2025</td>
<td>7.6773</td>
</tr>
<tr>
<td></td>
<td>(0.0250)</td>
<td>(0.0906)</td>
<td>[0.0276]</td>
<td>[0.022]</td>
</tr>
<tr>
<td>Hotel, rest, low skill svcs</td>
<td>0.1093***</td>
<td>0.3987***</td>
<td>2.4660</td>
<td>5.6963</td>
</tr>
<tr>
<td></td>
<td>(0.0305)</td>
<td>(0.1213)</td>
<td>[0.0137]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>Communication, finance, other prof svcs</td>
<td>0.0675***</td>
<td>0.1872***</td>
<td>4.0837</td>
<td>5.0402</td>
</tr>
<tr>
<td></td>
<td>(0.0122)</td>
<td>(0.0318)</td>
<td>[0.0000]</td>
<td>[0.030]</td>
</tr>
<tr>
<td>Office and bus support svcs</td>
<td>0.0244</td>
<td>0.2417***</td>
<td>5.3194</td>
<td>27.5699</td>
</tr>
<tr>
<td></td>
<td>(0.0175)</td>
<td>(0.0444)</td>
<td>[0.0000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Public administration</td>
<td>0.0681</td>
<td>0.1781</td>
<td>0.7713</td>
<td>6.2290</td>
</tr>
<tr>
<td></td>
<td>(0.0621)</td>
<td>(0.1556)</td>
<td>[0.4405]</td>
<td>[0.014]</td>
</tr>
<tr>
<td>Education, hosp, personal svcs</td>
<td>0.0455**</td>
<td>0.1118**</td>
<td>1.4140</td>
<td>11.5111</td>
</tr>
<tr>
<td></td>
<td>(0.0210)</td>
<td>(0.0514)</td>
<td>[0.1574]</td>
<td>[0.002]</td>
</tr>
</tbody>
</table>

Notes: Estimates of $\beta_k$ for Apprenticeship education level (equation 1.5). Dependent variable is log difference in daily wages for workers moving from manufacturing into each target sector $k$. Regressors included: sectoral tenure, age group, gender, education, state and year dummies, unemployment duration, and regional employment shares in each industry. Sample of displaced manufacturing workers in West Germany (1990-2010). Column 3 features results from a Hausman test of equality between the corrected and uncorrected coefficients. Column 4 presents test statistics of joint significance of the parameters of the correction function. *** p<0.01, ** p<0.05, * p<0.1, bootstrapped standard errors in parenthesis (250 replications), p-values shown in brackets.
### Table A.6: Corrected and Uncorrected Estimates $\alpha$

