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

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We analyze how skill transferability and the local industry mix affect the adjustment costs of workers hit by a trade shock. Using German administrative data and novel measures of economic distance, we construct an index of labor market absorptiveness that captures the degree to which workers from a particular industry are able to reallocate into other jobs. Among manufacturing workers, we find that the earnings loss associated with increased import exposure is much higher for those who live in the least absorptive regions. We conclude that the local industry composition plays an important role in the adjustment processes of workers.

I. 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

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and occupations, have resulted in significant labor market adjustments that 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 2010). 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 negative 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. For instance, Bloom et al. (2019) document how pervasive sectoral job reallocation from manufacturing to nonmanufacturing was when the United States faced rapidly increasing import competition from China. Indeed, there is a recent and growing literature studying the role of sectoral mobility costs on labor market adjustments (Artuc, Chaudhuri, and McLaren 2010; Dix-Carneiro 2014; Caliendo, Dvorkin, and Parro 2019).[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 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

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[1] See, e.g., Autor et al. (2014) and Walker (2013). These findings are also consistent with the extensive literature on the negative effects of job losses (Jacobson, LaLonde, and Sullivan 1993; Davis and Wachter 2017).

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

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 focus on a specific group that has experienced significant negative shocks in the last few decades: workers in the manufacturing sector. We proceed in three steps. We begin by estimating novel measures of skill transferability across sectors.[4] These measures capture how valuable the observed skills and human capital of manufacturing workers are when applied in other sectors. We interpret these as measuring the economic distance between sectors from the workers' perspective.[5] In the second step, we combine these distances with local industry employment shares to obtain a labor market absorptiveness index, which captures how easily a manufacturing worker with a given set of skills will be able to reallocate into other sectors.[6] In the last step, we test how manufacturing workers in regions with different degrees of labor market absorptiveness 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.

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

[3] This approach is grounded in the extensive labor literature on the importance of human capital as a determinant of wage growth and in 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).

[4] These measures and the empirical strategy we employ build on our recent work in Yi, Mueller, and Stegmaier (2017).

[5] 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, Hornbeck, and Moretti (2010) and Ellison, Glaeser, and Kerr (2010).

[6] Our labor market absorptiveness index is specific to workers initially employed in the manufacturing sector. Analogous indexes can be generated for other sectors, but they are beyond the scope of our paper.

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. 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, to address worker sorting into sectors, we employ a selection correction model (Dahl 2002; Bourguignon, Fournier, and Gurgand 2007).[7] 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.[8] The reasoning behind our selection instrument is that past coworkers 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 transfer 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 absorptiveness 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.

[7] See Beaudry, Green, and Sand (2012) and Bombardini, Gallipoli, and Pupato (2012) for recent applications of this type of selection model corrections.

[8] For recent examples, see Saygin, Weber, and Weynandt (2018), Glitz (2017), and Cingano and Rosolia (2012) on coworker networks, and see Hellerstein, Kutzbach, and Neumark (2019) on neighborhood networks.

Finally, in the last part of the paper, we analyze the relationship between labor market absorptiveness 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 absorptiveness. In this, we build on the empirical approach developed by Autor et al. (2014), who estimate the effect of trade-induced shocks on worker 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 the approach of Autor et al. (2014) by allowing the effects of import competition to vary across regions with different degrees of absorptiveness.

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 1.7% if she were to move to the office and business support services sector but only a 0.8% 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 absorptive regions relative to those in less absorptive regions. Among workers living in less absorptive 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 of 21% (as a share of initial annual earnings over a 10-year period). The earning losses of workers living in absorptive regions is much smaller at 9%. 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.[9] Our work is directly related to a recent strand of literature studying the distributional effects of external shocks when workers have sector-specific

[9] 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.

skills (Burstein, Morales, and Vogel 2019; Galle, Rodriguez-Clare, and Yi 2023). In these papers, workers posses a multidimensional vector of unobserved skills drawn from a parameterized distribution. Workers get sector-specific returns to unobservable skills and their distribution determines the incidence of external shocks. Related to this literature is work by Artuc, Chaudhuri, and McLaren (2010), Dix-Carneiro (2014), and Caliendo, Dvorkin, and Parro (2019), each of whom incorporate sectoral mobility costs—among other features—in their studies of labor market adjustments and trade.[10] A common feature of these studies is their reliance on distributional assumptions of unobserved skills (or idiosyncratic shocks) and observed labor flows to estimate relevant parameters that govern sectoral reallocation and the distributional effects of shocks. Our work complements this literature by focusing instead on sector-specific returns to observed skills (which are the basis for our skill transferability measures). Our use of observed wage changes and human capital (as opposed to labor flows) makes our approach less reliant on distributional assumptions.

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, Song, and Manchester 2007; Davis and Wachter 2017), environmental regulations (e.g., Walker 2013), and local demand shocks (e.g., Moretti 2010; Notowidigdo 2020). More related to this paper are recent studies of the effects of import competition on workers and local labor markets (for the United States, see Autor, Dorn, and Hanson 2013, 2016; Autor et al. 2014; Acemoglu et al. 2016; Bloom et al. 2019; for Germany, see Dauth, Findeisen, and Suedekum 2014; for Brazil, see Kovak 2013; Dix-Carneiro and Kovak 2017).[11] Our work contributes to this literature by identifying sources of heterogeneity in the adjustment 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.

Last, our work is also related to the literature on human capital specificity. Our measures of sectoral distance and the idea of skill transferability are

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

[11] The trade literature also includes a large number of studies of the effects of trade liberalization on sectoral reallocation (for developing countries, see Goldberg and Pavcnik 2007; Menezes-Filho and Muendler 2011; Wacziarg and Wallack 2004; for developed countries, see Revenga 1992; Artuc, Chaudhuri, and McLaren 2010).

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 Sullivan (2010), who studies both the occupation and the 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. Taking on board the regional perspective, Macaluso (2017) constructs a measure of local skill remoteness on the occupation level by weighting occupational distances with the regional occupational composition in US cities. Neffke, Otto, and Hidalgo (2018) also take the regional perspective to analyze how the local size of the predisplacement sector affects displaced workers' postdisplacement outcomes in Germany. 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. It also confirms that local specificities in occupational and sectoral structures affect outcomes of displaced workers. Our paper expands on this literature by exploring the heterogeneity in degrees of transferability of human capital across different sectors in a causal setting and by combining this with a local labor market approach.

The rest of the paper is structured as follows. Section II presents a simple theoretical framework to motivate our analysis. Section III describes the data employed in this paper. In section IV, we explain and estimate our measures of sectoral distances. Section V details the construction of our labor market absorptiveness index. Section VI presents our main results on the heterogeneous effects of shocks and their relation to our labor market absorptiveness measure. Section VII concludes.

II. Theoretical Framework

To motivate our empirical analysis, we present a stylized 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. All workers start in the manufacturing sector in the initial period. In period 2, they are forced to reallocate to other sectors (in response to a negative shock). This model will highlight the key components of our study:

1. Skill transferability varies across sectors. Therefore, wage losses for displaced workers will be determined by which sector they reallocate to.

2. The industry mix of regions is an important determinant of reallocation probabilities.
3. Given the first two components, the reallocation costs workers face will depend on the type of region they are in (even when exposed to a common shock).

We now delve on each point in detail.

A. Skill Transferability and Wage Losses

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:

$$\ln y^r_{i0} = \alpha_i + \beta_m X_i + T'_i\gamma, \tag{1}$$

where α_i represents worker i's unobserved general ability and β_m are sector-specific returns to human capital X_i. We also allow wages to be determined by other individual characteristics (T_i) but assume the returns to these characteristics are not sector specific.

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:

$$\ln y^r_{ik} = \alpha_i + \beta_k X_i + T'_i\gamma + \varepsilon_{ik}, \tag{2}$$

where ε_{ik} is an unobserved sector-specific ability draw that is independent and identically distributed (i.i.d.) and is such that $\alpha\varepsilon_{ik}$ follows an extreme value type I.

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:

$$\Delta\ln y^r_{i,m\to k} = (\beta_k - \beta_m)X_i + \varepsilon_{ik}. \tag{3}$$

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

$$\begin{aligned} E[\Delta\ln y^r_{i,m\to k}|X_i, D_{i,m\to k} = 1] &= E[(\beta_k - \beta_m)X_i + \varepsilon_{ik}|X_i, D_{i,m\to k} = 1] \\ &= \underbrace{\beta_{m\to k}\, X_i}_{\text{observed}} + \underbrace{E[\varepsilon_{ik}|D_{i,m\to k} = 1]}_{\text{unobserved}}. \end{aligned} \tag{4}$$

Equation (4) is a standard wage equation relating wages to both observed human capital (X_i) and unobserved sector-specific components. In this paper, we will focus on how the returns to observed human capital vary across sectors (i.e., estimating $\beta_{m\rightarrow k}$'s) while controlling for the unobserved components in the wage equations. Different values of βs 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, $\beta_{m\rightarrow k}$ will determine the wage loss (associated with observed human capital) that results from reallocating from sector m to sector k. We interpret this parameter $\beta_{m\rightarrow k}$ as a measure of economic distance between sectors m and k from worker i's perspective.

