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

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Online Appendix

A Theoretical Framework Extension - Reallocation probabilities and regional employment opportunities

In this section, we expand on subsection 2.2 by providing empirical evidence of the importance of sectoral employment shares on reallocation probabilities. We also present a generalized model with fewer restrictions that allows us to estimate non-pecuniary structural parameter $\tilde{\delta}$. This parameter captures the non-pecuniary channel through which sectoral employment shares influence reallocation probabilities. All empirical results in this sections are based on the sample of displaced manufacturing workers described in detail in Section 4.

We start by estimating a version of equation 6 which includes Z_i (the set of controls used elsewhere in the paper):[1]

$$V_{ik}^{r} = \ddot{\beta}_k X_i + \ddot{\delta}\pi_{rk} + Z_i'\ddot{\gamma}_k + \eta_{ik} \tag{A1}$$

The parameter $\ddot{\delta}$ in this model captures the overall effect that sectoral shares have on reallocation probabilities. It can be easily estimated using a multinomial logit model. Table A.1 below shows the estimated $\ddot{\delta}$ coefficient (column 1). The coefficient is positive and statistically significant, indicating that larger employment shares in a sector will increase the probability that worker reallocates to that sector. Under the assumptions of our stylized model (in which wage losses are solely determined by human capital X_i), sectoral shares affect reallocation probabilities solely through a non-pecuniary channel. This is a restrictive assumption, which we now proceed to relax. We will show that even when we allow for π_{rk} to influence wages (perhaps through matching/agglomeration channels), we still find robust empirical evidence for a non-pecuniary channel through which employment shares affect reallocation choices.

We start by allowing potential wage changes to be determined both by human capital X_i, a vector of controls Z_i and sectoral employment shares in a region (π_{rk}):

$$\Delta \ln y_{ik} = X_i\beta_k + Z_i'\gamma + \delta\pi_{rk} + \varepsilon_{ik}$$

Following the same steps we used in Section 2, we can then plug in this unrestricted wage loss

[1] Z_i includes the same list of regressors as in our main wage regression model (equation 8, section 4): state and 5-year period dummies, unemployment duration, 5 firm size dummies, and our coworker networks instruments. Region-level sectoral employment shares (π_{rk}'s) are included in both this model and equation 8. However, here we treat π_{rk} separately to highlight its role.

equation into the utility function (equation 5) to get:

$$\begin{aligned} V_{ik}^{r} &= \alpha\Delta\ln y_{i,m\to k}^{r} + \tilde{\beta}_k X_i + Z_i'\tilde{\gamma} + \tilde{\delta}\pi_{rk} + \sigma\theta_{ik} \\ &= \alpha\beta_k X_i + Z_i'\alpha\gamma + \alpha\delta\pi_{rk} + \alpha\varepsilon_{ik} + \tilde{\beta}_k X_i + Z_i'\tilde{\gamma} + \tilde{\delta}\pi_{rk} + \sigma\theta_{ik} \\ &= (\alpha\beta_k + \tilde{\beta}_k)X_i + Z_i'(\alpha\gamma + \tilde{\gamma}) + (\alpha\delta + \tilde{\delta})\pi_{rk} + \alpha\varepsilon_{ik} + \sigma\theta_{ik} \end{aligned}$$

Then, after rescaling all utilities by $\frac{1}{\sigma}$, the utility function can be simplified to:

$$V_{ik}^{r} = \ddot{\beta}_k X_i + Z_i'\ddot{\gamma} + \ddot{\delta}\pi_{rk} + \eta_{ik}$$

where $\ddot{\beta} \equiv (\alpha\beta_k + \tilde{\beta}_k)$, $\ddot{\delta} \equiv (\alpha\delta + \tilde{\delta})$. Importantly, this model implies that sectoral employment shares affect reallocation probabilities both through the wage channel (δ) and a non-pecuniary channel ($\tilde{\delta}$). Thus, under these less restrictive assumptions, the estimate $\ddot{\delta}$ does not tell us much about the underlying mechanisms through which employment shares affect reallocation probabilities. Fortunately, our estimation strategy allows us to disentangle $\ddot{\delta}$ into a pecuniary and a non-pecuniary component. We will do so by following an approach similar to Willis and Rosen (1979), who estimate determinants of education choices conditional on expected earnings.[2]

Recall that

$$V_{ik}^{r} = \alpha\Delta\ln y_{i,m\to k}^{r} + \tilde{\beta}_k X_i + Z_i'\tilde{\gamma} + \tilde{\delta}\pi_{rk} + \sigma\theta_{ik}$$

where $\Delta\ln y_{i,m\to k}^{r}$ is the potential outcome for worker i in sector k. As a potential outcome, $\Delta\ln y_{i,m\to k}^{r}$ is only observed in the sector worker i chose. In section 4, we show we can consistently estimate the (selection corrected) parameters of $\Delta\ln y_{i,m\to k}^{r}$. This allow us to construct predicted values $\Delta\ln \hat{y}_{i,m\to k}^{r} = X_i\hat{\beta}_k + Z_i'\hat{\gamma} + \hat{\delta}\pi_{rk(i)} + \lambda_k(\hat{p}_{i1}\ldots,\hat{p}_{iS})$ for all workers in all potential sectors.[3] We can use these values to estimate the model:

$$V_{ik}^{r} = \alpha\Delta\ln \hat{y}_{i,m\to k}^{r} + \tilde{\beta}_k X_i + Z_i'\tilde{\gamma} + \tilde{\delta}\pi_{rk} + \sigma\theta_{ik} \tag{A2}$$

in which $\tilde{\delta}$ captures the effect of sectoral employment shares on reallocation probabilities holding potential wage losses constant. In other words, $\tilde{\delta}$ captures the non-pecuniary channel through which sectoral employment shares operate.