<table>
<thead>
<tr>
<th>Target Industry</th>
<th>$\alpha_{OLS}$</th>
<th>$\alpha_{DMF1}$</th>
<th>Hausman Test</th>
<th>Wald Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, mining, energy</td>
<td>5.4463*</td>
<td>1.1089</td>
<td>-1.6285</td>
<td>6.1561</td>
</tr>
<tr>
<td></td>
<td>(2.7821)</td>
<td>(3.8516)</td>
<td>[0.1034]</td>
<td>[0.008]</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>-0.0932</td>
<td>0.1902</td>
<td>1.1743</td>
<td>47.3640</td>
</tr>
<tr>
<td></td>
<td>(0.2417)</td>
<td>(0.3416)</td>
<td>[0.2403]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Construction</td>
<td>-0.8355</td>
<td>-2.0347</td>
<td>-1.1332</td>
<td>6.0343</td>
</tr>
<tr>
<td></td>
<td>(1.4257)</td>
<td>(1.7756)</td>
<td>[0.2571]</td>
<td>[0.074]</td>
</tr>
<tr>
<td>Retail</td>
<td>0.1333</td>
<td>-0.0866</td>
<td>-0.3484</td>
<td>14.0879</td>
</tr>
<tr>
<td></td>
<td>(1.0475)</td>
<td>(1.2229)</td>
<td>[0.7275]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Transportation</td>
<td>2.5833</td>
<td>2.3003</td>
<td>-0.1594</td>
<td>7.6773</td>
</tr>
<tr>
<td></td>
<td>(3.5501)</td>
<td>(3.9606)</td>
<td>[0.8734]</td>
<td>[0.022]</td>
</tr>
<tr>
<td>Hotel, rest, low skill svs</td>
<td>-2.4823</td>
<td>-1.1354</td>
<td>0.7067</td>
<td>5.6963</td>
</tr>
<tr>
<td></td>
<td>(2.4234)</td>
<td>(3.0831)</td>
<td>[0.4798]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>Communication, finance, other prof svs</td>
<td>-2.1472**</td>
<td>-2.4906</td>
<td>-1.4814</td>
<td>5.0402</td>
</tr>
<tr>
<td></td>
<td>(1.0626)</td>
<td>(1.0876)</td>
<td>[0.1385]</td>
<td>[0.030]</td>
</tr>
<tr>
<td>Office and bus support svs</td>
<td>0.4458</td>
<td>0.3632</td>
<td>-0.0774</td>
<td>27.5699</td>
</tr>
<tr>
<td></td>
<td>(1.8193)</td>
<td>(2.1096)</td>
<td>[0.9383]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Public administration</td>
<td>2.5551</td>
<td>3.2555</td>
<td>0.2879</td>
<td>6.2290</td>
</tr>
<tr>
<td></td>
<td>(3.3785)</td>
<td>(4.1630)</td>
<td>[0.7734]</td>
<td>[0.014]</td>
</tr>
<tr>
<td>Education, hosp, personal svs</td>
<td>0.7212</td>
<td>-0.7112</td>
<td>-1.3277</td>
<td>11.5111</td>
</tr>
<tr>
<td></td>
<td>(1.8939)</td>
<td>(2.1796)</td>
<td>[0.1843]</td>
<td>[0.002]</td>
</tr>
</tbody>
</table>

**Notes:** Estimates of $\alpha_k$ (intercept) for equation 1.5. Dependent variable is log difference in daily wages for workers moving from manufacturing into each target sector $k$. Regressors included: sectoral tenure, age group, gender, education, state and year dummies, unemployment duration, and regional employment shares in each industry. Sample of displaced manufacturing workers in West Germany (1990-2010). Column 3 features results from a Hausman test of equality between the corrected and uncorrected coefficients. Column 4 presents test statistics of joint significance of the parameters of the correction function. *** p<0.01, ** p<0.05, * p<0.1, bootstrapped standard errors in parenthesis (250 replications), p-values shown in brackets.
A.4 \( LMF_{rt} \) Decomposition

Let \( \bar{X}_r = \frac{\sum_{i \in \Omega(r, t)} X_i}{N_{rt}} \), \( \bar{X} = \frac{\sum_i X_i}{N_r} \) be the regional and national average levels of observed human capital in our sample. Similarly, define \( \bar{p}_s \) as average employment share in sector \( s \) at the national level. Then \( LMF_{r1} \) can be decomposed into 4 components.

\[
LMF_{r1} = \sum_s \pi^r_s \bar{X}^t_s \beta_s
= \sum_s \pi^r_s \bar{X}^t_s \beta_s + \sum_s \pi^r_s (\bar{X}_r - \bar{X})^t \beta_s
= \sum_s \bar{p}_s \bar{X}^t_s \beta_s + \sum_s (\pi^r_s - \bar{p}_s) \bar{X}^t_s \beta_s + \sum_s \pi^r_s (\bar{X}_r - \bar{X})^t \beta_s
= \sum_s \bar{p}_s \bar{X}^t_s \beta_s + \sum_s (\pi^r_s - \bar{p}_s) \bar{X}^t_s \beta_s + \sum_s \bar{p}_s (\bar{X}_r - \bar{X})^t \beta_s + \sum_s (\pi^r_s - \bar{p}_s) (\bar{X}_r - \bar{X})^t \beta_s
\]

\[
\text{Components:} \quad \text{A} \quad \text{B} \quad \text{C} \quad \text{D}
\]