B. Reallocation Probabilities and Regional Employment Opportunities

To highlight the importance of regions in reallocation outcomes, we will denote π_{rk} as the share of region r's jobs in sector k; π_{rk}'s will vary across regions, reflecting different industry structures that translate into different types of employment opportunities for displaced workers. Workers are not mobile across regions. Therefore, workers living in different regions will face varying mixes of π_{rk}'s when searching for jobs.

Workers sort into the sector that maximizes their utility V^r_{ik}, which is determined both by the potential wage loss in each sector (eq. [3]) and by nonpecuniary factors and preferences. We allow nonpecuniary factors to include human capital X_i and π_{rk}, such that

$$V^r_{ik} = \alpha\Delta\ln y^r_{i,m\rightarrow k} + \tilde{\beta}_k X_i + \tilde{\delta}\pi_{rk} + \sigma\theta_{ik}, \tag{5}$$

where α represents the mapping from potential wage losses $\Delta\ln y^r_{i,m\rightarrow k}$ to utilities, while $\tilde{\beta}_k$ and $\tilde{\delta}$ capture how human capital and π_{rk} influence a worker's sectoral choice through nonpecuniary channels (hereafter we use tildes to denote structural parameters associated with nonpecuniary mechanisms). Finally, θ_{ik} is an i.i.d. preference shock that follows a Cardell distribution with parameter $1/\sigma$ (Cardell 1997).

Expanding the equation, we get

$$\begin{aligned} V^r_{ik} &= \alpha\Delta\ln y^r_{i,m\rightarrow k} + \tilde{\beta}_k X_i + \tilde{\delta}\pi_{rk} + \sigma\theta_{ik} \\ &= \alpha\beta_k X_i + \alpha\varepsilon_{ik} + \tilde{\beta}_k X_i + \tilde{\delta}\pi_{rk} + \sigma\theta_{ik} \\ &= (\alpha\beta_k + \tilde{\beta}_k)X_i + \tilde{\delta}\pi_{rk} + \alpha\varepsilon_{ik} + \sigma\theta_{ik}. \end{aligned}$$

Rescaling all utilities by $1/\sigma$, the utility function that characterizes worker i's choice can be simplified to the following expression:

$$V^r_{ik} = \ddot{\beta}_k X_i + \ddot{\delta}\pi_{rk} + \eta_{ik}, \tag{6}$$

where $\ddot{\beta} \equiv (\alpha\beta_k + \tilde{\beta}_k)$, $\ddot{\delta} \equiv \tilde{\delta}$, and $\eta_{ik} \equiv \theta_{ik} + (1/\sigma)\alpha\varepsilon_{ik}$. Under our distributional assumptions for θ_{ik} and ε_{ik}, η_{ik} is i.i.d. Gumbel distributed (EV1).[12] The EV1 distribution of η_{ik} allows us to obtain a reduced-form expression for the sectoral reallocation probabilities. The probability that worker i in region r chooses to reallocate from sector m to sector k is given by the following expression:

$$p^r_{i,m\to k} = \frac{\exp\left(\ddot{\beta}_k X_i + \ddot{\delta}\pi_{rk}\right)}{\sum_s \exp\left(\ddot{\beta}_s X_i + \ddot{\delta}\pi_{rs}\right)}.$$

From the equation above it is clear that π_{rk} influences a worker's reallocation choice. The overall effect will be captured by $\ddot{\delta}$. Since $p^r_{i,m\to k}$ is a (monotically) increasing function of $\ddot{\delta}\pi_{rk}$, a positive value of $\ddot{\delta}$ would indicate that workers living in regions with large employment shares in sector k are more likely to reallocate to such a sector. The term $\ddot{\delta}$ can be estimated using a standard multinomial logit model. In appendix A (apps. A–E are available online), we show that the estimated coefficient is positive and statistically significant. This is consistent with sectoral employment shares playing an important role in determining reallocation probabilities for displaced manufacturing workers.

Note that in this stylized model, π_{rk} affects reallocation probabilities only through a nonpecuniary channel. This arises from the fact that in our model wage losses are determined solely by human capital—an admittedly strong assumption made to simplify the model. In appendix A, we show that we can relax this assumption and allow $\ddot{\delta}$ to operate through both a wage channel (δ) and a nonpecuniary channel ($\tilde{\delta}$). Moreover, in appendix A we also show that it is possible to obtain estimates of the nonpecuniary component of $\ddot{\delta}$. Taking this approach to the data, we find that $\tilde{\delta}$ is also positive and statistically significant. That is, we find evidence that sectoral employment shares affect reallocation decisions through channels other than wages.

Given its nonpecuniary nature, we argue that $\tilde{\delta}$ captures how a large availability of jobs in a sector makes it more likely that workers will find information/openings in such a sector. In this scenario, even when facing equivalent wage losses in other sectors, workers will be more likely to reallocate to the sector with the most employment opportunities.

To sum up, our model predicts that sectoral employment shares will influence reallocation probabilities. Moreover, we find empirical evidence that this is the case and that there is a significant role for a nonpecuniary channel through which employment shares affect reallocation choices. This

[12] Cardell (1997) shows that if $\theta_{ik} \sim C(1/\sigma)$ and $\alpha\varepsilon_{ik} \sim$ EV1 and the two random variables are independent of each other, then $\theta_{ik} + (1/\sigma)\alpha\varepsilon_{ik} \sim$ EV1.

means that workers with similar characteristics but living in different regions (i.e., those with different $\pi_{rk(i)}$) will have different probabilities of choosing sector k—even when facing the same wage schedule.

C. Labor Market Absorptiveness and Adjustment Costs

Aggregating at the regional level, we have that for workers in region r, the expected postdisplacement wage loss associated with observed human capital can be written as

$$\Delta \ln y_m^r = \frac{1}{N_r} \sum_i \sum_s p_{i,m\to s}^r \hat{\beta}_{m\to s} X_i.$$

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 the following:

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

$$p_{i,m\to k}^r = \frac{\exp\left(\ddot{\beta}_k X_i + \ddot{\delta}\pi_{rk}\right)}{\sum_s \exp\left(\ddot{\beta}_s X_i + \ddot{\delta}\pi_{rs}\right)}.$$

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 on the basis of the parameters of equation (4) ($\beta_{m\to s}$). Then, having shown that sectoral employment shares play an important role in determining reallocation choices, we will combine sectoral distances and employment shares to construct an index of labor market absorptiveness for each region. This index will capture the adjustment costs workers would face in light of a national shock.

III. 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).[13] This rich linked employer-employee dataset contains

[13] We supplement this administrative database with data from other sources, such as trade flow figures from the United Nations Industrial Development Organization (UNIDO) database. Supplemental datasets are documented in app. E (the data appendix).

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 are highly detailed and reliable. Employment spells are measured on a daily basis (with the start and end date for each spell), and the industry and occupation of all employment spells are consistently defined and available for each worker throughout the entire time period.

The size and level of detail of the data allow us to observe workers moving across sectors as well as all of their relevant characteristics at the time of the move. These include the pre- and postmove 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, Ludsteck, and Schoenberg (2009) and Card, Heining, and Kline (2013), the earnings data are censored at the annual social security maximum. An additional limitation is the exclusion of some groups from the sample (due to the administrative purposes of the data). In particular, self-employed workers and civil servants are excluded from the data. 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 nine big sectors based on standardized Nomenclature of Economic Activities (NACE; rev. 2) 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 Bureau of Labor Statistics, each containing a minimum of 100,000 inhabitants as of December 2008. The regional identifiers have been modified to be consistent throughout the entire time period.

In all subsequent analysis, we focus on one particular group: male workers with an apprenticeship level of education who held blue-collar manufacturing jobs at any point between 1985 and 2010.[14] Focusing on this set of relatively similar workers ensures that our measures of human capital capture a homogeneous set of skills. This in turn allows us to focus on the transferability of these skills across sectors while avoiding potential issues with

[14] We use the occupational segment classification developed by Matthes, Burkert, and Biersack (2008).

sector-specific returns/premia to other worker characteristics (gender, education, or occupation).[15]

For identification purposes, we will employ additional sample restrictions in each estimation procedure. These will be described in detail in the corresponding sections.

