Supplementary Online Appendix

The Adjustment of Labor Markets to Robots

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Corresponding OLS Results of all Tables and Figures

Employment Effects, the Labor Share, and Productivity

Table B.1: Balancing tests for regional characteristics in 1994.

	Dependent variable:				
	ln(GDP capita)	% unemp. rate	% high skilled	% un-skilled	% manuf. employment
	(1)	(2)	(3)	(4)	(5)
[A] Unconditional					
△ predicted robot exposure	0.0115	-0.0231	-0.0346	0.0726	0.7076
	(0.002)	(0.040)	(0.024)	(0.044)	(0.088)
	[0.009]	[0.035]	[0.030]	[0.035]	[0.452]
p-value	0.217	0.507	0.245	0.041	0.119
R^2	0.068	0.002	0.005	0.017	0.205
[B] Conditional on full controls					
△ predicted robot exposure	0.0021	-0.0472			
	(0.003)	(0.027)			
	[0.002]	[0.033]			
p-value	0.252	0.149			
R^2	0.785	0.727			

Notes: $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*, GDP data not available for the two East German regions Eisenach and Wartburgkreis). Each entry represents the coefficient of a regression of the respective variable on the change in predicted robot exposure per 1000 workers between 1994 and 2014. All specifications include a constant. In panel B, we control for broad region dummies (west (reference); north; south; or east), employment shares of female, foreign, age ≥ 50, medium skilled (with completed apprenticeship), and high skilled (with a university-degree) workers relative to total employment (reference category: unskilled workers and with unknown education), broad industry shares (agriculture (reference); food products; consumer goods; industrial goods; capital goods; construction; consumer related services; business related services; public sector), and the change in German net exports vis-Ãă-vis China and 21 Eastern European countries (in 1000 € per worker), and the change in ICT equipment (in € per worker), both between 1994 and 2014. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.2: Composition Effects

	Total	**Manufacturing**			**Non-manufacturing**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Employment: % change in total employment between 1994 and 2014							
△ predicted robot exposure	0.0866	-0.5595	-0.5959	-0.4380	0.5575	0.5376	0.6990
	(0.122)	(0.176)	(0.171)	(0.158)	(0.275)	(0.271)	(0.275)
	[0.163]	[0.300]	[0.300]	[0.278]	[0.376]	[0.384]	[0.435]
[B] E/Pop: 100 x △ in employment/population between 1994 and 2014							
△ predicted robot exposure	0.0094	-0.0437	-0.0489	-0.0408	0.0395	0.0386	0.0502
	(0.060)	(0.028)	(0.029)	(0.030)	(0.039)	(0.039)	(0.038)
	[0.030]	[0.033]	[0.032]	[0.029]	[0.035]	[0.036]	[0.041]
Effect of 1 robot	0.3	-1.5	-1.7	-1.4	1.4	1.4	1.8
[C] Wages: 100 x Log-△ in average wage between 1994 and 2014							
△ predicted robot exposure	-0.0345	-0.1350	-0.1438	-0.0975	0.0861	0.0780	0.0867
	(0.049)	(0.048)	(0.049)	(0.058)	(0.039)	(0.040)	(0.039)
	[0.029]	[0.070]	[0.072]	[0.068]	[0.060]	[0.060]	[0.063]
[D] Wagebill: 100 x Log-△ in total wagebill on June 30							
△ predicted robot exposure	0.0830	-0.6331	-0.6863	-0.4643	0.4116	0.3874	0.5444
	(0.126)	(0.181)	(0.175)	(0.187)	(0.213)	(0.210)	(0.213)
	[0.194]	[0.340]	[0.341]	[0.336]	[0.300]	[0.306]	[0.364]
△ net exports in 1000 € per worker	Yes	No	Yes	Yes	No	Yes	Yes
△ ICT equipment in € per worker	Yes	No	No	Yes	No	No	Yes

Notes: In all regressions, the variable of interest is the change in predicted robot exposure per 1000 workers between 1994 and 2014. The estimates in panels A, B, and D are based $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*), while the unit of observation in the wage estimates in panel (C) are $N = 7,235$ region x demographic cells. Demographic cells are defined by gender, three age groups, and three education groups. We only include cells containing at least 10 observations, and perform the regressions at the region x demographic cell level including fixed effects for demographic cells. The dependent variable in Panel D is the log-difference total amount of gross salaries paid to employees subject to social security on June 30 in 1994 and 2014. All specifications include a constant, broad region dummies, demographic control variables, and employment shares of nine aggregate industry groups, measured in the base year 1994. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.3: Composition Effects: Routine vs. Non-Routine Intensive Manufacturing