[2] See Bertoli et al. (2013) for a similar approach to estimate international migration costs.

[3] This estimation corresponds to equation 10 and the results shown on Table 2. As explained in Section 4, X_i represents years of manufacturing work experience, and the vector of controls S_i includes state and 5-year period dummies, 5 firm size dummies (10-49; 50-249; 250-499; 500-999; 1000+ workers), and unemployment duration. Very importantly, S_i also includes a vector of regional employment shares in each industry.

We present the estimates of $\tilde{\delta}$ in Table A.1. Column 2 shows the estimated coefficients α and $\tilde{\delta}$, while column 3 presents estimates from a model where we allow $\tilde{\delta}$ to vary by sector. Columns 4 and 5 show analogous results using a version of $\Delta \ln \hat{y^r_{i,m\to k}}$ based only on observed characteristics ($\Delta \ln \hat{y^r_{i,m\to k}} = X_i \hat{\beta}_k + \hat{T}_i' \gamma + \hat{\delta} \pi_{rk(i)}$, ignoring the $\lambda_k(\hat{p}_{i1} \ldots, \hat{p}_{iS})$). In all cases, we use bootstrapped standard errors to account for the fact that $\Delta \ln \hat{y^r_{i,m\to k}}$ are estimates themselves.

In all cases, we obtain positive and statistically significant values of $\tilde{\delta}$. These findings indicate that the industry mix of regions plays a major role in determining the sectoral reallocation probabilities –through mechanisms that are non-pecuniary in nature. These robust findings are consistent with information and other non-pecuniary costs workers face in searching for jobs. In terms of magnitude, the $\tilde{\delta}$ estimate of 5.126 (column 2) would imply that for the average person in our sample, going from the 25th to 75th percentile in exposure to "Education, hosp, personal svcs." jobs would increase the probability of reallocation to that sector by 36%. The analogous figure for the Construction sector would be 15% (due to the smaller interquartile range). These effects are economically significant. It is worth pointing out that their magnitude is likely exacerbated by our setting and population: blue-collar (non-college educated) workers displaced from a declining industry and looking for jobs in the short-medium run. This particular group will be probably be less selective than the general workforce with regards to their reallocation choices, and will be more sensitive to available job openings in their labor markets.

Table A.1: Selection Model - Sectoral Employment Shares and Reallocation Probabilities

		$\Delta \ln \hat{y}^{r}_{i,m\to k}$ based on observables and unobservables		$\Delta \ln \hat{y}^{r}_{i,m\to k}$ based on observables only	
	Baseline Model	Constant Effect	Heterogeneous Effects	Constant Effect	Heterogeneous Effects
	(1)	(2)	(3)	(4)	(5)
$\ddot{\delta}$	4.740				
	(0.315)				
$\tilde{\delta}$		5.126		4.929	
		(0.289)		(0.288)	
$\tilde{\delta}_1$			8.846		9.189
			(1.833)		(1.847)
$\tilde{\delta}_3$			4.691		6.273
			(0.820)		(0.879)
$\tilde{\delta}_4$			4.176		4.156
			(0.602)		(0.604)
$\tilde{\delta}_5$			11.88		10.17
			(2.830)		(2.829)
$\tilde{\delta}_6$			14.66		17.02
			(7.564)		(7.561)
$\tilde{\delta}_7$			4.716		3.903
			(0.426)		(0.453)
$\tilde{\delta}_8$			14.74		12.70
			(1.933)		(1.973)
$\tilde{\delta}_{10}$			5.560		5.924
			(0.816)		(0.817)
α		-0.00220	-0.00296	0.0117	0.0131
		(0.00244)	(0.00245)	(0.00224)	(0.00260)
Observations			63913		

Notes: Table shows estimates of $\ddot{\delta}$ (equation A1) and $\tilde{\delta}$ (equation A2). The estimates capture the effect of π_{rk} on the sectoral choice of displaced workers. Controls include: years of manufacturing work experience, state and 5-year period dummies, 5 firm size dummies (10-49; 50-249; 250-499; 500-999; 1000+ workers), unemployment duration. Bootstrapped standard errors in parentheses (300 replications). Sample: Displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

B Selection Model - First Stage

In this section, we describe the construction of our coworker-based network instruments. We then present descriptives of the network instrument employed in section 4 and show results of the first stage of our selection model (equation 8).

Network instrument construction

We start by constructing the coworker network (for each displaced worker i) as follows:

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

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

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

Fourth, we use the job information of coworkers (at time t_1) to compute CN_{ik} –the number of unique firms in sector k associated with worker i's network. We refer to CN_{ik} as the number of "connected firms" in sector k. Our instrument is the vector containing nine elements (CN_{ik}'s), one for each sector k.

Alternative instruments

Formally, the exclusion restriction in our setting requires CN_{ik} and ε_{ik} to be independent of each other (see selection model 8). That is, that the presence of past coworkers in firms in a particular sector k is uncorrelated to the wage worker i gets in such sector (after controlling for observed characteristics).