IV. 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.

A. Empirical Approach

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

$$\Delta \ln y_{i,m\to k} = \beta_{m\to k}X_i + S_i'\gamma + \varepsilon_{ik}, \tag{7}$$

where ε_{ik} is an unobserved sector-specific ability, X_i measures the experience of worker i in sector m,[16] and S_i is a vector of additional demographic, region, and time-specific controls with coefficients that are constant across sectors. As mentioned earlier, a key feature of this specification is that we allow for returns to experience (X_i) to be sector specific. 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.

Ordinary least squares (OLS) estimation of equation (7) would result in biased coefficients due to endogenous sorting of workers into sectors. To address this problem, we restrict the sample to workers who were exogenously

[15] Restricting the sample to workers in blue-collar occupations also allows us to abstract from changes in the occupational structure of employment.

[16] 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.

displaced and employ a selection model to correct for postdisplacement sorting. The selection correction method we employ is based on work by Bourguignon, Fournier, and Gurgand (2007) and Dahl (2002). Formally, the model is as follows (we omit the m subscripts for simplicity):

$$\begin{aligned} \Delta \ln y_{ik} &= \beta_k X_i + S_i'\gamma + \varepsilon_{ik}, \\ V_{ik}^r &= \ddot{\beta}_k X_i + Z_i'\ddot{\gamma} + \eta_{ik} \quad (k = 1, \ldots, S), \\ D_{ik} &= \begin{cases} 1 \Leftrightarrow V_{ik} = \max(V_{i1}, \ldots, V_{iS}), \\ 0 \text{ otherwise}, \end{cases} \end{aligned} \tag{8}$$

where Z_i contains S_i and the coworker instrument introduced later in this section. This model tracks very closely the theoretical framework developed in section II, 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 nonpecuniary factors associated with each sector). As in the theoretical framework from section II, we assume that 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, Fournier, and Gurgand (2007). Specifically, we impose the following linearity assumption:

$$E[\varepsilon_{ik} | \eta_{i1} \ldots \eta_{iS}] = \sigma \frac{\sqrt{6}}{\pi} \sum_s r_k^s (\eta_{is} - E[\eta_{is}]), \tag{9}$$

where r_k^s are the correlation coefficients between the error term in the outcome equation ε_{ik} and the error term η_{ik} in the choice-specific utility equation. The r_k^s terms are therefore choice-specific constants to be estimated. Under these assumptions, the outcome equation can be written in the following manner:

$$\Delta \ln y_{ik} = \beta_k X_i + S_i'\gamma + \lambda_k(p_{i1}, \ldots, p_{iS}) + \omega_{ik}. \tag{10}$$

Here, $\lambda_k(\bullet)$ represents the selection correction function with the sector-choice probabilities p_{is}'s (that individual i from sector m moves to sector s)[17] as the arguments and ω_{ik} is assumed to be exogeneous. Dubin and McFadden (1984) show that under our assumptions the correction term is $\lambda_k(\bullet) = \sigma(\sqrt{6}/\pi)[\Sigma_{s \neq k} r_k^s (p_{is} \ln p_{is}/(1 - p_{is})) - r_k^k \ln p_{ik}]$. This specification leaves the

[17] These individual-level probabilities can be computed using the estimates from the selection model in our first stage.

sign of the bilateral error term correlations r_k^s unrestricted, and thus we allow for very rich and flexible patterns of sorting on unobservables.[18]

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.[19] In this paper, we build on our recent work (Yi, Mueller, and Stegmaier 2017) and propose a novel selection instrument based on the social networks of displaced workers. Specifically, our instrument is the number of firms in each potential target sector *s* where worker *i*'s past coworkers are located at the time of her displacement. This instrument is based on the growing literature on the importance of social networks in determining labor market outcomes.[20]

The reasoning behind our selection instrument is that past coworkers 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.

For each displaced worker *i*, we start by constructing a social network of past coworkers who by the time of worker *i*'s displacement had already moved into other firms and/or sectors. We then restrict this network to include coworkers who satisfy the following conditions:

1. Worker *i* and coworker *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 to address unobserved time-specific demand shocks that could affect both worker *i* and her coworkers' moving decisions.

Having constructed this network for each displaced worker *i*, we then obtain the number of coworkers located in each potential sector *s* at the time of displacement. Last, as a refinement, instead of using the total count of coworkers in each sector *s*, we compute the number of unique firms in sector *s* where worker *i* has at least one coworker. Looking at the number of firms instead of the total count of coworkers in a sector reduces the likelihood of

[18] In app. C, we show that our estimates are robust to alternative assumptions.

[19] In the context of occupational choice, Gathmann and Schoenberg (2010) use a task-based distance measure to other sectors within the same region. Bombardini, Gallipoli, and Pupato (2012) employ state of birth as an instrument for industry choice. In Dix-Carneiro (2014), the selection instrument for sectoral choice is the previous sector of employment (conditional on sectoral tenure).

[20] For recent examples, see Saygin, Weber, and Weynandt (2018) and Glitz (2017) on coworker networks and Hellerstein, Kutzbach, and Neumark (2019) on neighborhood networks.

our instrument being driven by flows to large firms in some sectors. It is also more consistent with the intuition of coworkers providing information about job openings in their own firms, in which case the value of multiple sources of information for a single opening would be low.

Our baseline selection instrument CN_{is} (included in Z_i in eq. [8]) is, therefore, the number of firms in each potential sector s that worker i is connected to through this restricted coworker network (at the time of her displacement). Additionally, to address the potential problem of worker i and coworker 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,[21] we conduct robustness tests imposing additional restrictions on who is included in the network. Namely, we restrict the network to include only worker i's coworkers who, at the time of their last interaction, had different occupations, had different education levels, or were in different within-firm wage groups. Appendix B describes in detail the construction of our various sets of instruments.

B. Implementation and Results

The results from estimating the separate wage regressions for each target sector (corresponding to eq. [10]) 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 III: male manufacturing workers with an apprenticeship and in blue-collar occupations. In this section, we impose additional restrictions to ensure our estimates are unbiased. First, we exclude workers from East Germany (i.e., the former socialist German Democratic Republic). 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 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 nonemployment spells longer than one quarter. Last, for tractability purposes we exclude workers moving to the

[21] This would be the case, e.g., if worker i and worker h sorted into worker i's predisplacement firm on the basis of some shared unobserved characteristics.

[22] For firm closures, we employ the measures developed by Hethey-Maier and Schmieder (2013). The construction of our mass-layoff indicator is described in detail in app. E.

Table 1
Descriptives for Sample

Industry	Age	Tenure	ΔLog(wage)	Non-employment	*N*
Agriculture, mining	28.5	10.3	8.38	.5	420
Manufacturing	29.9	11.9	8.41	.3	50,989
Construction	27.8	9.6	14.62	.5	3,111
Retail	28.5	10.1	10.68	.4	4,195
Transportation	27.7	9.4	9.59	.6	465
Hotel, restaurant, low-skill services	25.8	7.9	2.76	.7	51
Communication, professional services	30.0	11.6	4.80	.3	2,295
Office and business support services	28.6	10.3	.95	.7	1,338
Education, hospitality, personal services	33.2	14.9	−9.43	.3	1,049
Total	29.7	11.7	8.29	.3	63,913

NOTE.—This table contains descriptive statistics for workers' age, tenure in manufacturing sector, wage losses, nonemployment duration (in months), and number of workers. Sample: displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

public administration sector. This sector is the destination of less than 1% of displaced manufacturing workers, making the estimation of sector-specific parameters unfeasible.

Imposing these restrictions leaves us with a sample of 63,913 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 a majority of displaced workers in this sample chose to remain in manufacturing after displacement.[23] The figures in column 4 indicate that there is large variation in the wage losses workers experience. Workers moving to education and other personal services experience an unconditional wage loss of 9%, while workers moving to retail gain on average 11%.[24]

In appendix B, we show descriptive statistics for our baseline coworker selection instrument, as well as evidence of its predictive power. Table B.1 (tables A.1, B.1–B.4, C.1–C.4, D.1–D.3 are available online) shows that the workers in our sample had a large coworker network. The average number of connected firms (in any sector) at the time of displacement is 73. Table B.3 (also on app. B) presents 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, as well as several alternatives with different restrictions. The results from these regressions clearly show that having coworkers in potential

[23] The most frequent two-digit target industries outside manufacturing are specialized construction, wholesale, and retail trade. Workers moving to nonmanufacturing sectors typically still work in manufacturing occupations.