	Total	**Routine**			**Non-Routine**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Employment: % change in total employment between 1994 and 2014							
△ predicted robot exposure	-0.4380	-0.7350	-0.7295	-0.6048	-0.3702	-0.4551	-0.2682
	(0.158)	(0.191)	(0.181)	(0.185)	(0.237)	(0.236)	(0.225)
	[0.278]	[0.437]	[0.437]	[0.410]	[0.280]	[0.252]	[0.255]
[B] E/Pop: 100 x △ in employment/population between 1994 and 2014							
△ predicted robot exposure	-0.0408	-0.0653	-0.0648	-0.0625	0.0217	0.0159	0.0217
	(0.030)	(0.016)	(0.016)	(0.017)	(0.034)	(0.035)	(0.036)
	[0.029]	[0.042]	[0.042]	[0.039]	[0.021]	[0.019]	[0.020]
Effect of 1 robot	-1.4	-2.3	-2.3	-2.2	0.8	0.6	0.8
△ net exports in 1000 € per worker	Yes	No	Yes	Yes	No	Yes	Yes
△ ICT equipment in € per worker	Yes	No	No	Yes	No	No	Yes

Notes: In all regressions, the variable of interest is the change in predicted robot exposure per 1000 workers between 1994 and 2014. The estimates in panels A, B, and D are based $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*), while the unit of observation in the wage estimates in panel (C) are $N = 7,217$ region x demographic cells. Demographic cells are defined by gender, three age groups, and three education groups. We only include cells containing at least 10 observations, and perform the regressions at the region x demographic cell level including fixed effects for demographic cells. The dependent variable in Panel D is the log-difference total amount of gross salaries paid to employees subject to social security on June 30 in 1994 and 2014. All specifications include a constant, broad region dummies, demographic control variables, and employment shares of nine aggregate industry groups, measured in the base year 1994. Routine intensive is defined as being employed in an occupation that ranks above the 66th percentile of the share of routine tasks relative to all tasks (see Autor and Dorn; 2013; Spitz-Oener; 2006). Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.4: Composition Effects: Change in Task-Intensity

	(1)	(2)	(3)
[A] Manufacturing			
	routine	abstract	manual
△ predicted robot exposure	-0.0877	0.0757	0.0096
	(0.024)	(0.035)	(0.028)
	[0.061]	[0.059]	[0.016]
[B] Non-Manufacturing			
	routine	abstract	manual
△ predicted robot exposure	0.0357	0.0032	-0.0385
	(0.013)	(0.020)	(0.019)
	[0.021]	[0.015]	[0.022]

Notes: In all regressions, the variable of interest is the change in predicted robot exposure per 1000 workers between 1994 and 2014. The dependent variable is the percentage point change in the share of routine / abstract / manual tasks relative to all tasks. Task-intensity is measured at the level of occupations according to the BIBB/BAuA Survey in 1991. The estimates are based $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Adjust Mechanism I: Reduced Creation of New Jobs for Young Workers

Table B.5: Adjustment

	Dependent variable: 100 x Number of workers in 2014 / total employment in 1994						
	Incumbent workers		Entrants				total
Same plant as in 1994 Same sector as in 1994	yes yes	no yes	entered labor mkt. after 1994	same region, diff. sector in 1994	in diff. region in 1994	not emp. in 1994	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Manufacturing							
$\triangle$ predicted robot exposure	0.1583	-0.2413	-0.2248	-0.0605	0.0005	-0.0702	-0.4380
	(0.052)	(0.048)	(0.090)	(0.026)	(0.036)	(0.027)	(0.158)
	[0.074]	[0.116]	[0.135]	[0.042]	[0.057]	[0.039]	[0.278]
[B] Non-Manufacturing							
$\triangle$ predicted robot exposure	-0.0423	-0.0400	0.5519	-0.0121	0.1998	0.0417	0.6990
	(0.014)	(0.024)	(0.193)	(0.012)	(0.053)	(0.039)	(0.275)
	[0.029]	[0.024]	[0.331]	[0.006]	[0.106]	[0.036]	[0.435]

