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

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Abstract

We analyze the roles that skill transferability and the local industry mix have on the adjustment costs of workers affected by a negative trade shock. 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 ranging from 9 to 12% of initial annual income (over a 10 year period). The earning losses of workers living in flexible regions are much smaller (3.5 to 4%). These findings are robust to controlling for a wide array of region level characteristics, including region size and overall employment growth. Taken together, our findings indicate that the industry composition of local labor markets plays an important role on the adjustment processes of workers.

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1 Introduction

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 et al. (2010), Dix-Carneiro (2014), Caliendo et al. (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

[1] See for example 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 et al. (1993))

[2] An additional body of work on trade and labor market adjustments focuses on different types of frictions (e.g. Helpman et al. (2010) on within-industry labor market frictions; Kambourov (2009) and Topalova (2010) on labor market regulations).

[3] This 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 Robinson (2008), Neal (1995), Parent (2000), Kambourov and Manovskii (2009), and Sullivan (2010).

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' perspective*.[4] 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 accumulated human capital. 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 experience 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

[4]While 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 et al. (2010) and Ellison et al. (2010).

(2002), Bourguignon et al. (2007)).[5] In order to identify the relevant parameters, we rely on a novel instrument for industry choice based on 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.[6] 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 estimate parameters that measure how much human capital workers can transfers when moving from one sector to another. We interpret these parameters, which vary across 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 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 1.4% if she were to move to the Office and Business Support Services sector, but only a 0.97% loss in the Communications and Services 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 12% (as a share of initial annual earnings over a

[5] See Beaudry et al. (2012) and Bombardini et al. (2012) for recent applications of this type of selection model corrections.

[6] For recent examples, see Saygin et al. (2014), Glitz (2013), and Cingano and Rosolia (2012) on coworker networks; Hellerstein et al. (2015) on neighborhood networks.

10 year period). The earning losses of workers living in flexible regions is much smaller, ranging from 3.5 to 4%. 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.[7] Our measures of skill transferability build upon a Roy model (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 et al. (2015), Galle et al. (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 et al. (2010), Dix-Carneiro (2014), and Caliendo et al. (2015), each of whom incorporate sectoral mobility costs–among other features–in their studies of labor market adjustments and trade.[8] 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).[9]

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 (e.g. von Wachter et al. (2008), Davis and Von Wachter (2011)), environmental regulations (e.g. Walker (2013)), and local demand shocks (e.g. Moretti (2010) and Notowidigdo (2011)). More related to this paper are recent studies on the effects of import competition on workers and local labor markets (Autor et al. (2014) and Autor et al. (2013) for the U.S., Dauth et al. (2014) for Germany, and Kovak (2013) and Dix-Carneiro and Kovak (2014) for Brazil).[10] Our work contributes to this literature by identifying sources of heterogeneity in the adjustment

[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 sectoral reallocation (Goldberg and Pavcnik (2007), Menezes-Filho and Muendler (2011),Wacziarg and Wallack (2004) for developing countries; Revenga (1992), Artuc et al. (2010) for developed countries).

process following an 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 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 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 paper is structured as follows. Section 2 presents a simple theoretical framework to motivate our analysis. Section 3 describes the data employed in this paper. In Section 4, we explain and estimate our measures of sectoral distances. Section 5 details the construction of our labor market flexibility index. Section 6 presents our main results on the heterogenous effects of shocks and their relation to our labor market flexibility measure. Section 7 concludes.

[11] A related strand of literature explore the role of labor market "thickness" (e.g. Bleakley and Lin (2012)), finding that occupational and industry switching rates are higher in more densely populated regions.

2 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, measured as years of experience working in sector s. Importantly, the returns workers get on their experience 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:

$$\ln y_{i0}^r = \alpha_i + X_i' \beta_m \tag{1}$$

where α_i represents worker i's unobserved general ability, and elements of β_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:

$$\ln y_{ik}^r = \alpha_i + X_i' \beta_k + \epsilon_{ik} \tag{2}$$

where ϵ_{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_{ik}^r, which is determined by the wage they receive as well as non-pecuniary factors and preferences:[12]

$$\begin{aligned} V_{ik}^r &= \ln y_{ik}^r + X_i' \kappa_k + Z_i' \Lambda_k + \sigma \theta_{ik} \\ &= \alpha_i + X_i' \beta_k + \epsilon_{ik} + X_i' \kappa_k + Z_i' \Lambda_k + \sigma \theta_{ik} \\ &= \alpha_i + X_i' \left(\beta_k + \kappa_k\right) + Z_i' \Lambda_k + \sigma \theta_{ik} + \epsilon_{ik} \end{aligned}$$

where θ_{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 α_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:

$$V_{ik}^r = X_i' \gamma_k + Z_i' \Gamma_k + \eta_{ik}$$

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

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

For ease of exposition, let $Z_i'\Gamma_k = -\tau^r_{m\to k}$, a non-pecuniary utility cost of moving from sector m to sector k that varies across regions. An intuitive way to think of $\tau^r_{m\to k}$ 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 $\tau^r_{m\to k}$ 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:

$$p^r_{i,\,m\to k} = \frac{\exp\left(X_i'\gamma_k - \tau^r_{m\to k}\right)}{\sum_s \exp\left(X_i'\gamma_s - \tau^r_{m\to s}\right)}$$

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

From equations 1 and 2, we can write an expression for the potential wage change related to a move from sector m to sector k:

$$\Delta \ln y^r_{i,\,m\to k} = X_i'\left(\beta_k - \beta_m\right) + \epsilon_{ik}$$

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

$$\begin{aligned} E\left[\Delta \ln y^r_{i,\,m\to k} \,|\, X_i,\, D_{i,\,m\to k} = 1\right] &= E\left[X_i'\left(\beta_k - \beta_m\right) + \epsilon_{ik} \,|\, X_i,\, D_{i,\,m\to k} = 1\right] \\ &= \underbrace{X_i'\beta_{m\to k}}_{\text{Observed}} + \underbrace{E\left[\epsilon_{ik} \,|\, D_{i,\,m\to k} = 1\right]}_{\text{Unobserved}} \end{aligned} \tag{3}$$

Equation 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 $\beta_{m\to k}$'s) while controlling for the unobserved components in the wage equations. Different values of β'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, $\hat{\beta}_{m\to k}$ will determine the wage loss (associated with observed human capital) that results from reallocating from sector m to sector k. We interpret

[13] Cardell (1997) shows that if $\theta_{ik} \sim C\left(\frac{1}{\sigma}\right)$ and $\epsilon_{ik} \sim EV1$, and the two random variables are independent of each other, then $\theta_{ik} + \frac{1}{\sigma}\epsilon_{ik} \sim EV1$.

this parameter $\hat{\beta}_{m\to k}$ 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:

$$\Delta y^r_m = \frac{1}{N_r}\sum_i \sum_s p^r_{i,\,m\to s} X_i' \hat{\beta}_{m\to s}$$

This expression highlights the importance of two factors in the reallocation costs of workers. Even for regions with similar workers (i.e. with the same distribution of X_i), reallocation costs will vary depending on:

1. The economic distances between m and other sectors: $\hat{\beta}_{m\to s}$
2. The reallocation probabilities to each sector s, which are partly determined by the sectoral composition of each region:

$$p^r_{i,\,m\to k} = \frac{\exp\left(X_i'\gamma_k - \tau^r_{m\to k}\right)}{\sum_s \exp\left(X_i'\gamma_s - \tau^r_{m\to s}\right)}$$

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 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.

3 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).[14] 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. Of importance to 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.