Similarly, defining \( \bar{p}^r_s = \frac{\sum_{i \in \Omega(c, t)} \hat{p}_{is}}{N_{rt}} \) and \( \bar{p}_s = \frac{\sum \hat{p}_{is}}{N_t} \) as the regional and national average predicted probabilities of reallocating to sector \( s \), \( LMF_{r2} \) can be decomposed in the following manner:

\[
LMF_{r2} = \frac{1}{N_r} \sum_s \sum_i p_{is} X_i^t \beta_s
= \sum_s \bar{p}^r_s \bar{X}^t_s \beta_s + \frac{1}{N_r} \sum_s \sum_i (p_{is} - \bar{p}^r_s) (X_i - \bar{X})^t \beta_s
= \sum_s \bar{p}_s \bar{X}^t_s \beta_s + \sum_s (\bar{p}^r_s - \bar{p}_s) \bar{X}^t_s \beta_s + \sum_s \bar{p}_s (\bar{X}_r - \bar{X})^t \beta_s + \sum_s (\bar{p}^r_s - \bar{p}_s) (\bar{X}_r - \bar{X})^t \beta_s
+ \frac{1}{N_r} \sum_s \sum_i (p_{is} - \bar{p}^r_s) (X_i - \bar{X})^t \beta_s
\]

\[
\text{Components:} \quad \text{A} \quad \text{B} \quad \text{C} \quad \text{D} \quad \text{E}
\]

The results of this decomposition are shown in Table A.7.
Figure A.1: Geographic Distribution of $LMF_{rt}$

Notes: LMF calculated from equation 1.7. LMF quartiles based on average LMF for years 1988 and 1998. East Germany currently excluded.
Table A.7: $LMF_{rt}$ Variance Decomposition

<table>
<thead>
<tr>
<th></th>
<th>$LMF_{rt}^1$</th>
<th>$LMF_{rt}^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>B</td>
<td>0.71</td>
<td>0.60</td>
</tr>
<tr>
<td>C</td>
<td>0.28</td>
<td>0.36</td>
</tr>
<tr>
<td>D</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>E</td>
<td>-</td>
<td>0.04</td>
</tr>
<tr>
<td>Total Variance</td>
<td>0.13</td>
<td>0.08</td>
</tr>
<tr>
<td>Observations</td>
<td>458</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
### A.5 Earnings and Employment Reallocation by Industry

Table A.8: Employment Reallocation - By Quartile of $LMF_{it}$

<table>
<thead>
<tr>
<th>Cumulative Employment</th>
<th>National</th>
<th>$Q_1$</th>
<th>$Q_2$</th>
<th>$Q_3$</th>
<th>$Q_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$CumEmp_{it}^{Non-Manuf}$</td>
<td>1.574***</td>
<td>1.452**</td>
<td>1.189***</td>
<td>1.389***</td>
<td>1.910***</td>
</tr>
<tr>
<td></td>
<td>(0.285)</td>
<td>(0.548)</td>
<td>(0.358)</td>
<td>(0.282)</td>
<td>(0.421)</td>
</tr>
<tr>
<td>$CumEmp_{it}^1$</td>
<td>-0.161*</td>
<td>0.222</td>
<td>-0.094</td>
<td>-0.138</td>
<td>-0.239**</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.249)</td>
<td>(0.097)</td>
<td>(0.077)</td>
<td>(0.080)</td>
</tr>
<tr>
<td>$CumEmp_{it}^3$</td>
<td>0.149***</td>
<td>0.144</td>
<td>0.111</td>
<td>0.140***</td>
<td>0.177***</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.111)</td>
<td>(0.058)</td>
<td>(0.034)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>$CumEmp_{it}^4$</td>
<td>0.437***</td>
<td>0.422*</td>
<td>0.407**</td>
<td>0.274***</td>
<td>0.589*</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.173)</td>
<td>(0.133)</td>
<td>(0.063)</td>
<td>(0.245)</td>
</tr>
<tr>
<td>$CumEmp_{it}^5$</td>
<td>0.034*</td>
<td>-0.002</td>
<td>0.048</td>
<td>0.046*</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.032)</td>
<td>(0.030)</td>
<td>(0.021)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>$CumEmp_{it}^6$</td>
<td>0.008</td>
<td>-0.038</td>
<td>0.034*</td>
<td>0.013</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.064)</td>
<td>(0.014)</td>
<td>(0.009)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>$CumEmp_{it}^7$</td>
<td>0.800***</td>
<td>0.456**</td>
<td>0.464**</td>
<td>0.767**</td>
<td>1.001***</td>
</tr>
<tr>
<td></td>
<td>(0.172)</td>
<td>(0.155)</td>
<td>(0.149)</td>
<td>(0.250)</td>
<td>(0.211)</td>
</tr>
<tr>
<td>$CumEmp_{it}^8$</td>
<td>0.086***</td>
<td>0.056</td>
<td>0.078**</td>
<td>0.104***</td>
<td>0.076**</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.079)</td>
<td>(0.024)</td>
<td>(0.023)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>$CumEmp_{it}^9$</td>
<td>0.013</td>
<td>0.023</td>
<td>0.012</td>
<td>0.017*</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.031)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>$CumEmp_{it}^{10}$</td>
<td>0.209***</td>
<td>0.170*</td>
<td>0.129**</td>
<td>0.165***</td>
<td>0.287***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.084)</td>
<td>(0.044)</td>
<td>(0.031)</td>
<td>(0.056)</td>
</tr>
</tbody>
</table>