Notes: $N = 402$ In this table, the employment growth rate is additively split up into the contributions of different groups of incumbent workers or workers that enter the region's manufacturing (Panel A) or non-manufacturing sector (Panel B) between 1994 and 2014. The coefficients of columns 1-6 sum up to the coefficient in column 7. In all regressions, the variable of interest is the change in predicted robot exposure per 1000 workers between 1994 and 2014. The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.6: Manufacturing Adjustment - by shares union members (SOEP)

	Dependent variable: 100 x Number of workers in 2014 / total employment in 1994						
	Incumbent workers		Entrants				total
Same plant as in 1994 Same sector as in 1994	yes yes	no yes	entered labor mkt. after 1994	same region, diff. sector in 1994	in diff. region in 1994	not emp. in 1994	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[A] Above median share of union members							
$\triangle$ predicted robot exposure	0.2741	-0.2780	-0.1087	-0.0785	0.0234	-0.0506	-0.2183
	(0.072)	(0.051)	(0.135)	(0.051)	(0.046)	(0.040)	(0.257)
	[0.113]	[0.118]	[0.137]	[0.055]	[0.072]	[0.038]	[0.269]
[B] Below median share of union members							
$\triangle$ predicted robot exposure	0.0504	-0.2084	-0.3466	-0.0584	-0.0230	-0.1106	-0.6966
	(0.086)	(0.096)	(0.146)	(0.024)	(0.083)	(0.055)	(0.309)
	[0.060]	[0.106]	[0.213]	[0.051]	[0.108]	[0.075]	[0.431]

Notes: $N = 199$ (Panel A) and 203 (Panel B). In this table, the employment growth rate is additively split up into the contributions of different groups of incumbent workers or workers that enter the region's manufacturing sector between 1994 and 2014. The coefficients of columns 1-6 sum up to the coefficient in column 7. In all regressions, the variable of interest is the change in predicted robot exposure per 1000 workers between 1994 and 2014. The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, and SOEP, own calculations.

Adjust Mechanism II: Skill Upgrading

Table B.7: Occupational Upgrading Within and Across Firms

	(1)	(2)	(3)	(4)
[A] Occupational adjustment				
	Dependent variable: 100 x Number of workers in 2014 / total employment in 1994			
Same plant as in 1994	yes	yes	yes	
Same occupation as in 1994	yes	no	(total)	
△ predicted robot exposure	0.0368	0.1215	0.1583	
	(0.027)	(0.030)	(0.052)	
	[0.022]	[0.058]	[0.074]	
[B] Occupational upgrading: Wages and skills				
	Dependent variables:			
	△ log median wage in €		100 x △ college share	
Same plant as in 1994	yes	no	yes	no
△ predicted robot exposure	0.0625	0.0401	0.0694	0.0255
	(0.026)	(0.029)	(0.020)	(0.019)
	[0.046]	[0.033]	[0.038]	[0.015]
[C] Occupational upgrading: Tasks				
	Dependent variables:			
	100 x △ abstract task intensity		100 x △ routine task intensity	
Same plant as in 1994	yes	no	yes	no
△ predicted robot exposure	0.0811	-0.0094	-0.1286	-0.0461
	(0.024)	(0.022)	(0.031)	(0.024)
	[0.044]	[0.017]	[0.074]	[0.030]

Notes: $N = 402$. In this table, we analyze the effect of robots on the occupation dimension of exposed workers. In Panel A, the dependent variables are 100x the number of workers who stay in the manufacturing sector of their original region but show different kinds of job mobility, relative to total employment in 1994. The coefficients of Panel A, columns 1 and 2 add up to the coefficient in column 1 of Panel A, Table B.5 (also reported in column 3). In Panels B and C, we focus on the occupational quality of workers who stay in the manufacturing sector of their original region but possibly switch into a different occupation. The dependent variable in columns 1 and 2 of Panel B is the average difference of the median wage, measured in 1994, of the occupation of workers staying in the same plant in 2014 versus the occupation in 1994. The dependent variable in columns 3 and 4 of Panel B is the average difference of the percentage of people with a college degree, measured in 1994, of the occupation of workers staying in the same plant in 2014 versus the occupation in 1994. The dependent variable in Panel C is the average difference of the abstract (columns 1 and 2) and routine (columns 3 and 4) task intensities, measured in 1994, of the occupation of workers staying in the same plant in 2014 versus the occupation in 1994. In all regressions, the variable of interest is the change in predicted robot exposure per 1000 workers between 1994 and 2014. The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.8: Robots and skill share of people younger than 30