We already impose the restriction on the coworkers switch date to avoid problems with unobserved time specific shocks. Even then, the exclusion restriction will fail if past coworkers share other unobserved characteristics with worker i, and these characteristics enter the error term in the wage equation. Such would be the case if workers sort into firms (within manufacturing) based on unobserved characteristics such as absolute ability or by comparative advantage. To address these concerns, we construct alternative instruments by imposing additional restrictions on which coworkers are included in a workers "relevant" network. These alternative instruments impose the following restrictions (in addition to those of the baseline version):

1. Occupation restriction: worker i and coworker h had different occupations at the time of their last interaction. There are three occupational categories: blue-collar, white-collar, clerical.

2. Education restriction: worker i and coworker h had different education levels at the time of their last interaction. There are three educational categories: unskilled, apprenticeship and college educated.

3. Within-firm wage restriction: worker i and coworker h were, at the time and firm of their last interaction, in different parts of their firm wage distribution.[4]

Descriptives of network instruments

Table B.1 shows features of the network instruments of our main estimation sample (with all the restrictions described in Section 4.1). We present these figures separately by the industry k workers chose after displacement. Column 1 shows the average number of connected firms (in any sector) that workers in our sample had at the time of their displacement. Column 2 shows the average numbers of connected firms in the manufacturing sector (excluding worker i's predisplacement firm). Column 3 presents the average number of connected firms in the chosen sector k.

Table B.2 presents figures on the total number of connected firms ($\sum_k CN_k$) for the alternative versions of the network instrument. Columns 2, 3 and 4 show the figures corresponding to the occupation, education, and within-firm wage group restrictions. As expected, imposing the restrictions reduces the number of connected firms relative to the baseline instrument. However, in all cases we still observe a non-trivial number of connected firms. For example,

[4] For each firm, we computed the median of the wage distributions for all wages reported in each a year. We then assigned each worker and coworker to two groups ("high wage" and "low wage") based on the wage reported at the time of their last interaction.

Table B.1: Network Instrument - Average number of connected firms

Chosen Industry k	$\sum_k CN_k$ (1)	CN_{Manuf} (2)	CN_k (3)	N (4)
Agriculture, mining, energy and utilities	96.2	38.3	7.3	420
Manufacturing	71.0	31.4	5.3	50989
Construction	55.4	21.8	4.0	3111
Retail	72.4	29.0	5.4	4195
Transportation	92.0	36.5	6.5	465
Hotel, restaurants, low skill svcs	61.3	25.9	4.4	51
Communication, finance, and other professional svcs	99.1	40.2	7.4	2295
Office and business support svcs	110.7	41.8	9.2	1338
Education, hospitals and other personal svc activities	91.7	36.0	8.4	1049
Total	72.8	31.5	5.5	63913

Notes: Table contains descriptive statistics for coworker network size *CN* (any sector/manufacturing/target sector) and number of workers. Sample: Displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

the average number of connected firms after imposing the occupation restriction is 26. The analogous figures for the case with the education restriction is 36 firms.

Predictive power of coworker networks

From equation 8, we have that each worker i (displaced from sector m) chooses a new sector by maximizing her utility V_{ik}, defined as:

$$V_{ik} = \ddot{\beta}_k X_i + Z_i' \ddot{\gamma} + \eta_{ik}$$

where Z_i contains our coworker instrument CN_{ik}. For ease of exposition, we can split $Z_i \equiv S_i' \ddot{\gamma}_{1k} + \ddot{\gamma}_2 CN_{ik}$, where S_i is the set of all controls except for the coworker instrument CN_{ik}. We can then rewrite this equation to highlight the role of our instrument (which enters the model as an alternative specific regressor).

$$V_{ik} = \ddot{\beta}_k X_i + S_i' \ddot{\gamma}_{1k} + \ddot{\gamma}_2 CN_{ik} + \eta_{ik} \tag{A3}$$

Given our assumption of $\eta_{ik} \sim EV$, this first stage can be estimated using a multinomial logit regression. The results of this estimation are presented in Table B.3 for each of the four different versions of the network instrument. The entries in each column contain the estimated coefficient $\ddot{\gamma}_2$ from equation A3, which captures the effect of being connected to firms in sector

Table B.2: Average number of connected firms under different restrictions

Chosen Industry k	Baseline	Occupation	Education	Wage groups
		Network restriction		
	(1)	(2)	(3)	(4)
Agriculture, mining	96.2	33.6	50.1	42.6
Manufacturing	71.0	24.9	34.6	31.6
Construction	55.4	18.3	27.2	22.2
Retail	72.4	28.1	36.6	30.4
Transportation	92.0	31.4	47.2	36.1
Hotel, rest, low skill svcs	61.3	18.2	21.4	29.7
Communication, prof svcs	99.1	39.5	50.4	44.2
Office and bus support svcs	110.7	43.0	61.7	42.0
Education, hosp, personal svcs	91.7	32.8	43.6	40.9
Total	72.8	25.9	35.9	32.0

Notes: Sample: Displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

k (through past coworkers) on the probability that worker i moves to k. The first column contains our baseline instrument (the number of firms in each sector where worker i has relevant past coworkers). Columns 2 through 4 show the results for the instruments with the additional restrictions (occupation, education, and wage group). In all cases, the coworker variables have the expected sign and enter the selection model significantly, as shown by the large χ^2 statistics. We take this as strong evidence of our instrument's predictive power. Table B.4 presents the coefficients of the first stage of the selection model. In the following section, we show that our second stage estimates ($\hat{\beta}_{m\to k}$) are robust to our choice of instruments (Table C.1).