[14] We supplement this administrative database with data other sources, such as trade flow figures from the UNIDO database. Supplemental datasets are documented in the Data Appendix (Appendix 7).

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. There are limitations when using this administrative data that are worth mentioning. First, as discussed by Dustmann et al. (2009) and Card et al. (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 the the administrative purposes of the data). In particular, self-employed workers and civil servants are excluded from the data. Given the focus and scope of our study, such limitations are unlikely to influence our results.

For the purposes of our analysis, we divide the economy into 10 big sectors based on standardized NACE Rev2 industry classification codes. The geographic units of observation in this paper are German Labor Market Areas ("Arbeitsmarktregionen"). These regions are roughly equivalent to US Labor Market Regions constructed by the BLS. Our sample consists of 210 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.

4 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 Communications 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.

4.1 Empirical Approach

Using the notation developed in Section 2, the potential wage change for worker i moving from sector m to sector k will be given by:

$$\Delta \ln y_{i,\,m\to k} = X_i \beta_{m\to k} + \epsilon_{ik} \tag{4}$$

where ϵ_{ik} is an unobserved sector-specific ability and X_i measures the experience of worker i in sector m.[15] As mentioned earlier, a key feature of this specification is that we allow for returns to experience (X_i) be to sector-specific.[16] Given that we are taking first differences, the parameters in this model measure the transferability of skills between sector m and k, which will form the basis for our sectoral distance measures.

OLS estimation of equation 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 et al. (2007) and Dahl (2002). Formally, the model is as follows (we omit the m subscripts for simplicity):

$$\begin{aligned} \Delta \ln y_{ik} &= X_i \beta_k + \epsilon_{ik} \\ V_{ik} &= Z_i' \Gamma_k + \eta_{ik} \qquad (k = 1, \ldots, S) \\ D_{ik} &= \begin{cases} 1 & \iff V_{ik} = \max\left(V_{i1}, \ldots, V_{iS}\right) \\ 0 & otherwise \end{cases} \end{aligned} \tag{5}$$

This model tracks very closely the theoretical framework developed in Section 2, 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 2, we assume the error terms in the selection equation (η_{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 et al. (2007). Specifically, we impose the following linearity assumption:

$$E\left[\epsilon_{ik} | \eta_{i1} \ldots \eta_{iS}\right] = \sigma \frac{\sqrt{6}}{\pi} \sum_s r_k^s \left(\eta_{is} - E\left[\eta_{is}\right]\right)$$

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

[15] Note that X_i is time invariant, which reflects our assumption that worker i's experience does not change during the period in between jobs.

[16] In the empirical implementation, we control for other demographic variables such as education, gender and age. However, we do not allow returns to these variables to be sector-specific.

$$\Delta \ln y_{ik} = X_i' \beta_k + \lambda_k \left(p_{i1} \ldots, p_{iS} \right) + \omega_{ik} \tag{6}$$

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.[17]

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.[18] In this 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.[19]

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 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.

Restriction 1 establishes a relevant window of interaction among coworkers. We impose restriction 2 in order to address unobserved time-specific demand shocks that could affect both worker i and her coworkers' moving decisions. Additionally, in order to address the potential 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,[20] we conduct robustness tests imposing the additional restrictions that workers i and h have different occupations[21] and education levels at the time of their interaction. Appendix A describes in detail the construction of the coworker networks.

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

[18] In the context of occupational choice, Gathmann and Schoenberg (2010) use a task-based distance measure to other sectors within the same region. Bombardini et al. (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).

[19] For recent examples, see Saygin et al. (2014) and Glitz (2013) on coworker networks, Hellerstein et al. (2015) on neighborhood networks.

[20] 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.

[21] Occupations in this case are defined at the 1-digit level.

Table 1: Descriptives for Sample

Industry	Age	$Secten_{manuf}$	$\triangle Log(wage)$	Nonemp length	N
Manufacturing	27.5	9.2	0.10	0.9	168,109
Construction	25.9	7.6	0.13	1.7	8,549
Retail	26.6	8.0	0.12	1.4	24,440
Transportation	26.9	8.3	0.06	2.3	2,672
Hotel, restaurants, low skill svcs	23.4	5.4	0.08	1.9	2,384
Communication, prof svcs	28.9	9.4	0.05	1.2	9,417
Office and business support svcs	28.8	9.8	-0.05	3.2	5,843
Education, hosp, personal svcs	28.5	9.7	-0.09	2.2	5,385
Total	27.4	9.0	0.09	1.1	226,799

Notes: Main estimation sample.

4.2 Results

The results from estimating the separate wage regressions for each target sector (corresponding to equation (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 3 (German manufacturing workers). In this section, we impose additional restrictions to ensure our estimates are unbiased. 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 were displaced by firm closures or mass-layoffs.[22] 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, and workers with non-employment spells longer than one year. Lastly, for tractability purposes we exclude workers moving to the Agriculture/Mining and Public Administration sectors. These sectors are the destination of only 1.02% of displaced workers, making the estimation of sector-specific parameters unfeasible.

Imposing these restrictions leaves us with a sample of 226,799 workers who were displaced from a manufacturing firm and eventually found jobs (in any sector, including manufacturing). Table 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.

[22]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.

Workers moving to Education and other Personal Services experience an unconditional wage loss of 9%, while workers moving to Retail gain on average 12%.[23]

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 68. 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), using our baseline coworker instrument and the coworker instrument with the occupation restriction. The results from these regressions clearly show that having coworkers in potential target sectors increases the probability that displaced workers will choose such sector. Table A.4 presents additional robustness tests employing different restrictions on the coworker instrument (based on education level and occupation restrictions). In all cases, our instrument is highly predictive. In Appendix A, we also discuss the potential violations of our exclusion restriction and our planned robustness tests to address these.

We present the main set of the estimated coefficients from the full selection model on Table 2, which contains the sector-specific coefficients for sectoral tenure ($\hat{\beta}_{m \to k}$). These coefficients correspond to equation 6 with the dependent variable being the log difference in pre-displacement and initial post-displacement wages.[24] The full set of regressors in the estimation equations includes years of manufacturing work experience, age group, education, gender, state and year dummies, unemployment duration, regional employment shares in each industry, regional unemployment rate and population size. Importantly, we only allow for sector-specific returns to experience; the coefficients for all the other regressors are restricted to be equal across sectors.[25] In all cases, we bootstrap standard errors to account for the two-step estimation procedure. Column 1 shows the uncorrected estimates, while column 2 presents the estimates obtained from our selection model. Column 3 shows a Wald test of joint significance of the correction terms. All of these test statistics are significant at the 1% level, indicating the presence of selection bias in the uncorrected estimates.

From the point estimates, it is clear that there is heterogeneity across target sectors.[26] For example, for a manufacturing worker moving into another manufacturing firm, the wage loss associated with one extra year of experience is 0.78%. For a worker moving to Office and Business Support Services, each additional year of experience will result in a (much larger) 1.4% wage loss. 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

[23]Note that these are the differences between wages in the last job and initial wages in the new job.

[24]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.

[25]Our current specification allows the constant terms to vary across sectors, with the estimates presented on Appendix B, Table B.1. These estimates are much noisier, and in most cases are no statistically different from zero. Given this, our focus will be on the parameters of human capital transferability.

[26]A test of equality of the coefficients rejects the null that they are equal with a bootstrap p-value of 0.000.