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

Table 2
Estimates for Sectoral Tenure $\hat{\beta}_{m\rightarrow k}$

	OLS (1)	Selection Model (2)	Wald Test (3)
Agriculture, mining	−1.468	−1.366	28.9216
	(.246)	(.517)	(.001)
Manufacturing	−1.093	−.885	130.365
	(.0238)	(.174)	(.000)
Construction	−1.832	−1.437	77.009
	(.0832)	(.225)	(.000)
Retail	−1.599	−1.316	107.680
	(.0779)	(.215)	(.000)
Transportation	−2.208	−1.966	50.875
	(.229)	(.477)	(.000)
Hotel, restaurant, low-skill services	−1.325	−3.655	9.334
	(.645)	(2.393)	(.407)
Communication, professional services	−1.286	−.815	70.851
	(.100)	(.233)	(.000)
Office and business support services	−1.737	−1.678	60.779
	(.111)	(.275)	(.000)
Education, hospitality, personal services	−1.856	−.576	66.163
	(.115)	(.291)	(.000)
First stage:			
CN_{ik}		.00239	
		(.000294)	
N	63,913	63,913	
AIC	631,919.9	630,732.8	
χ^2		39.51	
p-value		.0000	

NOTE.—Dependent variable: difference in pre- and postdisplacement log wages. This table shows estimates for sectoral tenure when switching from manufacturing to target sector k. Column 1 shows uncorrected OLS estimates, and col. 2 shows estimates from the selection model. CN_{ik} denotes the selection instrument (number of connected firms in target sector k). Other covariates: years of manufacturing work experience, state and 5-year period dummies, five firm-size dummies (10–49, 50–249, 250–499, 500–999, ≥1,000 workers), and unemployment duration and regional employment shares in each industry. Bootstrapped standard errors are in parentheses (300 replications). Sample: displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch. AIC = Akaike information criterion.

target sectors increases the probability that displaced workers will choose such a sector. In all cases, our instruments are highly predictive, as evidenced by the large χ^2 statistics of significance.

We present the main set of the estimated coefficients from the full selection model in table 2, which contains the sector-specific coefficients for sectoral tenure ($\hat{\beta}_{m\rightarrow k}$). These coefficients correspond to equation (10) with the dependent variable being the log difference in predisplacement and initial postdisplacement wages.[25] The full set of regressors in the estimation equations includes years of manufacturing work experience, state and 5-year

[25] By using initial daily wages, we avoid potential issues with employer learning and differential wage growth across sectors.

period dummies, five firm-size dummies, unemployment duration, and regional employment shares in each industry. Importantly, we allow only for sector-specific returns to experience; the coefficients for all other regressors are restricted to be equal across sectors. We also restrict the intercept to be constant across sectors for several reasons.[26] First, as shown in Bourguignon, Fournier, and Gurgand (2007), selection correction models of this type do a poor job at estimating intercepts, given that such estimates are identified entirely from the distributional assumptions of the model. In appendix C, we present evidence consistent with the findings of Bourguignon, Fournier, and Gurgand (2007).[27] Importantly, we also show that the $\hat{\beta}_{m\to k}$ estimates are robust to changes in the distributional assumptions of the model as well as to the inclusion of sector-specific intercepts in their estimation (see tables C.2, C.3). Given this, our focus will be on the parameters of human capital transferability.

Table 2 presents the estimated coefficients $\hat{\beta}_{m\to k}$ for each target sector k. 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 statistic of joint significance of the correction terms. All except one 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.[28] For example, for a manufacturing worker moving into another manufacturing firm, the wage loss associated with one extra year of experience is 0.89 percentage points. For a worker moving to the transportation sector, each additional year of experience will increase her wage loss by a (much larger) 1.97 percentage points. Overall, our selection model works as expected. The coworker instrument is highly predictive, and the correction terms enter the wage equations significantly, indicating that our model is correcting the selection bias as intended. In appendix C, we show that our results are largely robust to the use of alternative instruments (table C.1) and to the distributional assumptions of the selection correction (table C.2). Our results are also robust to controlling for worker age.

It is worth comparing this section's results with those of Dix-Carneiro (2014), who estimates similar measures of imperfect transferability of

[26] Conceptually, this restriction implies that workers with no experience will incur the same losses across sectors. This restriction allows for the level of losses (from sectoral reallocation) to be determined jointly from the intercept and our skill transferability measures ($\hat{\beta}_{m\to k}$'s). However, the variation in wage losses across sectors is determined solely by different degrees of skill transferability.

[27] Table C.4 shows estimates of sector-specific intercepts that are imprecise and very sensitive to the distributional assumptions of the selection model.

[28] A test of equality of the coefficients rejects the null that they are equal with a bootstrap p-value of .000.

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 (capital mobility, overlapping generations, etc.). Our approach imposes fewer 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, and we rely on a different set of identifying assumptions. 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.

V. Measures of Labor Market Absorptiveness

In this section, we employ the estimated sectoral distance parameters of the previous section to construct measures of labor market absorptiveness for each region *r*. These measures capture how absorptive each region is from the perspective of manufacturing workers who are negatively affected by import shocks (and need to reallocate to sectors outside manufacturing).[29]

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 205 of these regions in West Germany. Table 3 shows descriptives for sectoral employment shares across regions for the year 1998. The figures show that there is indeed variation in the sectoral composition of regions, in both manufacturing and nonmanufacturing employment. As an example, in 1998 the average region had a 11% share of employment in the

[29] Dauth, Findeisen, and Suedekum (2014) and our own estimates show that import shocks cause an employment shift away from manufacturing and into other sectors. Hence, in constructing our measures of labor market absorptiveness we exclude the manufacturing sector as a potential target sector. This choice is also supported by recent findings of Dauth, Findeisen, and Suedekum (2017) of German manufacturing jobs. They show that while some export-oriented manufacturing industries expanded between 1994 and 2014, they did not absorb manufacturing workers from import-affected industries. We also show in sec. VI.C that controlling for initial manufacturing employment shares does not affect our main results on the role labor market absorptiveness plays in regional adjustment costs.

Table 3
Regional Employment Shares 1998

			Percentile	
Industry	Mean	SD	25th	75th
Agriculture, mining	.04	.02	.02	.05
Manufacturing	.32	.12	.23	.41
Construction	.11	.04	.08	.13
Retail	.16	.03	.14	.18
Transportation	.04	.02	.03	.05
Hotel, restaurant, low-skill services	.03	.02	.02	.03
Communication, professional services	.09	.04	.06	.10
Office and business support services	.03	.01	.02	.04
Education, hospitality, personal services	.19	.05	.15	.21

NOTE.—Based on 205 West German labor market areas. Calculated from worker-level data (Stichprobe der Integrierten Arbeitsmarktbiografien [SIAB] 7510 v1).

construction sector, while regions in the top quartile had shares that were at least 20% higher (i.e., shares above 13%).

We will use this variation in employment shares and our measures of sectoral distances to construct measures of labor market absorptiveness. 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 absorptive" regions. Less absorptive 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.

To capture this simple intuition, we construct our measure of labor market absorptiveness (LMA_{rt_0}) using the following formula:

$$\mathrm{LMA}_{rt_0} = \sum_{s\neq m} \pi^r_{st_0} \hat{\beta}_{m\to s}. \tag{11}$$

Here, $\hat{\beta}_{m\to s}$ is a proxy of the economic distance faced by manufacturing workers when moving to sector s. The term $\pi^r_{st_0}$ represents the number of jobs in sector s as a share of region r's nonmanufacturing employment base,[30] which serves as a proxy for the reallocation probability to sector s.[31] Our measure of labor market absorptiveness will therefore be the average sectoral distance

[30] That is, $\pi^r_{st_0} \equiv$ number of jobs in sector s in region r/ total number of nonmanufacturing jobs in r.

[31] As discussed in sec. II, sectoral employment shares are important determinants of reallocation choices and are associated with nonpecuniary utility costs of switching sectors. We empirically test for the importance of employment shares on sectoral reallocation choices in app. A. There, we show that the industry composition of a workers' labor market significantly influences her reallocation probability and that part of this effect occurs through a nonpecuniary channel.