Table B.3: Estimates of $\ddot{\gamma}_2$ - Alternative Coworker Instruments

	Baseline	Occupation	Education	Wage groups
		Network restriction		
	(1)	(2)	(3)	(4)
CN_{ik}	0.00239	0.00287	0.00244	0.00741
	(0.000294)	(0.000442)	(0.000368)	(0.000870)
χ^2_1	65.73	42.18	43.91	72.67
p-value	0.0000	0.0000	0.0000	0.0000

Notes: Robust standard errors in parentheses.

Table B.4: First stage coefficients

	Agriculture, mining	Construction	Retail	Transport	Hotel, rest, low skill svcs	Communic., prof svcs	Office and support svcs	Education, hospitals, pers svcs
Sectoral tenure	-.0248	-.0392	-.0203	-.0343	-.0565	-.0030	-.0605	.0201
	(.0089)	(.0034)	(.0028)	(.0090)	(.0338)	(.0037)	(.0045)	(.0047)
Unemployment duration	.4759	.3696	.2434	.5749	.6938	.0772	.7976	.2353
	(.0608)	(.0239)	(.0238)	(.0548)	(.1560)	(.0368)	(.0285)	(.0489)
Coworker Instrument	.0024	.0024	.0024	.0024	.0024	.0024	.0024	.0024
	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)	(.0003)
Constant	-4.9095	-2.9353	-2.5710	-4.9737	-8.1865	-3.2080	-4.0114	-4.2396
	(.0534)	(.0207)	(.0171)	(.0582)	(.1928)	(.0237)	(.0357)	(.0435)
Sectoral empl. shares:								
Agriculture, mining	6.6344	-1.6827	2.3531	10.7402	14.6997	-.8160	9.6750	-2.6825
	(4.0334)	(1.4159)	(1.3794)	(4.6594)	(11.2666)	(1.9569)	(2.4728)	(2.1444)
Manufacturing	-2.6987	-4.3933	.3312	4.8869	10.8544	1.5921	2.8621	-5.7035
	(3.0681)	(1.0291)	(1.0109)	(3.5579)	(8.3493)	(1.3883)	(1.8979)	(1.5929)
Retail	-.7706	-3.0978	2.9136	9.1090	16.7511	-.7675	4.2654	-9.3362
	(3.8956)	(1.3568)	(1.2598)	(4.1940)	(10.6265)	(1.7859)	(2.3538)	(2.2203)
Transport	-2.3690	.1712	2.9726	5.5614	16.5214	11.4161	10.3972	10.8224
	(4.5874)	(1.8157)	(1.6072)	(4.9247)	(15.0118)	(2.2084)	(2.9846)	(2.8572)
Hotel, rest, low skill svcs	-3.1019	-.4946	1.0268	.1939	24.7833	.5304	-5.4838	6.7222
	(6.0899)	(1.7128)	(1.7752)	(6.2636)	(12.5610)	(2.2823)	(3.4481)	(2.4648)
Communic., prof svcs	-1.8100	-4.9914	3.1356	8.5988	12.5251	5.2628	4.1484	-1.3141
	(2.9131)	(.9837)	(.9617)	(3.2840)	(7.9063)	(1.3085)	(1.7897)	(1.4109)
Office and support svcs	3.1579	-1.1613	.1149	13.5862	-12.5437	-2.0568	11.6265	-22.0159
	(5.2531)	(1.9835)	(1.8269)	(6.1260)	(19.6102)	(2.4408)	(2.7981)	(3.2606)
Education, hosp, pers svcs	-3.2461	-3.7458	.4698	5.3959	13.4242	3.0372	4.1561	-1.5441
	(3.5597)	(1.1798)	(1.1508)	(3.9889)	(9.9867)	(1.6088)	(2.1060)	(1.8043)

Notes: Table contains coefficients from the first stage of the selection model. Columns indicate target sectors. Dummies for states, 5-year periods, and size classes are included.

C Selection Model - Second Stage Robustness Tests

In this section we present estimates of skill transferability ($\hat{\beta}_{m \to k}$'s of equation 10) obtained with different selection instruments, control function assumptions, and specifications of the wage regression.

Alternative instruments

Table C.1 presents our skill transferability estimates obtained when employing the alternative network instruments described in Appendix B. The first column features our baseline estimates. Columns 2 through 4 present the estimates obtained when the selection instrument incorporates the occupation, education, and firm-wage group restrictions (see Appendix B for details on each instrument's construction).