Table 2: Corrected and Uncorrected Estimates of β

	OLS	Corrected	Wald Test
Manufacturing	-0.0110***	-0.00783***	422.0443
	(0.000140)	(0.000314)	[0.000]
Construction	-0.0175***	-0.0132***	118.249
	(0.000598)	(0.000932)	[0.000]
Retail	-0.0169***	-0.0127***	166.359
	(0.000364)	(0.000587)	[0.000]
Transportation	-0.0242***	-0.0189***	33.665
	(0.00107)	(0.00173)	[0.000]
Hotel, rest, low skill svcs	-0.0213***	-0.0163***	22.356
	(0.00139)	(0.00235)	[0.004]
Communication, prof svcs	-0.0133***	-0.00972***	90.052
	(0.000536)	(0.000735)	[0.000]
Office and bus support svcs	-0.0207***	-0.0140***	137.164
	(0.000568)	(0.000976)	[0.000]
Education, hosp, personal svcs	-0.0121***	-0.00773***	61.324
	(0.000631)	(0.00113)	[0.000]
N	226799	226799	
AIC	193175.7	191020.1	
χ^2		178.36	
		[0.0000]	

Notes: Bootstrapped standard errors in parentheses (250 replications).*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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.

Table 3: **Regional Employment Shares**

Sector	mean	sd	p25	p75
Year 1988:				
Manufacturing	0.42	0.11	0.34	0.50
Construction	0.09	0.03	0.08	0.11
Retail	0.16	0.04	0.13	0.18
Transportation	0.03	0.02	0.02	0.04
Hotel, rest, low skill svcs	0.03	0.02	0.02	0.03
Communication, prof svcs	0.10	0.04	0.07	0.11
Office and bus support svcs	0.01	0.01	0.01	0.01
Education, hosp, personal svcs	0.16	0.05	0.12	0.19
Year 1998:				
Manufacturing	0.33	0.12	0.24	0.42
Construction	0.11	0.04	0.08	0.14
Retail	0.16	0.03	0.14	0.18
Transportation	0.04	0.02	0.03	0.05
Hotel, rest, low skill svcs	0.03	0.02	0.02	0.03
Communication, prof svcs	0.09	0.04	0.07	0.10
Office and bus support svcs	0.03	0.02	0.02	0.04
Education, hosp, personal svcs	0.19	0.05	0.16	0.23

Source: Author's own calculations.

In addition to different empirical approaches, our study also differs from Dix-Carneiro (2014) in that we incorporate 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.

5 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 210 of these regions. Table 3 shows descriptives for sectoral employment shares across regions for the years 1988 and 1998. The figures show 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 11% share of employment in the Construction sector, while regions in the top quartile had shares that were 20% higher (i.e. 14% 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 regions with high employment shares in sectors "close" to manufacturing will make it more likely for workers to reallocate to such sectors, resulting in lower adjustment costs. We will refer to these as "Highly Flexible" regions. Inflexible regions, on the other hand, will have large employment in sectors distant to manufacturing, which will make it more likely that workers will reallocate to distant sectors and suffer larger adjustment costs as a result.

Formally, let $\Omega\left(r,\ \tau_0\right)$ be the set of workers working in manufacturing in region r in year τ_0, and let $N_{r\tau_0}$ be the size of this set. Our measure of labor market flexibility ($LMF_{r\tau_0}$) will be given by:

$$LMF_{r\tau_0} = \frac{1}{N_{rt}} \sum_{i\in\Omega(r,\ \tau_0)} \sum_{s} \hat{p}^{r}_{i,\,m\rightarrow s} \hat{\beta}_{m\rightarrow s} \tag{7}$$

where $\hat{\beta}_{m\rightarrow s}$ is a proxy of the economic distance faced by manufacturing workers when moving to sector s, and $\hat{p}^{r}_{i,\,m\rightarrow s}$ represents the reallocation probability of worker i to sector s. Our measure of labor market flexibility will, therefore, be the expected reallocation costs (in terms of wages) for workers living in region r at time τ_0. This measure depends on sectoral distances faced by workers and their probabilities of reallocation (which vary at the individual and regional level).

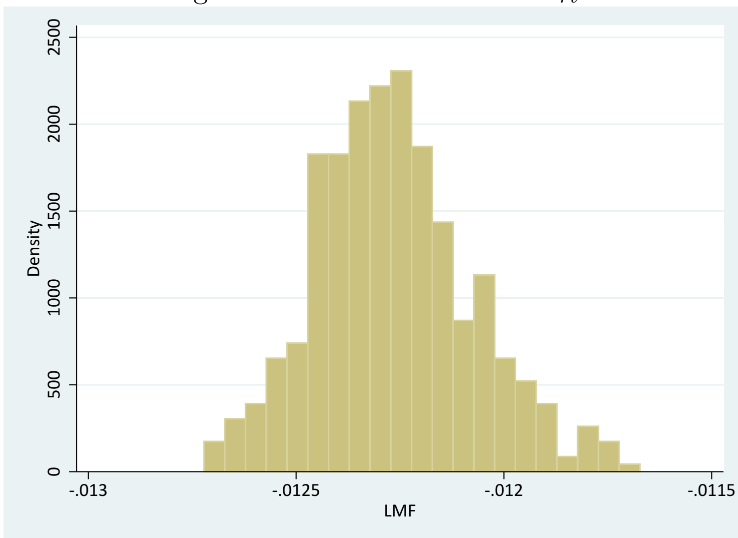
Our measures of sectoral distance ($\hat{\beta}_{m\rightarrow s}$'s) are derived directly from the estimated parameters in Table 2, which measure the transferability of human capital (as measured by experience) from manufacturing to other sectors. In order to obtain the reallocation probabilities $\hat{p}^{r}_{i,\,m\rightarrow s}$, we employ the estimated parameters of our selection model in Section 4. 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).[27] Formally, we let $\hat{p}^{r}_{i,\,m\rightarrow s} = f\left(Z_i;\, \hat{\Gamma}_s\right)$ where Z_i is the vector of individual and regional characteristics from equation 5, and $\hat{\Gamma}_s$ represents the vector of corresponding parameters estimated in Section 4.[28]

We compute this measure for workers in manufacturing jobs in the years 1988 and 1998. The distribution of $LMF_{r\tau_0}$ is presented in figure 1. The mean is -0.012, with a standard deviation of 0.0002. Note that by construction all the variance in $LMF_{r\tau_0}$ comes from varying reallocation

[27]We employ the same list of regressors employed in the wage regressions (equation 5): region-level sectoral employment shares, years of manufacturing work experience, age group, education, gender, state and year dummies, unemployment duration, in each industry, regional unemployment rate, region population size, and 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.

[28]In Appendix C (Tables C.1, C.2 and C.3), we present results from our sectoral choice model that indicate that a region's sectoral employment shares play a major role in the reallocation probabilities of workers.

Figure 1: Distribution of LMF_{rt}



Notes: LMF calulated from equation 7.

probabilities across regions. Lastly, Figure D.1 in Appendix D presents the spatial distribution of $LMF_{r\tau_0}$.

6 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 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:

$$E_{ij\tau} = \gamma_\tau + \psi \triangle IP_{j\tau} + X'_{i\tau}\theta + Z'_{j\tau}\kappa + \epsilon_{ij\tau} \tag{8}$$

where j represent the 3-digit manufacturing subindustry where worker i is employed at the beginning of period τ. $E_{ij\tau}$ 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. $\triangle IP_{j\tau}$ represents the increase in (normalized) import flows from

Table 4: Descriptives - Full Sample

	mean	sd	p25	p50	p75	count
△ Imports per worker	14	26	3	8	14	11,418,672
Cumulative Earnings	9.71	5.39	6.27	10.37	11.98	11,418,672
Cumulative Employment	2,887	1,084	2,192	3,532	3,653	11,418,672
Experience	14	5	11	13	18	11,418,672

Notes: Sample of workers in manufacturing jobs in the years 1988 and 1998.