	Dependent variable:			
	100 x △ Share of workers with		Task intensity	
	university degree	apprenticeship degree	abstract	routine
	(1)	(2)	(3)	(4)
△ predicted robot exposure	0.0944	-0.0690	0.0693	-0.0577
	(0.039)	(0.033)	(0.030)	(0.020)
	[0.049]	[0.041]	[0.041]	[0.038]

Notes: In this table, we analyze the effect of robots on occupational quality of younger workers. The estimates are based on $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). The dependent variables is the change in various measures for occupation quality of workers 30 years old or less between 1994 and 2014: Share of workers with university degree (column 1), share of workers with apprenticeship degree (2), average abstract task intensity (3), and average routine task intensity (4). In all regressions, the variable of interest is the change in predicted robot exposure per 1000 workers between 1994 and 2014. The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Individual Level Results

Table B.9: Balancing checks, worker level

	Unconditional mean	(se)	Conditional mean	(se)
Manufacturing workers in 1994 (720,562 observations).				
100 × ln base year earnings	0.181	(0.066)	-0.015	(0.036)
100 × ln base year average wage	17.112	(6.426)	-2.686	(3.580)
100 × dummy, 1=female	-0.080	(0.044)	0.056	(0.029)
100 × dummy, 1=foreign	0.021	(0.020)	0.025	(0.011)
Birth year	0.000	(0.001)	0.001	(0.001)
100 × dummy, 1=low skilled	-0.007	(0.033)	0.031	(0.018)
100 × dummy, 1=medium skilled	0.011	(0.027)	0.012	(0.027)
100 × dummy, 1=high skilled	-0.004	(0.017)	-0.043	(0.016)
Tenure (in years)	0.017	(0.004)	-0.003	(0.001)
100 × ln plant size	2.887	(0.650)	1.546	(0.881)

Notes: Coefficients from regressions of the respective individual characteristic on Δ robots per 1000 workers. Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (3 categories), tenure (3 categories), plant size (6 categories), manufacturing industry groups (8 categories), and 16 federal states, excluding the respective dependent variable. Standard errors clustered by 20 ISIC Rev.4 industries in parentheses.

Sources: IFR, COMTRADE, EU KLEMS, and IEB V12.00.00, own calculations.

Table B.10: Individual Adjustment to Robot Exposure (Employment)

[A] Industry mobility	(1) all employers	(2) manufacturing	(3)	(4) service sector
Same employer		yes	no	no
Δ robots per 1000 workers	0.7926	8.2929	-5.5482	-1.9521
	(1.283)	(1.881)	(2.277)	(1.392)

[B] Occupational mobility	(1) all jobs	(2) same employer	(3)	(4) other employer	(5)
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	0.7926	2.5366	5.7562	-6.3765	-1.1238
	(1.283)	(1.580)	(1.326)	(1.616)	(0.828)

Notes: Based on 720,562 workers. OLS results for period 1994-2014. The outcome variables are cumulated days of employment. For column 1, employment days are cumulated over all employment spells in the 20 years following the base year. Panel A: For column 2 employment days are cumulated only when they occurred at the original workplace. For the other columns, employment days are cumulated only when they occurred at a different plant in the manufacturing sector (3) or outside the manufacturing sector (4), respectively. Panel B: Employment days are cumulated only when they occurred in the original occupation and workplace (column 2), in a different occupation but at the original workplace (3), in the original occupation but at a different workplace (4), and in a different occupation and workplace (5), respectively. Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (3 categories), tenure (3 categories), plant size (6 categories), manufacturing industry groups (8 categories), and 16 federal states. Standard errors are clustered by 20 ISIC Rev.4 industries in parentheses.

Sources: IFR, Comtrade, EU KLEMS, and IEB V12.00.00, own calculations.