Table C.1: Estimates of $\hat{\beta}_{m\to k}$ - Alternative Coworker Instruments

		Network restriction		
	Baseline	Occupation	Education	Wage groups
	(1)	(2)	(3)	(4)
Agriculture, mining	-1.366	-1.038	-1.061	-1.243
	(0.517)	(0.518)	(0.517)	(0.518)
Manufacturing	-0.885	-0.569	-0.595	-0.766
	(0.174)	(0.188)	(0.185)	(0.183)
Construction	-1.437	-1.097	-1.127	-1.331
	(0.225)	(0.242)	(0.239)	(0.230)
Retail	-1.316	-0.979	-0.998	-1.199
	(0.215)	(0.230)	(0.228)	(0.224)
Transportation	-1.966	-1.648	-1.664	-1.884
	(0.477)	(0.486)	(0.485)	(0.477)
Hotel, rest, low skill svcs	-3.655	-3.436	-3.428	-3.519
	(2.393)	(2.430)	(2.440)	(2.365)
Communication, prof svcs	-0.815	-0.522	-0.543	-0.717
	(0.233)	(0.245)	(0.240)	(0.241)
Office and bus support svcs	-1.678	-1.382	-1.413	-1.561
	(0.275)	(0.289)	(0.286)	(0.282)
Education, hosp, personal svcs	-0.576	-0.291	-0.318	-0.470
	(0.291)	(0.301)	(0.301)	(0.294)
N	63913	63913	63913	63913
AIC	630732.8	630700.2	630732.7	630750.5
χ^2	39.51	37.69	37.47	41.11
p-value	0.0000	0.0000	0.0000	0.0000

Notes: Network restrictions as described in Appendix B. Dependent variable: Difference in pre- and post-diplacement log wages. Table shows estimates for sectoral tenure when switching from manufacturing to target sector *k*. Controls include: years of manufacturing work experience, state and 5-year period dummies, 5 firm size dummies (10-49; 50-249; 250-499; 500-999; 1000+ workers), unemployment duration and regional employment shares in each industry. Bootstrapped standard errors in parentheses (300 replications). Sample: Displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

Alternative control function assumptions

In this section we present results obtained under different distributional assumptions of the error terms, which lead to varying functional forms of the control function $\lambda_k(p_{i1}\dots,p_{iS})$ of equation 10.

We show results for three different approaches: a restricted version of the Dubin and McFadden (1984) model, the Dahl (2002) model, and our own variant of the Dubin and McFadden (1984) model. Each approach is based on different model assumptions, which result in differing control functions. We briefly discuss the three approaches below[5]:

1. The original Dubin and McFadden (1984) approach, which in addition to the linearity assumption (equation 9) imposes a restriction on the sum of the correlation parameters r_k^s: $\sum_s r_k^s = 0\ \forall k$. With this additional restriction, the control function takes the form:

$$\lambda_k(\bullet) = \sigma\frac{\sqrt{6}}{\pi}\left[\sum_{s\neq k} r_k^s\left(\frac{p_{is}\ln p_{is}}{1-p_{is}}\right)+\ln p_{ik}\right]$$

2. Dahl (2002) index sufficiency assumption (using a quadratic function on the first best probability), with the control function:

$$\lambda_k(\bullet) = r_k^0 + r_k^1 p_{ik} + r_k^2 p_{ik}^2$$

3. Extended DMF variant. We impose the set of restrictions: $r_k^m = \bar{r}\ \forall k$ (where m represents the manufacturing sector). This is a set of $(S-1)$ restrictions on the correlation parameters across observed/chosen sectors k. The baseline model is absorptive enough to allow workers to sort on levels and gains. It can be shown that these additional restrictions discard certain types of sorting on gains. With these restrictions, the functional form of the control function ($\lambda_k(\bullet)$) for any given sector k remains the same as in the baseline case. The restrictions apply to parameters across different control functions.

Tables C.2 presents the estimates of $\hat{\beta}_{m\to k}$ obtained with each of the three approaches described above. In each case, the estimates follow closely those obtained under our baseline model (shown on column 1).

[5]The modified Dubin and McFadden (1984) model and the Dahl (2002) model are described in depth in Bourguignon et al. (2007).

Table C.2: Estimates of $\hat{\beta}_{m \to k}$ - Alternative Distributional Assumptions

	Baseline (1)	DMF orig (2)	Dahl (3)	DMF restricted (4)
Agriculture, mining	-1.366	-1.521	-1.776	-1.508
	(0.517)	(0.532)	(0.527)	(0.505)
Manufacturing	-0.885	-1.102	-1.023	-0.982
	(0.174)	(0.182)	(0.195)	(0.164)
Construction	-1.437	-1.805	-1.661	-1.795
	(0.225)	(0.233)	(0.234)	(0.226)
Retail	-1.316	-1.530	-1.552	-1.412
	(0.215)	(0.235)	(0.232)	(0.206)
Transportation	-1.966	-2.140	-2.276	-2.103
	(0.477)	(0.488)	(0.493)	(0.477)
Hotel, rest, low skill svcs	-3.655	-3.601	-4.384	-3.352
	(2.393)	(2.334)	(2.725)	(1.847)
Communication, prof svcs	-0.815	-1.108	-1.043	-0.955
	(0.233)	(0.251)	(0.249)	(0.223)
Office and bus support svcs	-1.678	-1.881	-1.917	-1.792
	(0.275)	(0.296)	(0.293)	(0.263)
Education, hosp, personal svcs	-0.576	-0.844	-0.916	-0.594
	(0.291)	(0.276)	(0.326)	(0.236)
N	63913	63913	63913	63913
AIC	630732.8	630769.0	630594.0	630840.0
χ^2	39.51	42.97	48.14	49.30
p-value	0.0000	0.0000	0.0000	0.0000

Notes: Dependent variable: Difference in pre- and post-displacement log wages. Table shows estimates for sectoral tenure when switching from manufacturing to target sector k. Controls include: years of manufacturing work experience, state and 5-year period dummies, 5 firm size dummies (10-49; 50-249; 250-499; 500-999; 1000+ workers), unemployment duration and regional employment shares in each industry. Bootstrapped standard errors in parentheses (300 replications). Sample: Displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