China and Eastern Europe to Germany in industry j during time period τ.[29] As in ADHS, we instrument $\triangle IP_{j\tau}$ with the increase in import competition from China and Eastern Europe to other countries "similar" to Germany. In this setting, ψ represents the causal effect of increases in import competition on worker outcomes. All estimates of ψ shown in this section are from IV regressions.

We expand on ADHS's strategy by studying how the effect of trade shocks (ψ) 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.

6.1 Estimation Sample

We focus on German manufacturing workers during the periods 1988-1998 and 1998-2008 as in Dauth et al. (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.[30] Tables 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 times of pre-period earnings, and cumulative employment averages 2,887 days.[31]

[29] The construction of our trade exposure measures is detailed on Appendix 7.

[30] As in ADHS, we normalize earnings in period τ by the average annual earnings of the 5 years preceding period τ. Formally, let $E_{ijt} \equiv$ Earnings in year t. Then, $E_{ij\tau} = \sum_{t\in\tau} \frac{E_{ijt}}{E_{it_0}}$. 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).

[31] 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.

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

In this section, we show the results of estimating the baseline estimation equation (8) and allowing the estimated effects to vary with our measures of labor market flexibility (which are based on each region's characteristics in the initial year of period τ). 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 $\triangle IP_{j\tau}$ with dummies for each of these quartiles. Thus, we estimate the following specification using the IV approach described above:

$$E_{ij\tau} = \gamma_\tau + \mu_Q + \psi_Q \triangle IP_{j\tau} + X'_{i\tau}\theta + Z'_{j\tau}\kappa + \epsilon_{ij\tau} \tag{9}$$

Our vector of individual level controls $X_{i\tau}$ includes: age, gender, education, firm tenure and labor market experience, state of residence dummies, and region-level trade shocks.[32] The industry-level control vector $Z_{j\tau}$ includes industry level export growth during time period τ (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 5 presents the main results of this paper. 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.[33] 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 ψ_{Q_1} is negative and statistically significant. The estimates for regions in the other three quartiles are smaller in magnitude and become smaller with higher labor market flexibility. A χ^2 test of equality for the four coefficients is rejected at the 0.005% confidence level. In terms of economic significance, the -0.826 coefficient means that moving a worker from the 25th to the 75th percentile of import competition exposure would result in a loss of 9.1% of initial annual earnings (over a 10 year period). The effect of import shocks on workers in more flexible regions is much smaller at 3.5%. In other words, the negative effects of import exposure are more than 2.5 times larger for workers in the most inflexible regions. The results on employment are less precise, though point-wise they exhibit a similar pattern. Inflexible regions experience larger declines in total employment than regions in the upper end of the flexibility distribution. However, a test of equality for the four coefficients fails to reject the null hypothesis that they are equal to each other (with a large p-value of 0.43).

In table 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.

[32]We follow Autor et al. (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 7.

[33]Dauth et al. (2014) estimate that a €1,000 import shocks leads to a reduction in employment of 1.4 days.

Table 5: Regressions by Quartile of LMF_{rt}

	(1) Earnings	(2) Earnings	(3) Employment	(4) Employment
$\triangle IP_{j,\tau}$	-0.503***		-0.596***	
	(0.0914)		(0.149)	
$\triangle IP_{j,\tau} \cdot (D_{Q_1} = 1)$		-0.826***		-0.861*
		(0.164)		(0.350)
$\triangle IP_{j,\tau} \cdot (D_{Q_2} = 1)$		-0.801***		-0.829**
		(0.154)		(0.283)
$\triangle IP_{j,\tau} \cdot (D_{Q_3} = 1)$		-0.510***		-0.641***
		(0.110)		(0.194)
$\triangle IP_{j,\tau} \cdot (D_{Q_4} = 1)$		-0.318***		-0.448**
		(0.0962)		(0.145)
Observations	11438854	11418672	11438854	11418672
χ^2_3		13.002		2.761
		0.005		0.430

Notes: Cumulative earnings normalized by the average annual earnings of the 5 years preceding period τ. Cumulative employment measured in days. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 τ. 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 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 Table 7, we further analyze the effect of import exposure on reallocation of employment across sectors. We estimate the same regression (equation 9) but use cumulative employment by sector as the dependent variable. Columns 2 and 3 present the estimates of our baseline regression at the national level with the dependent variables being cumulative employment in manufacturing and non-manufacturing sectors (respectively). The estimates indicated that at the national level import exposure led to a large employment shift away from manufacturing and into the non-manufacturing sector. Columns 4 to 5 report the same estimates but for each type of region. In all types of regions import exposure caused a reduction in manufacturing employment and an shift towards the non-manufacturing sector. Moreover, the estimated effects are similar across regions (χ^2 tests of the four coefficients fail to reject the null hypothesis that they are equal). The results from this analysis indicate that while import exposure leads to a shift towards non-manufacturing sectors, this shift is of similar magnitude for both flexible and

Table 6: Regressions by Quartile of LMF_{rt} - Robustness Tests

	(1) Earnings	(2) Earnings	(3) Earnings	(4) Employment	(5) Employment	(6) Employment
$\triangle IP_{j,\tau} \cdot (D_{Q_1} = 1)$	-0.918***	-0.788***	-0.782***	-0.875*	-0.642	-0.797*
	(0.191)	(0.157)	(0.158)	(0.377)	(0.335)	(0.342)
$\triangle IP_{j,\tau} \cdot (D_{Q_2} = 1)$	-0.879***	-0.753***	-0.759***	-0.731**	-0.701**	-0.785**
	(0.168)	(0.159)	(0.150)	(0.270)	(0.271)	(0.280)
$\triangle IP_{j,\tau} \cdot (D_{Q_3} = 1)$	-0.528***	-0.574***	-0.475***	-0.540**	-0.641**	-0.595**
	(0.121)	(0.113)	(0.110)	(0.172)	(0.214)	(0.194)
$\triangle IP_{j,\tau} \cdot (D_{Q_4} = 1)$	-0.307**	-0.275**	-0.341***	-0.397**	-0.400	-0.456**
	(0.103)	(0.0979)	(0.0906)	(0.124)	(0.207)	(0.166)
Excluding age 50 over	Yes	No	No	Yes	No	No
Excluding large LMAs	No	Yes	No	No	Yes	No
Excluding East Germany	No	No	Yes	No	No	Yes
Observations	8383458	7775784	10876830	8383458	7775784	10876830
χ^2_3	15.057	16.631	11.448	2.807	1.538	1.723
	0.002	0.001	0.010	0.422	0.673	0.632

Notes: Version 'version'. Cumulative earnings normalized by the average annual earnings of the 5 years preceding period τ. Cumulative employment measured in days. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

inflexible regions. This finding implies that the differential earning losses reported in table 5 are not due to workers in inflexible regions remaining in manufacturing, but instead are likely to arise from the non-manufacturing industries workers move to.

One concern that arises when focusing local labor market characteristics as determinants of adjustments costs is that workers can move across regions in response to negative shocks. In the extreme case of costless geographic mobility, we would not find differential effects across different types of regions. Therefore, our heterogeneous estimates are consistent with the existence of some degree of costly geographic mobility. In terms of the interpretation of our analysis, it is important to note that we do not restrict the geographic location of workers beyond their initial location (i.e. workers can move in response to import exposure). In this light, one can interpret our results as measuring the role of the initial worker location in explaining the magnitude of trade-induced adjustment costs.