Observations 8,024,522

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered in 1125 State-Industry cells. Each row features estimates of $\psi$ for separate regressions with the dependent variable being cumulative employment (in days) in each non-manufacturing sector. Row 1 dependent variable is cumulative employment in all non-manufacturing sectors. Same sample, estimation and controls as Table 1.5 (equation 1.9).
### A.6 Alternative $LMF_{rt}$ based on employment shares

Table A.9: Regressions by Quartile of $LMF_{rt}$ - Alternative $LMF_{rt}$ Measure

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Earnings</td>
<td>Earnings</td>
<td>Employment</td>
<td>Employment</td>
</tr>
<tr>
<td>$\Delta IP_{j,t}$</td>
<td>-0.381***</td>
<td></td>
<td>-0.762***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td></td>
<td>(0.128)</td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_1} = 1)$</td>
<td>-0.606***</td>
<td>-1.030**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.381)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_2} = 1)$</td>
<td>-0.489***</td>
<td>-0.990***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.139)</td>
<td>(0.269)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_3} = 1)$</td>
<td>-0.420***</td>
<td>-0.729***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.125)</td>
<td>(0.158)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta IP_{j,t} \cdot (D_{Q_4} = 1)$</td>
<td>-0.269**</td>
<td>-0.664***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.122)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>8023968</td>
<td>8023968</td>
<td>8023968</td>
<td>8023968</td>
</tr>
<tr>
<td>$\chi_3^2$</td>
<td>17.829</td>
<td>21.445</td>
<td>35.599</td>
<td>37.612</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Notes:** $LMF_{rt}$ based on employment shares. Cumulative earnings normalized by the average annual earnings of the 5 years preceding period $\tau$. Cumulative employment measured in days. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
### Table A.10: Regressions by Quartile of $LMF_{rt}$ - Alternative $LMF_{rt}$ Measure

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earnings</td>
<td>Earnings</td>
<td>Employment</td>
<td>Employment</td>
<td>Employment</td>
<td>Employment</td>
</tr>
<tr>
<td>$\Delta IP_{t,\tau} \cdot (D_{Q1} = 1)$</td>
<td>-0.598***</td>
<td>-0.586***</td>
<td>-0.495***</td>
<td>-1.015**</td>
<td>-0.931**</td>
</tr>
<tr>
<td>(0.134)</td>
<td>(0.145)</td>
<td>(0.118)</td>
<td>(0.326)</td>
<td>(0.330)</td>
<td>(0.280)</td>
</tr>
<tr>
<td>$\Delta IP_{t,\tau} \cdot (D_{Q2} = 1)$</td>
<td>-0.435***</td>
<td>-0.450**</td>
<td>-0.416***</td>
<td>-0.750***</td>
<td>-0.832**</td>
</tr>
<tr>
<td>(0.126)</td>
<td>(0.147)</td>
<td>(0.123)</td>
<td>(0.217)</td>
<td>(0.269)</td>
<td>(0.229)</td>
</tr>
<tr>
<td>$\Delta IP_{t,\tau} \cdot (D_{Q3} = 1)$</td>
<td>-0.357***</td>
<td>-0.381*</td>
<td>-0.319**</td>
<td>-0.544***</td>
<td>-0.637***</td>
</tr>
<tr>
<td>(0.102)</td>
<td>(0.152)</td>
<td>(0.099)</td>
<td>(0.124)</td>
<td>(0.188)</td>
<td>(0.135)</td>
</tr>
<tr>
<td>$\Delta IP_{t,\tau} \cdot (D_{Q4} = 1)$</td>
<td>-0.256**</td>
<td>-0.364**</td>
<td>-0.285***</td>
<td>-0.562***</td>
<td>-0.795***</td>
</tr>
<tr>
<td>(0.081)</td>
<td>(0.125)</td>
<td>(0.084)</td>
<td>(0.121)</td>
<td>(0.204)</td>
<td>(0.138)</td>
</tr>
</tbody>
</table>