Alternative control function assumptions with sector-specific intercepts ($\hat{\alpha}_{m\to k}$)

In this subsection, we present estimation results of the full selection model when we allow the intercept to vary across sectors. Table C.3 and C.4 present the estimates for our measures of skill transferability ($\hat{\beta}_{m\to k}$) and the sector-specific intercepts ($\hat{\alpha}_{m\to k}$) for different selection correction approaches. The results of Table C.3 show that the $\hat{\beta}_{m\to k}$ estimates are fairly robust to whether we allow for sector-specific intercepts. On the other hand, the $\hat{\alpha}_{m\to k}$ estimates of Table C.4 are very imprecise and sensitive to the control function assumptions. These results are consistent with findings by Bourguignon et al. (2007), who in Monte Carlo simulations find that selection correction methods of this sort perform poorly at estimating intercepts. This is because the identification of the intercepts relies entirely on the distributional assumptions of the selection model.

Table C.3: Estimates of $\hat{\beta}_{m \to k}$ with sector-specific intercepts

	Baseline	DMF orig	Dahl	DMF restricted
Agriculture, mining	-1.591	-1.443	-1.807	-1.324
	(0.495)	(0.534)	(0.525)	(0.516)
Manufacturing	-0.947	-1.047	-1.021	-0.839
	(0.186)	(0.188)	(0.219)	(0.178)
Construction	-1.543	-1.541	-1.656	-1.379
	(0.232)	(0.234)	(0.253)	(0.231)
Retail	-1.408	-1.457	-1.550	-1.268
	(0.227)	(0.232)	(0.250)	(0.221)
Transportation	-2.059	-2.092	-2.275	-1.918
	(0.480)	(0.496)	(0.501)	(0.480)
Hotel, rest, low skill svcs	-3.743	-3.863	-4.541	-3.639
	(2.571)	(2.424)	(2.943)	(2.362)
Communication, prof svcs	-0.963	-0.978	-1.120	-0.772
	(0.245)	(0.245)	(0.268)	(0.236)
Office and bus support svcs	-1.700	-1.826	-1.865	-1.637
	(0.279)	(0.304)	(0.307)	(0.278)
Education, hosp, personal svcs	-0.562	-0.821	-1.049	-0.473
	(0.295)	(0.280)	(0.348)	(0.294)
N	63913	63913	63913	63913
AIC	630645.7	630677.4	630592.8	630700.3
χ^2	41.45	36.85	45.85	39.12
p-value	0.0000	0.0000	0.0000	0.0000

Notes: Dependent variable: Difference in pre- and post-displacement log wages. Table shows estimates for sectoral tenure when switching from manufacturing to target sector k. Controls include: years of manufacturing work experience, state and 5-year period dummies, 5 firm size dummies (10-49; 50-249; 250-499; 500-999; 1000+ workers), unemployment duration and regional employment shares in each industry. Bootstrapped standard errors in parentheses (300 replications). Sample: Displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

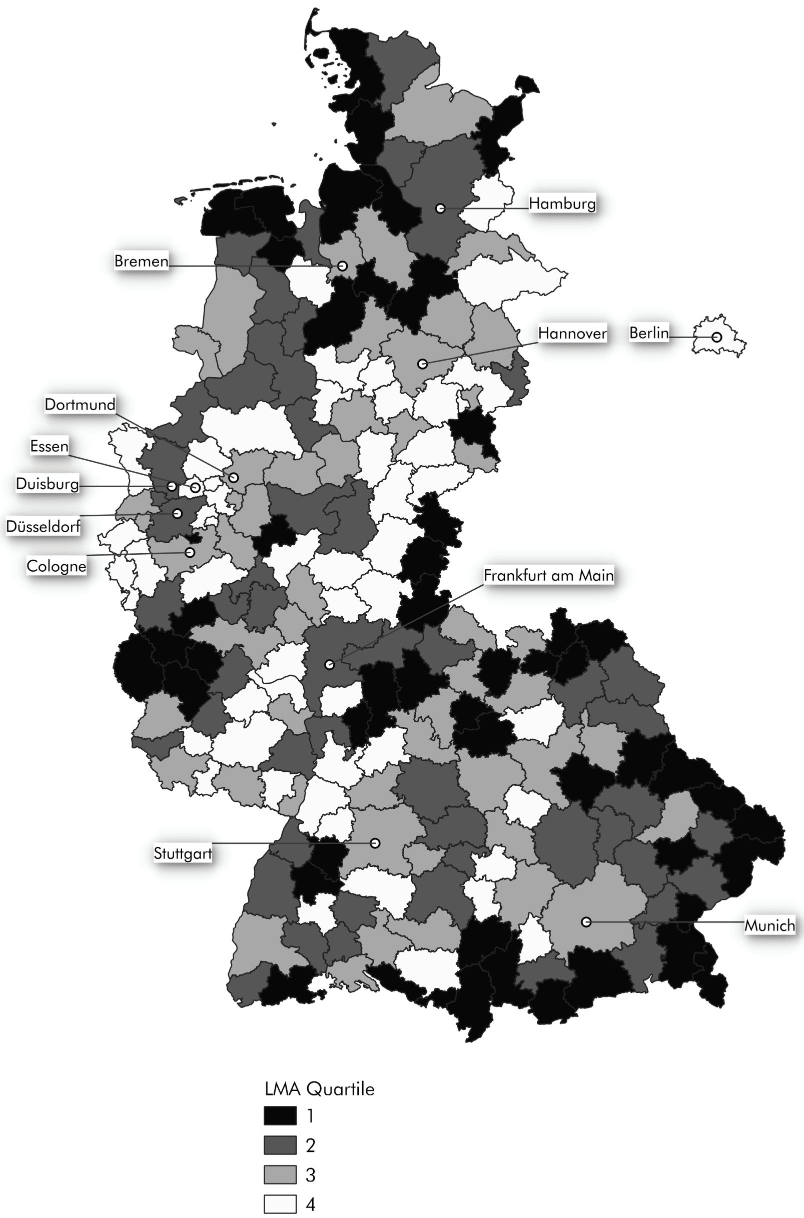
Table C.4: Estimates of $\hat{\alpha}_{m\rightarrow k}$ with sector-specific intercepts