Table 8 conducts an additional analysis on the effect of import exposure on employment shifts analogous to Table 7, but focusing instead on the geographic location of workers (i.e. whether the employment took place in a worker's initial year region or in a different region). Columns 1 to 3 report estimates of regressions at the national level, while columns 4 to 6 present estimates of the import exposure effect by type of region. The estimates in columns 1 through 3 show that import exposure did cause an employment shift to regions different from a worker's initial region. This induced shift, however, is similar across regions with different levels of labor market flexibility (based on the results from columns 4 to 6). Column 6, for example, shows that

Table 7: Employment Reallocation by Quartile of LMF_{rt} (By Sector)

	(1) All	(2) Manuf	(3) Non-Manuf	(4) All	(5) Manuf	(6) Non-Manuf
$\triangle IP_{j,\tau}$	-0.598***	-3.090***	2.492***			
	(0.149)	(0.422)	(0.357)			
$\triangle IP_{j,\tau} \cdot (D_{Q_1} = 1)$				-0.861*	-3.675***	2.814***
				(0.350)	(1.000)	(0.803)
$\triangle IP_{j,\tau} \cdot (D_{Q_2} = 1)$				-0.829**	-3.056***	2.227***
				(0.283)	(0.675)	(0.488)
$\triangle IP_{j,\tau} \cdot (D_{Q_3} = 1)$				-0.641***	-3.198***	2.557***
				(0.194)	(0.524)	(0.434)
$\triangle IP_{j,\tau} \cdot (D_{Q_4} = 1)$				-0.448**	-2.835***	2.386***
				(0.145)	(0.519)	(0.478)
Observations	11418672	11418672	11418672	11418672	11418672	11418672
χ^2_3				2.761	0.839	0.919
				[0.430]	[0.840]	[0.821]

Notes: Cumulative employment measured in days. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

workers in the most inflexible regions shift employment to other regions in a similar magnitude as do workers living in the most flexible regions (the point estimate for flexible regions is slightly smaller, but a test of equality across the four coefficients fails to reject the null that they are all equal). This suggests a region's labor market flexibility affects earnings losses through the types of jobs workers end up in, as opposed to differential geographic migration patterns that might be themselves costly.

6.3 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 8) but at the regional level, obtaining a set of $\psi_{r\tau}$ parameters for each region. In the second step, we regress $\psi_{r\tau}$ on our $LMF_{r\tau}$ index and a host of region-level controls. Formally, we have:

Table 8: Employment Reallocation by Quartile of LMF_{rt} (Geographic)

	(1) All	(2) Same Region	(3) Different Region	(4) All	(5) Same Region	(6) Different Region
$\triangle IP_{j,\tau}$	-0.598***	-1.419***	0.820***			
	(0.149)	(0.236)	(0.162)			
$\triangle IP_{j,\tau} \cdot (D_{Q_1} = 1)$				-0.861*	-1.848***	0.987**
				(0.350)	(0.515)	(0.324)
$\triangle IP_{j,\tau} \cdot (D_{Q_2} = 1)$				-0.829**	-1.571***	0.742***
				(0.283)	(0.407)	(0.181)
$\triangle IP_{j,\tau} \cdot (D_{Q_3} = 1)$				-0.641***	-1.308***	0.667**
				(0.194)	(0.327)	(0.207)
$\triangle IP_{j,\tau} \cdot (D_{Q_4} = 1)$				-0.448**	-1.362***	0.914***
				(0.145)	(0.266)	(0.194)
Observations	11418672	11418672	11418672	11418672	11418672	11418672
χ^2_3				2.761	1.501	1.549
				[0.430]	[0.682]	[0.671]

Notes: Cumulative employment measured in days. Standard errors clustered in 1125 State-Industry cells.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

$$E_{ijr\tau} = \gamma_\tau + \psi_{r\tau} \cdot \triangle IP_{j\tau} + X'_{i\tau}\theta + Z'_{j\tau}\kappa + \epsilon_{ij\tau} \tag{10}$$

$$\psi_{r\tau} = \eta_\tau + \delta \, LMF_{r\tau} + W'_{r\tau}\theta + \omega_{r\tau} \tag{11}$$

where $W_{r\tau}$ is a vector of region characteristics that includes: initial employment size, employment share in manufacturing, unemployment rate, net employment growth during period τ, regional trade exposure during period τ.[34] We also add additional region-level that include pre-trends in employment and wages, as well as the following region demographic characteristics: share of female workers, share of workers with apprenticeships, share of college graduates, and share of workers of age 50 and over. We estimate each step separately and weight the second step by the inverse of variance of $\hat{\psi}_{r\tau}$. For the second step, we normalize all the region level regressors so that their coefficients are comparable.

The results from this estimation are presented in Table 9. The bottom row shows the mean and standard deviation of the first stage estimates ($\hat{\psi}_{r\tau}$). In the average region, the negative effect of import exposure on earnings was -0.318. The negative effects vary substantially across regions, as evidenced by the large standard deviation of 3.9. The results of the second step

[34]The construction of region-level trade exposure is detailed in footnote 32 and data appendix 7.

Table 9: Two-Step Estimation (Second Step)

	Cumulative Earnings			
	(1)	(2)	(3)	(4)
$LMF_{r\tau_0}$	0.587**	0.755**	0.715*	0.653*
	(0.209)	(0.283)	(0.289)	(0.329)
Net Employment Growth $_{r\tau}$		0.235	0.288	-0.0912
		(0.373)	(0.378)	(0.422)
Employment Size$_{r\tau_0}$		-0.262	-0.268	-0.167
		(0.183)	(0.185)	(0.237)
Manufacturing Share$_{r\tau_0}$		-0.327	-0.300	-0.0287
		(0.302)	(0.312)	(0.442)
$\triangle$Net Imports$_{r\tau}$		0.213	0.212	0.278
		(0.181)	(0.181)	(0.195)
Region-level Controls	No	Yes	Yes	Yes
Pre-trends (3-yr)	No	No	Yes	Yes
Region-level Demographic Controls	No	No	No	Yes
$\hat{\psi}_{r\tau}$	-0.318			
	(3.906)			
Observations	410	410	410	410
Adjusted R^2	0.0172	0.0188	0.0158	0.0372

Notes: Estimates from equation 11. Region-level controls (in SD units) include: initial year employment size, employment share in manufacturing and unemployment rate; net employment growth during period τ, region-level trade exposure during period τ (see footnote 32 for details on this variable). Pre-trends include 3yr pretrend growth rates in regional employment and manufacturing employment. Region-level demographic controls include share of female workers, workers with apprenticeships, college graduates, and age 50 and over.

estimation are shown in columns 1 through 4, with each column adding an additional set of controls. Column 1 shows the coefficient of $LMF_{r\tau}$ without any controls, column 2 adds the baseline region-level controls listed above, column 3 adds region-level pre-trends in employment and wages, and column 4 adds additional region-level demographic controls.

In all cases, the coefficient for $LMF_{r\tau}$ is significant and a strong predictor of the effects of import exposure on workers. Importantly, labor market flexibility is a stronger predictor of $\hat{\psi}_{r\tau}$ than a region's net employment growth (both in terms of magnitude and statistical significance). In fact, it is the strongest predictor out of all the regressors. 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. Quantitatively, the point estimates lead to conclusions similar to those in section 6.2. Taking column 4 for example, our estimates imply that (holding all other region characteristics at their national averages) workers in a region on the 25th percentile of the $LMF_{r\tau}$ distribution will face an adjustment cost of $\hat{\psi}_{r\tau} = -1.14$, while workers in a region on the 75th percentile of the $LMF_{r\tau}$ distribution will experience a much smaller adjustment cost of $\hat{\psi}_{r\tau} = -0.392$. In economic terms, this means that moving a worker from the 25th to the 75th percentile of the import exposure distribution would lead to an earnings loss of 12.5% (of initial year earnings) in an inflexible region at the 25th percentile of the $LMF_{r\tau}$ distribution. A worker in more flexible region (at the 75th percentile), would experience a smaller loss of 4.3%. This differential effects are similar to those obtained in Section 6.2 employing a different methodology (the loss differentials in that case were 9.1% and 3.5% for workers in inflexible vs. flexible regions), and confirm that labor market flexibility is an important determinant of the adjustment costs of workers affected by import shocks.