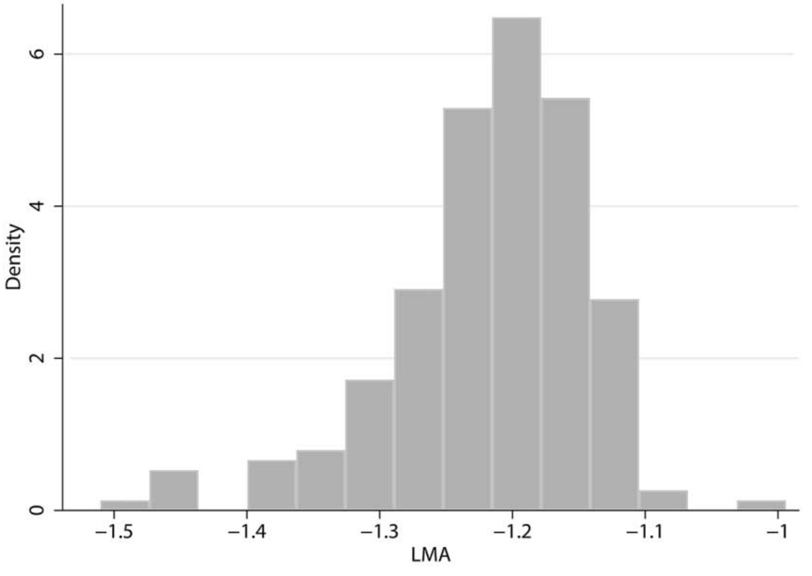

FIG. 1.—Distribution of the labor market absorptiveness measure LMA_r for 1998. LMA is calculated from equation (11).

workers living in region r at time t_0 will face, with the weights being the (nonmanufacturing) sectoral employment shares in their region.[32]

We compute this measure for all West German regions in the year 1998. Our measures of sectoral distance ($\hat{\beta}_{m\rightarrow s}$'s) are derived directly from the estimated parameters in table 2, while $\pi^r_{st_0}$ are obtained from employment figures based on the same administrative dataset employed throughout the paper. The distribution of LMA_{rt_0} is presented in figure 1. The mean is -1.22, with a standard deviation of 0.08. Note that by construction all of the variance in LMA_{rt_0} comes from varying sectoral employment shares across regions. Figure D.1 (available online) presents the spatial distribution of LMA_{rt_0}. The map shows a large degree of geographic variation with regard to labor market absorptiveness, with many instances in which the least absorptive regions border highly absorptive regions. Last, we report descriptive statistics for regions in different LMA_{rt_0} quartiles in table D.1. Regions in different quartiles do not differ much in worker characteristics or industry structure. Among

[32] Note that the formulation of eq. (11) allows us to obtain region-level absorptiveness measures that are independent of worker characteristics in each region. While this approach has the benefit of being tractable, it ignores the possibility that differences in worker characteristics across regions might also result in different adjustment costs. In sec. VI.C, we show that even when accounting for varying worker characteristics our measure of labor market absorptiveness is an important predictor of trade-induced adjustment costs.

the few notable differences, we see that the least absorptive regions (quartile 1) do better in terms of the initial unemployment rate and that quartile 3 regions have a somewhat larger automobile sector share,[33] which may partly explain their somewhat higher import and export growth. We will discuss these features when presenting the results of the next section and will specifically control for them in section VI.C.

VI. Import Shocks and Worker Adjustment

In this section, we provide evidence of the importance of labor market absorptiveness 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 (IV) strategy. As in Autor et al. (2014), 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 (same education, initial tenure on the job, etc.), some of whom worked in manufacturing subindustries 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

$$E_{ijt} = \gamma_t + \psi \Delta \mathrm{IP}_{jt} + X'_{irt}\theta + Z'_{jt}\kappa + \varepsilon_{ijt}, \tag{12}$$

where j represent the three-digit manufacturing subindustry where worker i is employed at the beginning of period t. The term E_{ijt} represents the outcomes of interest, such as cumulative earnings or employment. The term X_{irt} is a vector of worker and region characteristics, and Z_{jt} represents a vector of initial-year industry-level controls. The term $\Delta\mathrm{IP}_{jt}$ represents the increase in (normalized) import flows from China and Eastern Europe to Germany in industry j during time period t.[34] As in Autor et al. (2014), we instrument $\Delta\mathrm{IP}_{jt}$ 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 the strategy of Autor et al. (2014) by studying how the effect of trade shocks (ψ) varies with the degree of absorptiveness of each labor market. If it is the case that our (selection-corrected) skill distance measures are indeed causal, then we would expect workers in regions with many distant jobs to experience the worst outcomes in response to a negative

[33] We used the narrow definition incorporating NACE codes 341 to 343.

[34] The construction of our trade exposure measures is detailed in app. E.

shock.[35] To test this hypothesis, we employ two different strategies: estimating the baseline equation by quartiles of LMA_{rt} and a two-step estimation approach.[36] We discuss each in detail below.

A. Estimation Sample

We focus on West German manufacturing workers during the time period from 1998 to 2008.[37] Our sample consists of all workers employed in manufacturing at the beginning of the period. For consistency, we impose the same demographic restrictions listed in section III—that is, we will focus solely on male workers with an apprenticeship and in blue-collar manufacturing jobs.

Our main outcome variables E_{ijt} will be cumulative employment (measured in days) and normalized cumulative earnings.[38] Table 4 presents the

[35] Note that while related, this new set of estimations is different from those employed to obtain the skill transferability measures in previous sections. Our skill transferability measures were estimated from a particular sample with the aim of avoiding potential endogeneity issues. Most importantly, such a sample was restricted to workers who were exogenously displaced by firm closures and mass layoffs, workers who had never switched sectors before, and workers who did not have long spells of unemployment in between jobs (over one quarter). The goal of such an exercise was to obtain clean measures of skill distance across sectors in the short run. The analysis in this section focuses on the medium run and avoids the aforementioned restrictions. Instead, it focuses on workers in manufacturing jobs at a particular point in time and their subsequent medium-term outcomes. The estimation samples are quite different. In fact, the first estimation sample is a very small subset of this section's estimation sample (3.5%). We believe that the different settings and approaches, as well as the small sample overlap, make it likely that our results reflect underlying structural links between sectoral distances, local labor market opportunities, and adjustment costs, as opposed to being the result of similar samples and regressions.

[36] Remember that we base our endogenous switching model and thus the LMA measure on switches between aggregated sectors. Conditional on having enough switches to more disaggregated target sectors, we expect that results of the endogenous switching model would be more pronounced at the subsector level and that we would get more variation in the estimated β_k. To the extent that the subsector composition differs between labor market regions with the same one-digit sector composition and conditional on covariates, an LMA measure based on more disaggregated data likely carries more variation than our current LMA measure, and we would expect to see standard errors decreasing and significance levels rising when estimating adjustment costs by LMA. In practice, however, the limited number of sector switches by target sector in more disaggregated data would lead to imprecision in the estimates of skill transferability in the first place, and that is why we estimate it on a relatively aggregated level.

[37] This is one of the periods of analysis in Dauth, Findeisen, and Suedekum (2014), who kindly provided us with several of the region and industry-level variables they employ in their paper.

[38] As in Autor et al. (2014), we normalize earnings in period t by the average annual earnings of the 5 years preceding period t and multiply this by 100 in our

Table 4
Descriptives—Estimation Sample

	Mean	SD	Percentile 25th	50th	75th	N
ΔImports per worker	20	29	8	13	24	1,824,678
Cumulative earnings	10.13	4.95	8.14	10.49	11.75	1,824,678
Cumulative employment	3,150	954	3,042	3,652	3,652	1,824,678
Experience	17	6	12	20	23	1,824,678

NOTE.—Imports per worker is measured in €1,000. Cumulative earnings 1998–2008 are normalized by the average annual earnings of the 5 years preceding period t. Cumulative employment 1998–2008 is measured in days. Sample: male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany 1998–2008.

descriptives for these variables. On average, workers in our sample experienced an increase in import competition of €20,000 per worker. There is large variation in the trade exposure as well. Workers in industries in the 25th percentile of trade exposure saw a €8,000 increase in import competition, while workers in the 75th percentile were affected by a €24,000 shock. Cumulative earnings are on average 10.13 times preperiod earnings, and cumulative employment averages 3,150 days.[39]

B. Regressions by Quartile of LMA_{rt}

In this section, we show the results of estimating the baseline estimation equation (12) and allowing the estimated effects to vary with our measures of labor market absorptiveness (which are based on each region's characteristics in the initial year of period t). We split regions into four quartiles based on their computed LMA_{rt} index ($Q = 4$ being the highest, most absorptive group) and then interact the main regressor $\Delta\mathrm{IP}_{jt}$ and the instruments with dummies for each of these quartiles. Thus, we estimate the following specification using the IV approach described above:

$$E_{ijt} = \gamma_t + \mu_Q + \psi_Q \Delta\mathrm{IP}_{jt} + X'_{irt}\theta + Z'_{jt}\kappa + \varepsilon_{ijt}. \tag{13}$$

Our vector of individual-level controls X_{irt} includes age, gender, education, firm tenure and labor market experience, state of residence dummies, and region-level trade shocks.[40] The industry-level control vector Z_{jrt} includes

regressions. Formally, let $E_{ij\tau} \equiv$ earnings in year τ. Then, $E_{ijt} = \Sigma_{\tau\in t}(E_{ij\tau}/\bar{E}_{i\tau_0})$. As Autor et al. (2014) 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 postshock outcomes (since they are constructed using preshock years).