	Baseline	DMF orig	Dahl	DMF restricted
Agriculture, mining	902.8	46.15	719.7	75.94
	(398.4)	(142.9)	(410.8)	(55.46)
Manufacturing	27.57	36.82	207.9	19.78
	(10.03)	(12.63)	(336.4)	(9.134)
Construction	428.2	275.7	211.1	167.8
	(87.52)	(74.14)	(139.0)	(25.30)
Retail	119.8	84.72	88.25	24.16
	(86.20)	(53.85)	(142.2)	(26.24)
Transportation	195.0	-8.840	133.3	64.07
	(285.9)	(114.1)	(332.7)	(50.24)
Hotel, rest, low skill svcs	-158.0	-344.0	-378.3	-14.26
	(1813.8)	(321.5)	(2446.4)	(152.2)
Communication, prof svcs	360.4	274.6	572.8	59.65
	(122.9)	(75.87)	(191.2)	(17.67)
Office and bus support svcs	-44.84	-23.88	151.2	34.24
	(44.13)	(41.12)	(170.9)	(20.17)
Education, hosp, personal svcs	-76.92	-20.14	458.1	52.76
	(57.37)	(56.81)	(199.7)	(19.58)
N	63913	63913	63913	63913
AIC	630645.7	630677.4	630592.8	630700.3
χ^2	34.72	23.59	8.31	44.22
p-value	0.0000	0.0027	0.4037	0.0000

Notes: Dependent variable: Difference in pre- and post-displacement log wages. Table shows estimates for sector specific intercepts when switching from manufacturing to target sector k. Controls include: years of manufacturing work experience, state and 5-year period dummies, 5 firm size dummies (10-49; 50-249; 250-499; 500-999; 1000+ workers), unemployment duration and regional employment shares in each industry. Bootstrapped standard errors in parentheses (300 replications). Sample: Displaced male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany who experience first sectoral switch.

D Appendix - LMA_{rt_0} Geographic Distribution

Figure D.1: Geographic Distribution of LMA_{rt_0}



Notes: LMA_{rt_0} calculated from equation 11 for t_0 =1998. The lowest quartile (in black) represents the least absorptive regions. The top quartile (in white) corresponds to the most absorptive regions.

Table D.1: Descriptive statistics by quartiles of LMA (means at region level, year 1998)

	LMA 1	LMA 2	LMA 3	LMA 4
Initial employment size (100,000 workers)	20	56	67	55
Manufacturing share	0.35	0.36	0.35	0.31
Automobile share	0.02	0.02	0.04	0.02
Unemployment rate	8.3	8.9	9.9	10.2
Worker demographics:				
Female	0.41	0.41	0.41	0.43
Age $\leq$ 19	0.01	0.01	0.01	0.00
Age 20 - 29	0.22	0.20	0.19	0.19
Age 30 - 39	0.32	0.32	0.33	0.33
Age 40 - 49	0.26	0.27	0.27	0.27
Age $\geq$ 50	0.19	0.20	0.20	0.21
Daily wage (Euro)	77.6	81.2	82.4	81.9
Highest educational degree:				
No vocational degree	0.18	0.19	0.18	0.17
Vocational degree	0.75	0.72	0.72	0.70
Higher secondary degree	0.03	0.03	0.04	0.05
College degree	0.05	0.06	0.07	0.08
Changes 1998 - 1988:				
Employment growth	0.07	0.09	0.05	0.05
Manuf. employment growth	-0.05	-0.02	-0.10	-0.11
Non-manuf. employment growth	0.16	0.18	0.16	0.14
Import exposure (1000 Euro per worker)	6.6	6.0	6.9	5.7
Export (1000 Euro per worker)	6.2	6.5	6.8	6.5
Changes 2008 - 1998:				
Employment growth	0.02	0.04	0.03	0.01
Manuf. employment growth	-0.06	-0.07	-0.07	-0.11
Non-manuf. employment growth	0.07	0.09	0.09	0.06
Import exposure (1000 Euro per worker)	18.1	17.7	21.6	18.1
Export (1000 Euro per worker)	22.7	24.1	25.4	23.9
Number of regions	51	51	51	50

Table D.2: Regressions by Tercile of LMA_{rt} - Sectoral Reallocation and Compensation Rates