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 exposure, 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.

7 Conclusion

The findings in this paper 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 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.

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Appendix A - 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 4 and show results of the first stage of our selection model (equation 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 4.1). 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

Chosen Industry k	CN_{All}	CN_{Manuf}	CN_k	N
Manufacturing	56.8	24.6	4.8	168109
Construction	47.7	19.2	3.7	8549
Retail	62.6	22.8	5.4	24440
Transportation	88.7	34.8	7.0	2672
Hotel, restaurants, low skill svcs	24.3	9.3	2.4	2384
Communication, finance, and other professional svcs	116.1	42.9	9.9	9417
Office and business support svcs	89.5	33.6	8.1	5843
Education, hospitals and other personal svc activities	72.9	27.5	7.4	5385
Total	60.8	25.2	5.2	226799

Notes: Main estimation sample.

Predictive power of coworker networks

From equation 5, we have that each worker i (displaced from sector m) chooses a new sector by maximizing her utility V_{ik}, defined as:

$$V_{ik} = X_i'\Gamma_k + \sum_{s=1}^{10} \gamma_k^s CN_{is} + \sum_{s=1}^{10} \kappa_k^s EmpShare_{rs} + \eta_{ik} \tag{12}$$

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 A.2 (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 γ_{sk} 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.

In all cases, the coworker variables have the expected sign and enter the selection model significantly, as shown by the large χ^2 statistics. We take this as strong evidence of our instrument's predictive power.

Table A.2: Multinomial Logit Model - Baseline Coworker Instrument

	1	2	3	4	5	6	7	8
CN_{i1}	0	-0.0115***	-0.00924***	-0.00236**	-0.0250***	-0.00174**	-0.000215	-0.00240**
	(.)	(0.00118)	(0.000615)	(0.000908)	(0.00420)	(0.000536)	(0.000591)	(0.000889)
CN_{i2}	0	0.0489***	0.00302*	-0.00880**	0.0127	0.00422**	0.00600**	-0.000144
	(.)	(0.00343)	(0.00147)	(0.00270)	(0.00853)	(0.00148)	(0.00195)	(0.00220)
CN_{i3}	0	-0.00310	0.0159***	0.000858	0.0102	0.00954***	0.00572***	0.00632*
	(.)	(0.00299)	(0.00193)	(0.00243)	(0.00579)	(0.00184)	(0.00166)	(0.00322)
CN_{i4}	0	-0.0215**	-0.000410	0.0524***	-0.000952	-0.00601	-0.00771*	-0.0000811
	(.)	(0.00656)	(0.00322)	(0.00498)	(0.0232)	(0.00334)	(0.00330)	(0.00455)
CN_{i5}	0	-0.0620***	0.00576	-0.0218**	0.164***	-0.0343***	-0.0291***	-0.0469***
	(.)	(0.0139)	(0.00422)	(0.00741)	(0.0148)	(0.00478)	(0.00607)	(0.00610)
CN_{i6}	0	0.0126***	0.00435***	0.000831	0.0191***	0.00147*	-0.000880	-0.00306**
	(.)	(0.00147)	(0.000731)	(0.00177)	(0.00366)	(0.000690)	(0.000919)	(0.000979)
CN_{i7}	0	0.00498	-0.00328	-0.00521	-0.0573***	0.00944***	0.0211***	0.00652*
	(.)	(0.00467)	(0.00222)	(0.00398)	(0.0163)	(0.00226)	(0.00251)	(0.00297)
CN_{i8}	0	-0.00976	-0.0113***	-0.00698	-0.0442***	-0.00332	-0.00608	0.0158***
	(.)	(0.00575)	(0.00199)	(0.00407)	(0.0109)	(0.00201)	(0.00323)	(0.00281)
χ^2	.	379.609	330.070	404.431	248.712	468.719	285.537	212.726
	.	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
N				226799				

Notes: Estimates from equation 12. Each column represents a potential target sector k. Each cell contains the estimated coefficient γ_k^s for CN_{is} (the number of coworkers with jobs in sector s at the time of worker i's switch). χ^2 statistics test for joint significance of coefficients γ_k^s (for $s = 1, ..., 8$). Robust standard errors in parenthesis, p-values in brackets. Base outcome=manufacturing.

Table A.3: Multinomial Logit Model - Occupation Restriction

	1	2	3	4	5	6	7	8
CN_{i1}	0	-0.000723**	-0.000554***	0.000420***	-0.00672	0.0000372	-0.000170	-0.000151
	(.)	(0.000262)	(0.000116)	(0.0000998)	(0.00571)	(0.0000703)	(0.000133)	(0.000113)
CN_{i2}	0	0.0128***	0.00279	0.00573**	0.000514	0.00518**	-0.00279	-0.000919
	(.)	(0.00190)	(0.00236)	(0.00175)	(0.0198)	(0.00158)	(0.00252)	(0.00207)
CN_{i3}	0	-0.00154	0.00431***	0.00175*	-0.00849	0.000599	0.00416***	0.00200***
	(.)	(0.00145)	(0.000366)	(0.000726)	(0.00604)	(0.000422)	(0.000527)	(0.000519)
CN_{i4}	0	0.000205	-0.00295	0.00101	0.00431	-0.000550	-0.00109	-0.000490
	(.)	(0.00268)	(0.00517)	(0.000594)	(0.00299)	(0.00102)	(0.00137)	(0.00116)
CN_{i5}	0	0.00895	-0.000344	-0.00633	0.0660***	-0.00257	-0.0118*	-0.0142**
	(.)	(0.00840)	(0.00657)	(0.00558)	(0.0155)	(0.00389)	(0.00581)	(0.00521)
CN_{i6}	0	0.000674**	0.000127	-0.00274***	0.00280**	0.000197**	-0.000847	-0.000626
	(.)	(0.000206)	(0.000145)	(0.000657)	(0.000902)	(0.0000722)	(0.000437)	(0.000360)
CN_{i7}	0	-0.00980	0.00407***	0.00692***	-0.00735	0.00119	0.00320*	0.00223
	(.)	(0.00775)	(0.000868)	(0.00155)	(0.0172)	(0.00102)	(0.00151)	(0.00140)
CN_{i8}	0	-0.00476	-0.00435*	0.000886	-0.0591**	0.00337**	0.00777***	0.0103***
	(.)	(0.00332)	(0.00184)	(0.00257)	(0.0199)	(0.00122)	(0.00158)	(0.00171)
χ^2	.	59.123	297.932	149.644	61.043	264.433	237.751	149.510
	.	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
N				226799				

Notes: Estimates from equation 12. Each column represents a potential target sector k. Each cell contains the estimated coefficient γ_k^s for CN_{is} (the number of coworkers with jobs in sector s at the time of worker i's switch). χ^2 statistics test for joint significance of coefficients γ_k^s (for $s = 1, ..., 8$). Robust standard errors in parenthesis, p-values in brackets. Base outcome=manufacturing.