[39] Note that because we compute cumulative earnings and employment including both initial and end years, the figures we estimate are for a period of 11 years.

[40] This variable captures region-level differences in trade exposure stemming from differences in the importance of manufacturing subsectors. We follow Autor, Dorn, and Hanson (2013) in constructing region-level measures of trade exposure by apportioning the national changes in industry imports to each region based on

Table 5
Regressions by Quartile of LMA_{rt}

	Earnings		Employment	
	(1)	(2)	(3)	(4)
$\Delta \mathrm{IP}_{jt}$	−.590		−1.037	
	(.0858)		(.140)	
$\Delta \mathrm{IP}_{jt} \cdot (D_{Q_1} = 1)$		−1.280		−2.116
		(.164)		(.307)
$\Delta \mathrm{IP}_{jt} \cdot (D_{Q_2} = 1)$		−.725		−1.425
		(.153)		(.174)
$\Delta \mathrm{IP}_{jt} \cdot (D_{Q_3} = 1)$		−.405		−.660
		(.108)		(.166)
$\Delta \mathrm{IP}_{jt} \cdot (D_{Q_4} = 1)$		−.538		−.942
		(.113)		(.211)
Observations	1,824,678	1,824,678	1,824,678	1,824,678
F	797.105	116.769	797.105	116.769
χ^2_3		21.791		24.575
p-value		.000		.000

NOTE.—Dependent variables: 100 × cumulative earnings 1998–2008 normalized by the average annual earnings of the 5 years preceding period t. Cumulative employment 1998–2008 is measured in days. Main regressors: $\Delta \mathrm{IP}_{jt}$ denotes the import shock and D_Q the quartiles of the labor market absorptiveness measure LMA. Controls include age, gender, education, firm tenure and labor market experience, state of residence dummies, region-level trade shocks, industry-level export growth during time period rt (at the three-digit subindustry level), the Herfindahl index, the Ellison-Glaeser agglomeration index, and one-digit industry dummies. Standard errors are clustered in labor market areas. Sample: male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany 1998–2008. Interquartile range of import shock: 16.05.

industry-level export growth during time period t (at the three-digit subindustry level), the Herfindahl index, the Ellison-Glaeser agglomeration index, and one-digit industry dummies. In all estimations, we also include period and LMA_{rt} 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 with previous findings, exposure to import competition leads to a reduction in cumulative employment.[41] Columns 2 and 4 show how these effects vary with the degree of labor market absorptiveness of each region. In terms of earnings, import shocks seem to have significantly larger negative effects on workers in the least absorptive regions (those in the first quartile of the LMA_{rt} 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

its initial employment structure. The construction of this variable is detailed in app. E.

[41] Dauth, Findeisen, and Suedekum (2014) estimate that a €1,000 import shock leads to a reduction in employment of 1.4 days. As in Dauth, Findeisen, and Suedekum (2014), we cluster standard errors at the level of labor market regions. Estimates mostly stay statistically significant when we cluster standard errors at the three-digit industry level.

tend to become smaller with higher labor market absorptiveness. A χ^2 test of equality for the four coefficients is rejected at the 1% confidence level. In terms of economic significance, the −1.280 coefficient means that moving a worker from the 25th to the 75th percentile of import competition exposure would result in a loss of 20.5% of initial annual earnings (over a 10-year period). The effect of import shocks on workers in more absorptive regions is much smaller at 8.6%. In other words, the negative effects of import exposure are more than two times larger for workers in the least absorptive regions. The results on employment exhibit a similar pattern. Workers in less absorptive regions experience larger declines in total employment than regions at the upper end of the absorptiveness distribution.

It is worth noting that these results seem to indicate that quartile 3 regions fare slightly better than the most absorptive regions in quartile 4. While the difference between the two coefficients is never statistically significant, quartile 3 regions stand out with a bigger automobile sector and associated export growth relative to regions in other quartiles (table D.1).[42] To quantify the importance of differential automobile exports for our regression coefficients, we added regional per-worker automobile export growth as a further control variable in a robustness check and find virtually unchanged results (available on request). Furthermore, we will directly control for these regional characteristics in section VI.C and find consistent results.

It is also worth placing the economic magnitude of our estimated adjustment costs in context. Our estimates imply adjustment costs that are lower than the full adjustment costs as estimated in Dix-Carneiro (2014). This was expected, as we focus on the human capital channel. Further candidate reasons for modest losses are the German apprenticeship system certifying human capital that is transferable across employers (Acemoglu and Pischke 1998), relatively low wage dispersion in Germany, and the prevalence of collective wage agreements at the sectoral level. Despite being modest in magnitude, our estimates allow us to discriminate between absorptive and less absorptive regions in a meaningful way.

In table 6, we conduct several robustness tests to our main specification (for both earnings and employment). Columns 1 and 3 restrict our estimation sample to workers below age 50. Columns 2 and 4 exclude from the estimation sample all large labor market areas (defined as having more than one million workers at the beginning of period *t*). All of the results are qualitatively similar and follow the same pattern of larger losses for workers in less absorptive regions. Overall, the results obtained so far are consistent

[42] There are main automobile productions sites in each of our four LMA quartiles (e.g., LMA1, Emden [Volkswagen]; LMA2, Ingolstadt [Audi]; LMA3, Munich [BMW]; LMA4, Ruesselsheim [Opel]).

Table 6
Regressions by Quartile of LMA_{rt}—Robustness Tests

	Earnings		Employment	
	(1)	(2)	(3)	(4)
$\Delta IP_{j,\tau} \cdot (D_{Q_1} = 1)$	−1.127	−1.273	−1.404	−1.977
	(.168)	(.175)	(.199)	(.312)
$\Delta IP_{j,\tau} \cdot (D_{Q_2} = 1)$	−.594	−.905	−1.105	−1.487
	(.135)	(.169)	(.148)	(.199)
$\Delta IP_{j,\tau} \cdot (D_{Q_3} = 1)$	−.408	−.323	−.573	−.514
	(.100)	(.164)	(.112)	(.252)
$\Delta IP_{j,\tau} \cdot (D_{Q_4} = 1)$	−.574	−.535	−.954	−.771
	(.104)	(.153)	(.185)	(.286)
Excluding age 50 and over	Yes	No	Yes	No
Excluding large LMAs	No	Yes	No	Yes
Observations	1,428,014	1,352,147	1,428,014	1,352,147
F	111.564	110.420	111.564	110.420
χ^2_3	14.065	20.318	18.438	19.960
p-value	.003	.000	.000	.000

NOTE.—Dependent variables: 100 × cumulative earnings 1998–2008 normalized by the average annual earnings of the 5 years preceding period t. Cumulative employment 1998–2008 is measured in days. Main regressors: ΔIP_{jt} denotes the import shock and D_Q the quartiles of the labor market absorptiveness measure LMA. Controls include age, gender, education, firm tenure and labor market experience, state of residence dummies, region-level trade shocks, industry-level export growth during time period rt (at the three-digit subindustry level), the Herfindahl index, the Ellison-Glaeser agglomeration index, and one-digit industry dummies. Standard errors are clustered in labor market areas. Sample: male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany 1998–2008. Interquartile range of import shock: 16.05.

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

Labor Market Absorptiveness and Sectoral Reallocation

In this subsection we explore the mechanisms through which labor market absorptiveness leads to different adjustment costs. The model described in section II predicts that regional absorptiveness affects adjustment costs because it determines the types of jobs workers can reallocate to. Absorptive regions are, by construction, regions with many employment opportunities in sectors close to manufacturing (i.e., those where the returns to manufacturing sector tenure are larger). Therefore, we would expect that trade-affected workers in absorptive regions will be able to reallocate more easily out of the manufacturing sector and that the nonmanufacturing jobs they find will be in sectors closer to manufacturing. Below, we provide evidence consistent with these predictions. Specifically, we find that in response to trade shocks, workers in more absorptive regions are more likely to (1) compensate manufacturing employment losses with nonmanufacturing employment gains, (2) compensate manufacturing employment losses with employment gains in nonmanufacturing sectors closer to manufacturing, and as a result (3) recover a higher share of their manufacturing earnings loss with nonmanufacturing earnings.