	Employment					Earnings	
			Distance to manufacturing				
	Mfg	Non-mfg	Farther	Mid	Close	Mfg	Non-mfg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\triangle IP_{j,\tau} \cdot (D_{T_1} = 1)$	-3.532	1.954	0.140	0.231	1.546	-1.506	0.576
	(0.457)	(0.354)	(0.0483)	(0.0957)	(0.261)	(0.173)	(0.135)
Compensation rate		[0.55]	[0.04]	[0.07]	[0.44]		[0.38]
$\triangle IP_{j,\tau} \cdot (D_{T_2} = 1)$	-2.756	1.563	0.0553	0.201	1.292	-1.167	0.491
	(0.298)	(0.299)	(0.0306)	(0.164)	(0.234)	(0.114)	(0.103)
Compensation rate		[0.57]	[0.02]	[0.07]	[0.47]		[0.42]
$\triangle IP_{j,\tau} \cdot (D_{T_3} = 1)$	-2.774	2.120	0.0770	0.0708	1.944	-1.070	0.715
	(0.550)	(0.508)	(0.0436)	(0.0461)	(0.507)	(0.200)	(0.185)
Compensation rate		[0.76]	[0.03]	[0.03]	[0.70]		[0.67]
Observations	1824678	1824678	1824678	1824678	1824678	1824678	1824678
F	141.049	141.049	141.049	141.049	141.049	141.049	141.049
χ^2_3		0.049	1.63	3.10	8.71		6.03
p-value		0.029	0.444	0.212	0.013		0.049

Notes: See notes to Table 7. This table is analogous to Table 7, the only difference is that it splits regions into terciles of LMA_{rt} instead of quartiles (T=3 being the highest, most absorptive group). Columns 1 and 2 report employment effects within and outside manufacturing. Columns 3 to 5 split the non-manufacturing 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 non-manufacturing 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 GMM (standard errors clustered in labor market areas).

Table D.3: Unconditional transition probabilities to non-manufacturing sectors by LMA Quartiles

Quartiles of LMA_{rt}	1	2	3	4	Total
Agriculture, mining	4.17	3.61	3.18	3.27	3.45
Construction	13.61	12.65	11.64	11.80	12.20
Retail	20.77	21.80	21.86	21.46	21.62
Transportation	8.89	8.99	8.40	7.67	8.44
Hotel, rest, low skill svcs	3.54	2.90	2.86	2.64	2.89
Communication, prof svcs	24.02	23.11	24.45	22.55	23.52
Office and bus support svcs	13.30	14.31	14.28	15.46	14.48
Education, hosp, personal svcs	11.70	12.63	13.34	15.13	13.40
Total	100	100	100	100	100

Notes: Sample: male manufacturing workers with an apprenticeship in blue-collar occupations from West Germany 1998-2008 (excluding workers who transitioned to the public sector).

E Data Appendix

Measures of Exogenous Displacement

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

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

Bankruptcies are mainly identified using administrative data routinely collected by the BA's local branches. This data results from the administrative process of the *Insolvenzgeld*, which is a compensation scheme each employee who has not received his wage due to employer bankruptcy is eligible to. We define bankruptcy as a vanishing plant ID for plants with a bankruptcy spell. One advantage of using bankruptcies is that it does not rely on worker flows and that it is therefore possible to identify failure of very small firms. Detailed information about the data on bankruptcies is given in Fackler et al. (2017). We employ bankruptcy related closures for the years 2008–2010.

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

[6] To be more precise, they require that the largest cluster of workers moving from the vanishing ID to the same new plant ID makes up less than a certain percentage of the source plant's employment.

Measures of Import Exposure

Following Autor et al. (2014), we construct measures of exogenous trade shocks arising from import competition from China and Eastern Europe.[7] These measures have been adapted to the German context in Dauth et al. (2014). As in the two aforementioned papers, we obtained trade flow figures at the commodity level (HS6 codes) from the UNComtrade database. We then proceeded to map these trade flows to 3-digit industries (NACE Rev3 codes) using the same correspondence tables employed by Dauth et al. (2014).[8]

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

$$\Delta IP_{jt} = \frac{\Delta IM_{jt}^{East \to Germany}}{E_{jt_0}}$$

Where $\triangle IM_{jt}^{East \to Germany}$ is the change in industry j imports to Germany from China and Eastern Europe during time period t, and E_{jt_0} is the number of workers in Germany employed in industry j at the beginning of time period t. We construct these trade measures for two time periods: 1988–1998 and 1998–2008. To control for possible unobserved industry shocks, we employ the same IV strategy as ADHS: we instrument $\triangle IP_{jt}$ with $\Delta IP_{jt}^{East \to Other}$, the increase in industry level import competition from China and Eastern Europe to a group of countries "similar" to Germany. Formally,

$$\Delta IP_{jt}^{East \to Other} = \frac{\Delta IM_{jt}^{East \to Other}}{E_{jt_0}}$$

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

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

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

Measures of Region-Level Import Exposure

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

$$\Delta IP_{rt} = \sum_{j} \frac{E_{rjt_0}}{E_{rt_0}} \frac{\Delta IM_{jt}^{East \to Germany}}{E_{jt_0}}$$

where $\Delta IM_{jt}^{East \to Germany}$ and E_{jt_0} are defined as in the previous section, $\frac{E_{rjt_0}}{E_{rt_0}}$ is the share of manufacturing workers in region r who work in industry j at the beginning of period t.

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