Table A.4: Coworker Instrument - Robustness Tests

	Different Occupation		Different Education	
	Unique Firms	Coworkers	Unique Firms	Coworkers
CN_{ik}	0.334***	0.671***	0.847***	0.321***
	(0.0311)	(0.0564)	(0.0266)	(0.0404)
Observations		1814392		

Notes: γ estimates for the alternative specific conditional logit specification (equation 13). Coworker instruments in %. Interaction window set at 3-8 years. Unique firms excludes multiple coworkers working at the same potential firm.

Lastly, we conduct additional robustness tests by employing different variations of the coworker instrument. For ease of exposition, we presents these robustness estimates using an alternative specification in which we allow the coworker instrument to enter as an alternative specific variable. Formally, this specification takes the form:

$$V_{ik} = X_i'\Gamma_k + \gamma CN_{ik} + \eta_{ik} \tag{13}$$

where γ is our parameter of interest. Table A.4 shows the results for these tests, in which we define CN_{ik} as the share of potential coworkers in each target sector k (as opposed to the count of coworkers). Columns 2 and 4 show estimates using coworkers in different occupations and education levels. In columns 1 and 3, we exclude multiple coworkers working in the same potential firm (in effect, CN_{ik} in these cases is the number of unique firms in sector k that worker i is connected to through her coworkers).

Potential violations of the exclusion restriction

Formally, the exclusion restriction in our setting requires CN_{ik} and ϵ_{ik} to be independent of each other (see selection model 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).

Appendix B - Selection Model - Second Stage

Table B.1: Corrected and Uncorrected Estimates of α

	OLS	Corrected	Wald Test
Manufacturing	0.0979***	-0.0845***	422
	(0.000909)	(0.0220)	[0.000]
Construction	0.103***	0.0186	118.3
	(0.00511)	(0.0568)	[0.000]
Retail	0.0981***	0.0598	166.4
	(0.00248)	(0.0454)	[0.000]
Transportation	0.0474***	0.0258	33.7
	(0.00750)	(0.0717)	[0.000]
Hotel, rest, low skill svcs	0.00646	-0.203*	22.4
	(0.0105)	(0.0949)	[0.004]
Communication, prof svcs	0.0568***	-0.0378	90.1
	(0.00405)	(0.0518)	[0.000]
Office and bus support svcs	-0.0206***	-0.00672	137.2
	(0.00506)	(0.0558)	[0.000]
Education, hosp, personal svcs	-0.0688***	-0.257***	61.3
	(0.00547)	(0.0677)	[0.000]
N	226799	226799	
AIC	193175.7	191020.1	

Notes: Bootstrapped standard errors in parentheses (250 replications).*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix C - $LMF_{r\tau_0}$ - Reallocation Probabilities and Sectoral Employment Shares

Tables C.1 and C.2 shows the estimated coefficients for sectoral employment shares ($EmpShare_{rk}$'s) in our sectoral choice model (equation 12). Table C.1 presents the estimates of our baseline model (with the baseline coworker instrument), while Table C.2 presents the estimates of the selection model employing the coworker instrument with the occupation restriction. We employ the same list of regressors as in the wage regressions (equation 5): region-level sectoral employment shares ($EmpShare_{rk}$'s), years of manufacturing work experience, age group, education, gender, state and year dummies, unemployment duration, in each industry, regional unemployment rate, region population size, and worker i's coworker networks.

As expected, the industry mix of regions plays a major role in determining the sectoral reallocation probabilities of workers. In all cases, the employment share of a sector affects reallocation probabilities significantly and with the expected sign. Just as with the results of Tables A.2 and A.3 (for our coworker instruments), χ^2 tests of joint significance indicate that local employment structures have big explanatory power in our sectoral choice model.

Our measure of labor market flexibility (equation 7) will use the parameters estimated from these models to predict the reallocation probabilities $\hat{p}^r_{i,m\rightarrow s}$ for all workers employed in manufacturing in the years 1988 and 1998.

Table C.1: Coefficients for Employment Shares - Baseline Selection Model

	1	2	3	4	5	6	7	8
$EmpShare_{r2}$	0	3.458***	-1.751***	-2.008	-1.102	-2.096**	-3.732***	3.567***
	(.)	(0.582)	(0.386)	(1.173)	(1.168)	(0.644)	(0.879)	(0.729)
$EmpShare_{r3}$	0	0.539	2.549***	2.174**	1.006	-0.628	0.510	-1.867**
	(.)	(0.467)	(0.284)	(0.806)	(0.865)	(0.473)	(0.588)	(0.582)
$EmpShare_{r4}$	0	4.641***	1.610**	5.293***	2.447	3.867***	6.909***	6.452***
	(.)	(0.890)	(0.548)	(1.511)	(1.697)	(0.843)	(1.059)	(1.074)
$EmpShare_{r5}$	0	2.390**	1.461**	-2.067	8.832***	1.639	-2.524*	6.439***
	(.)	(0.786)	(0.535)	(1.730)	(1.248)	(0.844)	(1.209)	(0.900)
$EmpShare_{r6}$	0	-0.275	1.593***	1.277*	2.503***	2.756***	0.443	2.534***
	(.)	(0.330)	(0.200)	(0.559)	(0.616)	(0.298)	(0.381)	(0.397)
$EmpShare_{r7}$	0	1.170	0.457	3.256	4.165	0.513	4.523***	-5.018***
	(.)	(1.077)	(0.678)	(1.973)	(2.159)	(1.031)	(1.084)	(1.389)
$EmpShare_{r8}$	0	0.240	-0.465*	-0.0409	2.036***	-0.490	1.141**	3.413***
	(.)	(0.324)	(0.203)	(0.575)	(0.591)	(0.321)	(0.390)	(0.377)
χ^2		96.034	439.034	115.715	156.367	381.348	221.473	314.278
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
N					226799			

Notes: Estimates from equation 12. Each column represents a potential target sector k. Each cell contains the estimated coefficient κ_k^s for $EmpShare_{rs}$ (region r's employment share in sector s at the time of worker i's switch). χ^2 statistics test for joint significance of coefficients κ_k^s (for $s = 1, ..., 8$). Robust standard errors in parenthesis, p-values in brackets. Base outcome=manufacturing.

Table C.2: Coefficients for Employment Shares - Selection Model with Coworker Occupation Restriction

	1	2	3	4	5	6	7	8
$EmpShare_{r2}$	0	4.731***	-1.572***	-1.869	-0.611	-1.974**	-3.469***	3.715***
	(.)	(0.568)	(0.385)	(1.161)	(1.162)	(0.640)	(0.873)	(0.728)
$EmpShare_{r3}$	0	0.628	2.842***	2.152**	0.941	-0.346	0.647	-1.803**
	(.)	(0.466)	(0.283)	(0.805)	(0.855)	(0.470)	(0.587)	(0.579)
$EmpShare_{r4}$	0	5.059***	1.789**	6.339***	2.551	3.814***	7.464***	6.872***
	(.)	(0.877)	(0.550)	(1.501)	(1.683)	(0.843)	(1.053)	(1.072)
$EmpShare_{r5}$	0	2.382**	1.925***	-1.951	10.59***	1.481	-3.134**	6.302***
	(.)	(0.787)	(0.532)	(1.723)	(1.217)	(0.839)	(1.215)	(0.894)
$EmpShare_{r6}$	0	-0.312	1.699***	1.515**	3.173***	3.116***	0.291	2.403***
	(.)	(0.328)	(0.198)	(0.563)	(0.610)	(0.298)	(0.375)	(0.392)
$EmpShare_{r7}$	0	2.079	0.478	3.278	4.212	0.542	5.243***	-4.654***
	(.)	(1.074)	(0.677)	(1.972)	(2.153)	(1.030)	(1.074)	(1.386)
$EmpShare_{r8}$	0	0.536	-0.271	-0.229	2.200***	-0.582	1.220**	3.591***
	(.)	(0.320)	(0.202)	(0.574)	(0.583)	(0.321)	(0.388)	(0.375)
χ^2		154.917	521.670	147.529	224.708	458.246	245.108	332.266
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
N	226799							

Notes: Estimates from equation 12. Each column represents a potential target sector k. Each cell contains the estimated coefficient κ_k^s for $EmpShare_{rs}$ (region r's employment share in sector s at the time of worker i's switch). χ^2 statistics test for joint significance of coefficients κ_k^s (for $s = 1, ..., 8$). Robust standard errors in parenthesis, p-values in brackets. Base outcome=manufacturing.