Table 7
Regressions by Quartile of LMA_{rt}—Sectoral Reallocation and Compensation Rates

	Employment					Earnings	
			Distance to Manufacturing				
	Mfg (1)	Non-mfg (2)	Farther (3)	Mid (4)	Close (5)	Mfg (6)	Non-mfg (7)
$\Delta IP_j, \tau \cdot (D_{Q_1} = 1)$	−3.656	1.540	.173	.151	1.176	−1.641	.361
	(.498)	(.292)	(.0615)	(.0705)	(.218)	(.196)	(.0809)
Compensation rate		[.42]	[.05]	[.04]	[.32]		[.22]
$\Delta IP_j, \tau \cdot (D_{Q_2} = 1)$	−3.147	1.722	.0679	.119	1.51	−1.26	.536
	(.353)	(.307)	(.0316)	(.0903)	(.231)	(.157)	(.122)
Compensation rate		[.55]	[.02]	[.04]	[.48]		[.43]
$\Delta IP_j, \tau \cdot (D_{Q_3} = 1)$	−2.779	2.119	.0455	.189	1.871	−1.12	.715
	(.486)	(.473)	(.0326)	(.157)	(.469)	(.170)	(.170)
Compensation rate		[.76]	[.02]	[.07]	[.67]		[.64]
$\Delta IP_j, \tau \cdot (D_{Q_4} = 1)$	−2.522	1.579	.112	.122	1.307	−1.053	.515
	(.439)	(.331)	(.0572)	(.0621)	(.286)	(.164)	(.120)
Compensation rate		[.63]	[.04]	[.05]	[.52]		[.49]
Observations	1,824,678	1,824,678	1,824,678	1,824,678	1,824,678	1,824,678	1,824,678
F	116.769	116.769	116.769	116.769	116.769	116.769	116.769
χ^2_3 (compensation rate)		23.53	4.20	.46	21.09		27.65
p-value		.000	.241	.928	.000		.000

NOTE.—See note to table 6. Columns 1 and 2 report employment effects within and outside manufacturing. Columns 3–5 split the nonmanufacturing sector into groups of industries based on their distance to manufacturing as described in the text. The compensation rate measures the ratio of the effect on nonmanufacturing gains relative to the effect on manufacturing losses as described in the text. χ^2 tests of equality are performed on the compensation rates based on the joint estimation of the models using generalized method of moments (standard errors are clustered in labor market areas).

Table 7 conducts an analysis of the effect of import exposure on employment shifts focusing on the reallocation of workers between the manufacturing sector and the broad nonmanufacturing sector. We further expand this analysis by splitting the nonmanufacturing sector into three groups stratified by the sectoral distances estimated in section IV (table 2).[43] The estimates in column 1 show that import exposure caused a decline in nonmanufacturing employment in all types of regions. Column 2 shows the effect of import exposure on nonmanufacturing employment. Below the coefficients and standard errors, we show in brackets the implied compensation rate, which is the ratio of the effect on nonmanufacturing employment relative to the effect on manufacturing employment. This measure captures how much of the trade-induced manufacturing employment loss workers are

[43] We group our eight nonmanufacturing sectors into three groups to ensure precision in our estimates. The first group with the farther distance includes hotel, restaurant, and low-skill services; transportation; and office and business support services. The medium-distance group includes construction as well as agriculture and mining. The low-distance group includes retail, communication and professional services, and education, hospitality, and personal services.

able to compensate with nonmanufacturing employment. The compensation rates in column 2 show that in the most absorptive regions, workers were able to compensate a much larger fraction of the manufacturing employment loss with employment in (any) nonmanufacturing sector (a χ^2 test of equality of the four compensation rates is easily rejected at the 1% level). More specifically, we find that 63% of manufacturing employment loss is compensated by nonmanufacturing employment in regions with the highest manufacturing absorptiveness, whereas this number is only 42% in the least absorptive regions.[44]

Columns 3–5 split the nonmanufacturing sector into groups of industries based on their distance to manufacturing. The results of column 5 (sectors closer to manufacturing) show that in the least absorptive regions, a much smaller fraction of the overall manufacturing employment loss is compensated by employment in close nonmanufacturing sectors. In the least absorptive regions (quartile 1), only 32% of manufacturing employment loss is compensated by employment in sectors close to manufacturing. In the highly absorptive regions (quartiles 3 and 4), the compensation rate for close nonmanufacturing jobs is much higher (at 67% and 52%, respectively).[45] This differential reallocation to close sectors seems to be driving the overall differential reallocation responses to nonmanufacturing jobs shown in column 2. The estimated shifts to more distant nonmanufacturing sectors (cols. 3 and 4) show similar compensation rates across regions (equality tests cannot reject that the compensation rates are the same even at the 10% level).

These results suggest that workers in absorptive regions make up the manufacturing employment loss with nonmanufacturing employment at higher rates; they also indicate that they do so with employment in nonmanufacturing jobs that are better for them (lower economic distance to manufacturing).[46]

[44] Note that while the compensation rate in regions in quartile 3 is higher than in quartile 4, they are not statistically different from each other. A χ^2 test of equality between the two effects fails to reject the hypothesis that they are equal with a p-value of .123. Analogous tests comparing compensation rates between quartiles 1 and 3 and between quartiles 1 and 4 both reject equality with p-values of .000 and .007, respectively. Qualitatively, our main story holds—workers in more absorptive regions (quartiles 3 and 4) get higher compensation rates than those in less absorptive regions (quartiles 1 and 2). To further support the qualitative nature of our findings, we estimated these models grouping regions into terciles instead of quartiles. The results, shown in table D.2, confirm our findings. Compensation rates are larger in regions in the highest tercile of the absorptiveness distribution.

[45] As with col. 2, the difference between quartiles 3 and 4 is not statistically significant (the χ^2 test p-value is .159), but we can easily reject equality between quartiles 1 and 3 and between quartiles 1 and 4. The same pattern applies to the earnings results in col. 7. Specific test statistics are available on request.

[46] This pattern is confirmed in table D.3, which shows the unconditional transition probabilities of manufacturing workers in our sample to target nonmanufacturing sectors (for regions of different absorptiveness). We see that workers shy away from moving to the hotels and transportation sectors (the two sectors with the lowest

Because the mix of nonmanufacturing employment is different across regions, we would expect the trade-induced effect on overall nonmanufacturing earnings to be more favorable to workers in the more absorptive regions.[47] Columns 6 and 7 show that this is indeed the case. In more absorptive regions, a much larger fraction of the overall manufacturing earnings loss is compensated with nonmanufacturing earnings (64% and 49% in quartiles 3 and 4 vs. 22% in quartile 1). Taken together, these results are consistent with the mechanisms described in section II. Workers in more absorptive regions can adjust more favorably to negative shocks by replacing manufacturing employment with nonmanufacturing jobs. This higher compensation rate is also driven by jobs in sectors closer to manufacturing, which in turn leads to higher nonmanufacturing earnings.

Labor Market Absorptiveness and Geographic Mobility

One concern that arises when focusing on 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 labor market absorptiveness in a worker's initial 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 focusing 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 1–3 report estimates of regressions at the national level, while columns 4–6 present estimates of the import exposure effect by type of

returns to manufacturing tenure). Importantly, we also see that they are more likely to transition to these sectors in regions with low absorptiveness. Conversely, returns are highest in the education and personal service sector, and more workers move to this sector in the most absorptive regions. Hence, as expected from our selection model, workers in absorptive regions are more (less) likely to go to sectors for which we estimated the returns to manufacturing sector tenure to be highest (lowest). Note that this pattern is also consistent with the evidence from table A.1 showing that a larger employment share increases the reallocation probabilities to a particular sector. More absorptive regions have, by construction, larger employment shares in close sectors. Hence, we should expect higher reallocation to close sectors in those regions. In that analysis, we focused on a restricted sample of displaced workers, so it is reassuring that a similar pattern applies to trade-induced reallocation in this setting.

[47] Note that this applies to nonmanufacturing earnings, not earnings in each nonmanufacturing sector. Conditional on reallocating to a close/distant sector, effects should not vary across regions of different absorptiveness.