Excluding age 50 over: Yes | No | No | Yes | No | No | No
Excluding large LMAs: No | Yes | No | No | Yes | No | No
Excluding East Germany: No | No | Yes | No | No | No | Yes

| N | 5887698 | 5514732 | 7137718 | 5887698 | 5514732 | 7137718 |
| $\chi^2$ | 25.322 | 18.969 | 23.020 | 32.552 | 24.686 | 31.046 |

Notes: $LMF_{rt}$ based on employment shares. Cumulative earnings normalized by the average annual earnings of the 5 years preceding period $\tau$. Cumulative employment measured in days. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
## A.7 Additional Results

Table A.11: Two-Step Estimation (Placebo Tests)

<table>
<thead>
<tr>
<th></th>
<th>Cumulative Earnings</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline $\bar{y}$</td>
<td>$\bar{y}_{m \rightarrow k}$</td>
</tr>
<tr>
<td>$LMF_{rt}$</td>
<td>0.217**</td>
<td>-0.197***</td>
</tr>
<tr>
<td></td>
<td>(0.0713)</td>
<td>(0.0402)</td>
</tr>
<tr>
<td>$\text{Manufacturing Share}_{r0}$</td>
<td>0.176**</td>
<td>0.153**</td>
</tr>
<tr>
<td></td>
<td>(0.0634)</td>
<td>(0.0551)</td>
</tr>
<tr>
<td>$\text{Regional Trade Exposure}_{rt}$</td>
<td>0.0372*</td>
<td>0.0320</td>
</tr>
<tr>
<td></td>
<td>(0.0177)</td>
<td>(0.0174)</td>
</tr>
<tr>
<td>$\text{Net Employment Growth}_{rt}$</td>
<td>-0.0508</td>
<td>-0.0731</td>
</tr>
<tr>
<td></td>
<td>(0.0479)</td>
<td>(0.0460)</td>
</tr>
<tr>
<td>$\text{Initial Employment Size}_{r0}$</td>
<td>-0.0161</td>
<td>-0.00778</td>
</tr>
<tr>
<td></td>
<td>(0.0283)</td>
<td>(0.0267)</td>
</tr>
</tbody>
</table>

|                          | Yes | Yes | Yes |
| Region Level Controls    |     |     |     |
| Pre-trends (wage/emp)    | Yes | Yes | Yes |
| Observations             | 458 | 458 | 458 |
| Adjusted $R^2$           | 0.069 | 0.098 | 0.057 |

**Notes:** Estimates from equation 1.11 analogous to results from Table 1.8 but under different $LMF_{rt}$ specifications. Column 1 shows the baseline results (Table 1.8, column 3). Column 2 shows results for the case in which $LMF_{rt}$ is constructed using the average (unconditional) wage changes for displaced manufacturing workers moving into each target sector (Table 1.1). Column 3 shows results for the case in which $LMF_{rt}$ is constructed using the uncorrected OLS $\hat{\beta}_{m \rightarrow k}$ coefficients.
Appendix B

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

B.1 First-stages of estimation procedures

Figure B.1: First stage for Table 2.8

First Stage BMV
Figure B.2: First stage for Table 2.9