For ease of exposition, we also present estimates of an alternative specification in which we allow regional employment shares in each sector to enter as an alternative specific variable. Formally, this specification takes the form:

$$V_{ik} = Z_i'\Gamma_k + \kappa EmpShare_{rk} + \eta_{ik} \tag{14}$$

The results are presented in Table C.3, and show again that local employment shares are important determinants of sectoral choice.

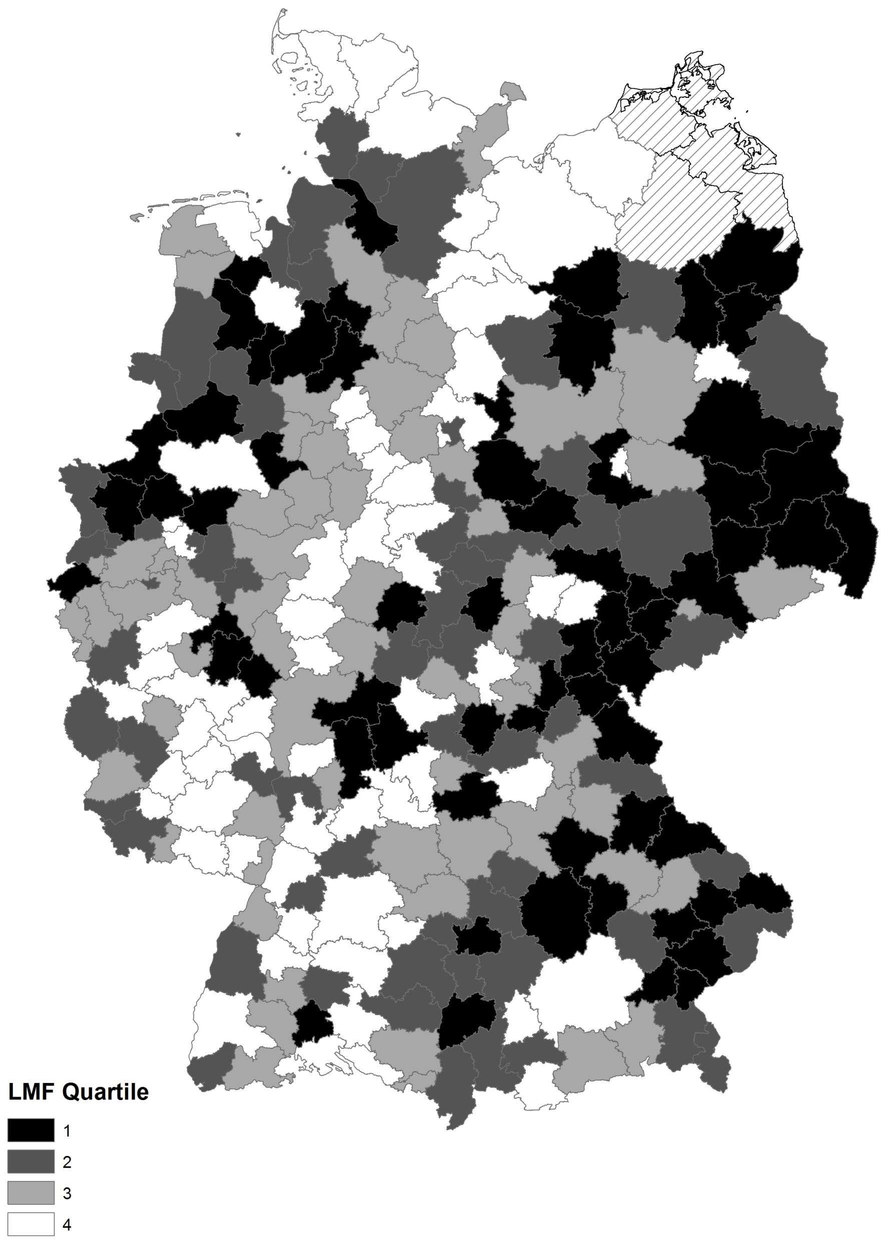
Table C.3: Selection Model - Sectoral Employment Shares

	Baseline Regression	Alternative Coworker Instrument
$EmpShare_{rk}$	1.964***	2.290***
	(0.0710)	(0.0868)
Observations	1814392	

Notes: $\hat{\kappa}$ estimates for the alternative specific conditional logit specification (equation 14). Main estimation sample of displaced manufacturing workers (Section 4.2). $EmpShare_{rk}$ defined as region r's employment share in sector k at time of displacement.

Appendix D - LMF_{rt} Geographic Distribution

Figure D.1: Geographic Distribution of LMF_{rt}



Notes: LMF calulated from equation 7. LMF quartiles based on average LMF for years 1988 and 1998.

Appendix D - 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.[35] 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-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.

[35] To 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.

Measures of Import Exposure

Following Autor et al. (2014), we construct measures of exogenous trade shocks arising from import competition from China and Eastern Europe.[36] These measures have been adapted to the German context in a recent paper by Dauth et al. (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 et al. (2014).[37]

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 ($\triangle IP_{j\tau}$) in time period τ. Each measure is constructed as follows:

$$\Delta IP_{j\tau} = \frac{\Delta IM_{j\tau}^{East \to Germany}}{E_{j\tau_0}}$$

Where $\triangle IM_{j\tau}^{East \to Germany}$ is the change in industry j imports to Germany from China and Eastern Europe during time period τ, and $E_{j\tau_0}$ is the number of workers in Germany employed in industry j at the beginning of time period τ. 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 $\triangle IP_{j\tau}$ with $\Delta IP_{j\tau}^{East \to Other}$, the increase in industry level import competition from China and Eastern Europe to a group of countries "similar" to Germany. Formally,

$$\Delta IP_{jt}^{East \to Other} = \frac{\Delta IM_{j\tau}^{East \to Other}}{E_{j\tau_0}}$$

We follow Dauth et al. (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 et al. (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 Autor et al. (2013) and Dauth et al. (2014), these measures capture the import exposure of all manufacturing workers initially located in a given region. They

[36] 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.

[37] Following Dauth et al. (2014), we focus on manufacturing sub-industries only (NACE codes 150-380). This excludes agriculture and mining industries.

are constructed by combining the national changes in imports for each 3-digit manufacturing industry and the industry composition of each region r. Formally, our measure of region-level trade exposure for region r during time period τ can be written as:

$$\Delta IP_{r\tau} = \sum_j \frac{E_{rj\tau_0}}{E_{r\tau_0}} \frac{\Delta IM_{j\tau}^{East \to Germany}}{E_{j\tau_0}}$$

where $\Delta IM_{j\tau}^{East \to Germany}$ and $E_{j\tau_0}$ are defined as in the previous section, $\frac{E_{rj\tau_0}}{E_{r\tau_0}}$ is the share of manufacturing workers in region r who work in industry j at the beginning of period τ.