Table 8
Employment Reallocation by Quartile of LMA_{rt}—Geographic Mobility

	All (1)	Same Region (2)	Different Region (3)	All (4)	Same Region (5)	Different Region (6)
$\Delta IP_{j,\tau}$	−1.037	−2.053	1.016			
	(.140)	(.256)	(.227)			
$\Delta IP_j, \tau \cdot (D_{Q_1} = 1)$				−2.116	−3.251	1.135
				(.307)	(.559)	(.389)
$\Delta IP_j, \tau \cdot (D_{Q_2} = 1)$				−1.425	−2.062	.636
				(.174)	(.234)	(.171)
$\Delta IP_j, \tau \cdot (D_{Q_3} = 1)$				−.660	−1.921	1.260
				(.166)	(.444)	(.410)
$\Delta IP_j, \tau \cdot (D_{Q_4} = 1)$				−.942	−1.824	.882
				(.221)	(.336)	(.224)
Observations	1,824,678	1,824,678	1,824,678	1,824,678	1,824,678	1,824,678
F	797.105	797.105	797.105	116.769	116.769	116.769
χ^2_3				24.575	5.646	3.394
p-value				.000	.130	.335

NOTE.—Dependent variables: cumulative employment 1998–2008 measured in days. Main regressors: ΔIP_{jt} denotes the import shock and D_Q the quartiles of the labor market absorptiveness measure LMA. Controls include age, gender, education, firm tenure and labor market experience, state of residence dummies, region-level trade shocks, industry-level export growth during time period rt (at the three-digit subindustry level), the Herfindahl index, the Ellison-Glaeser agglomeration index, and one-digit industry dummies. Standard errors are clustered in labor market areas. Sample: male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany 1998–2008. Interquartile range of import shock: 16.05.

region. The estimates in columns 1–3 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 absorptiveness (based on the results from cols. 4–6). Column 6, for example, shows that workers in the least absorptive regions shift employment to other regions at a magnitude similar to that of workers living in the most absorptive regions (the point estimate for absorptive regions is slightly smaller, but a test of equality across the four coefficients fails to reject the null that they are all equal). These results suggest that geographic mobility is costly—costly enough to prevent workers from the least absorptive labor markets to move out of their regions. Moreover, the similar mobility patterns across different types of regions suggests that the differential earning effects we observe are not the result of higher geographic mobility for workers in the most absorptive regions. Overall, the results highlight the importance of local labor markets (due to the lack of geographic mobility) and support our model's prediction that local labor markets (and their absorptiveness) affect workers' adjustment costs by influencing the types of jobs workers reallocate to.

C. Two-Step Estimation Approach

Our results in the previous section point to the important role that labor market absorptiveness plays in the effect of trade shocks on workers. To address concerns that our findings could result from our LMA_{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 influence 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 (eq. [12]) but interact the trade shock with region dummies, obtaining a set of ψ_{rt} parameters for each region. In the second step, we regress ψ_{rt} on our LMA_{rt} index and a host of region-level controls. Formally, we have

$$E_{ijrt} = \gamma_t + \psi_{rt} \cdot \Delta\mathrm{IP}_{jt} + X'_{irt}\theta + Z'_{jt}\kappa + \varepsilon_{ijrt}, \tag{14}$$

$$\psi_{rt} = \eta_t + \delta\mathrm{LMA}_{rt} + W'_{rt}\theta + \omega_{rt}, \tag{15}$$

where W_{rt} is a vector of region characteristics that includes initial employment size, employment share in manufacturing, unemployment rate, net employment growth during period t, and regional trade exposure during period t.[48] Importantly, to allay concerns that some regions might be influenced by the strong presence of the automobile sector, we include the following region-level regressors: initial employment share in automobile manufacturing and import and export growth in the automobile sector. We also add region-level controls that include pretrends 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 $\hat{\psi}_{rt}$. For the second step, we normalize all of 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 ($\hat{\psi}_{rt}$). In the average region, the negative effect of import exposure on earnings was -0.46. The negative effects vary substantially across regions, as evidenced by the large standard deviation of 0.84. The results of the second-step estimation are shown in columns 1–4, with each column adding an additional set of controls. Column 1 shows the coefficient of LMA_{rt} without any controls, column 2 adds the baseline region-level controls listed above, column 3 adds region-level pretrends in employment and wages, and column 4 adds additional region-level demographic controls. In all cases, the coefficient for LMA_{rt} is significant and a strong predictor of the effects of import exposure on workers. Importantly, labor market absorptiveness is a stronger predictor of $\hat{\psi}_{rt}$ 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 of the regressors.

[48] The construction of region-level trade exposure is detailed in n. 40 and app. E.

Table 9
Two-Step Estimation (Second Step)

	Cumulative Earnings			
	(1)	(2)	(3)	(4)
$\text{LMA}_{r\tau_0}$	.174	.151	.163	.160
	(.0781)	(.0813)	(.0821)	(.0878)
Net employment growth$_{r\tau}$		.0663	.110	.0258
		(.0852)	(.0869)	(.0954)
Employment size$_{r\tau_0}$		.0487	.0442	−.0234
		(.0491)	(.0492)	(.0649)
Manufacturing share$_{r\tau_0}$		.0918	.0904	−.119
		(.0857)	(.0857)	(.119)
Automobile manufacturing share$_{r\tau_0}$		.183	.238	.262
		(.112)	(.115)	(.115)
Automobile import growth$_{r\tau}$		.0511	.0596	.0715
		(.109)	(.108)	(.110)
Automobile export growth$_{r\tau}$		.148	.144	.119
		(.0971)	(.0972)	(.0985)
Region-level controls	No	Yes	Yes	Yes
Pretrends (3 year)	No	No	Yes	Yes
Region-level demographic controls	No	No	No	Yes
$\psi_{r\tau}$			−.458	
			(.838)	
Observations	203	203	203	203
Adjusted R^2	.242	.242	.244	.265

NOTE.—Estimates are from eq. (15). Region-level controls (in standard deviation units) include initial-year employment size, employment share in manufacturing, employment share in automobile manufacturing, and unemployment rate; net employment growth during period t; region-level trade exposure during period t (see n. 40 for details on this variable); import growth in automobile industries during period t; and export growth in automobile industries during period t. Pretrends include 3-year 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. Sample: male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany 1998–2008.

Qualitatively, these results are similar and consistent with those in the previous section. Labor market absorptiveness ameliorates the negative effects of import competition on workers' earnings. Quantitatively, the point estimates lead to conclusions similar to those in section VI.B. Taking column 4, for example, our estimates imply that (holding all other region characteristics at their national averages) workers in a region at the 25th percentile of the LMA_{rt} distribution will face an adjustment cost of $\hat{\psi}_{rt} = -0.52$, while workers in a region at the 75th percentile of the LMA_{rt} distribution will experience a much smaller adjustment cost of $\hat{\psi}_{rt} = -0.35$. 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 8.32% (of initial-year earnings) in a less absorptive region at the 25th percentile of the LMA_{rt} distribution. A worker in more absorptive region (at the 75th percentile) would experience a smaller loss of 5.6%. A more direct comparison to the results of section VI.B is to take the average LMA_{rt} of regions in the top and bottom quartiles of the distribution. In that case, the resulting loss differential would be 10.6% versus 4.48% for workers in the least absorptive versus most absorptive regions. While the overall magnitudes are smaller under this approach, their relative sizes are similar to those obtained in section VI.B employing a different methodology (the loss differentials in that case were 20.5% and 8.6% for workers in the least vs. most absorptive regions, respectively) and confirm that labor market absorptiveness 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 absorptive 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 absorptiveness is one of the most important determinants of the adjustment costs faced by negatively affected workers.

VII. 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 on manufacturing workers, we estimate new measures of skill transferability and show that there is indeed large heterogeneity in how these workers can transfer their skills when they move to different 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 absorptiveness and show that import shocks have a much smaller effect on manufacturing workers located in absorptive regions than on those located in less absorptive 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. They 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. More broadly, our findings inform the literature on the impact of sectoral transformations on the labor market, the literature on job mobility and displacement costs, and the skills and spatial mismatch literature. In all of these cases, our findings have direct implications in assessing transitional costs and related incidence analyses.

From a policy perspective, our work can inform policy makers concerned with sectoral structural change and its differential impacts on different groups or regions. In particular, our approach and methodology can be generalized to study other time periods, subpopulations of workers, or sector-specific shocks other than trade shocks. Current examples include the COVID-19 pandemic hitting the hospitality sector very hard and the transition to electric cars heavily affecting car manufacturers and their suppliers. Policy makers could use the regional measure of sector absorptiveness to design special programs for adversely affected regions. This may in particular be relevant for redesigning place-based policies, which often come in the form of investment subsidies aiming to change the sectoral structure of adversely affected regions. Our measure of sector absorptiveness may provide superior information on which future sectoral structure fits best to the skill set of displaced workers. In general, we can also say that regional immobility exaggerates the costs of job displacement, as workers will be more likely to end up in sectors with lower returns to their human capital if they stay in their regions. This is in particular the case in regions with low levels of sectoral absorptiveness. A sensible policy reaction to this that both mitigates workers losses and could improve allocative efficiency is providing very generous mobility assistance to workers in those regions.

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