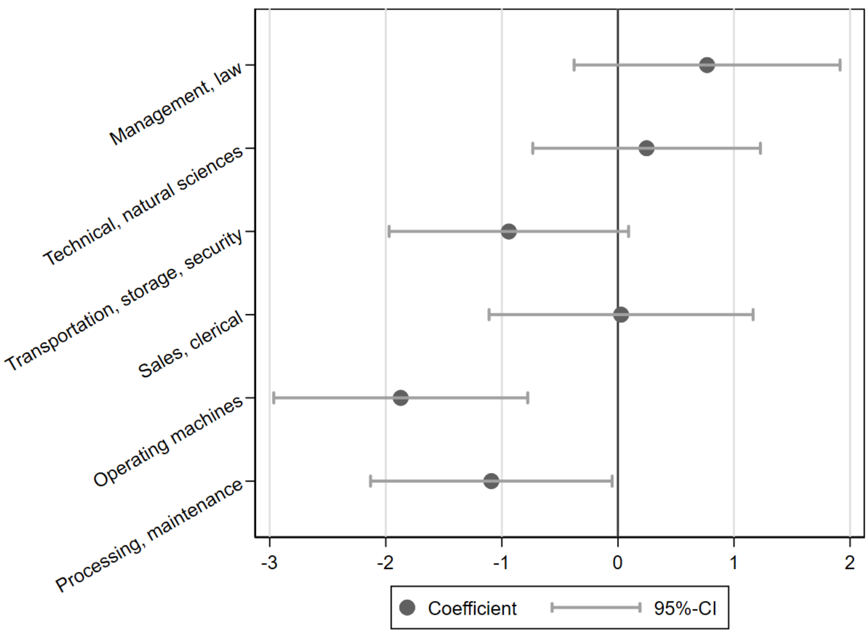
Table B.11: Individual Adjustment to Robot Exposure (Earnings)

[A] Industry mobility	(1) all employers	(2) manufacturing	(3)	(4) service sector	
Same employer		yes	no	no	
Δ robots per 1000 workers	-0.5477	2.1758	-2.1528	-0.5707	
	(0.888)	(0.700)	(0.889)	(0.489)	

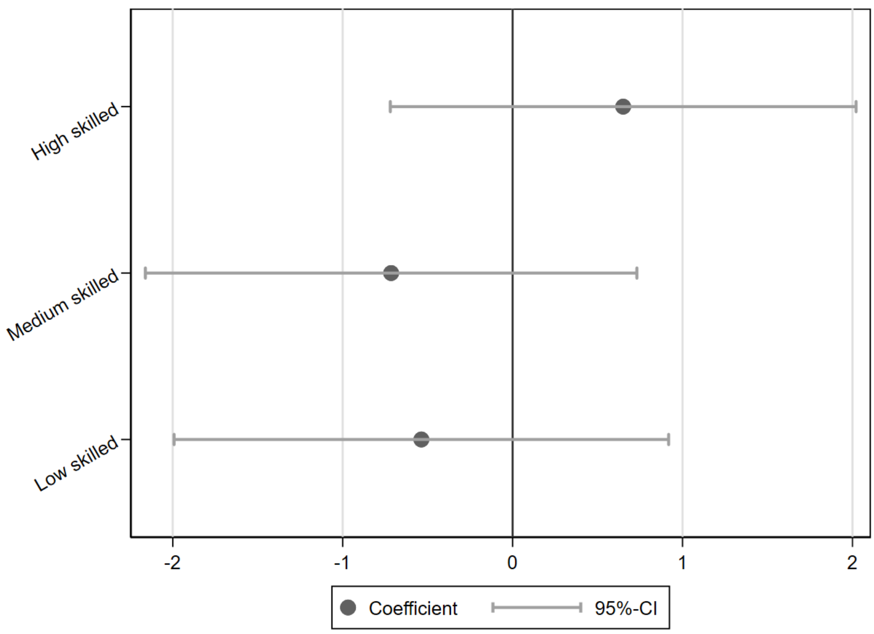
[B] Occupational mobility	(1) all jobs	(2) same employer	(3)	(4) other employer	(5)
Same occupational field		yes	no	yes	no
Δ robots per 1000 workers	-0.5477	0.3420	1.8339	-2.2906	-0.4328
	(0.888)	(0.560)	(0.481)	(0.656)	(0.346)

Notes: Based on 720,562 workers. OLS results for period 1994-2014. The outcome variables are 100 x earnings (normalized by earnings in the base year) cumulated over the 20 years following the base year. For column 1, earnings are cumulated over all employment spells in the 20 years following the base year. Panel A: For column 2 earnings are cumulated only when they occurred at the original workplace. For the other columns, employment days are cumulated only when they occurred at a different plant in the manufacturing sector (3) or outside the manufacturing sector (4), respectively. Panel B: Employment days are cumulated only when they occurred in the original occupation and workplace (column 2), in a different occupation but at the original workplace (3), in the original occupation but at a different workplace (4), and in a different occupation and workplace (5), respectively. Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (3 categories), tenure (3 categories), plant size (6 categories), manufacturing industry groups (8 categories), and 16 federal states. Standard errors clustered by 20 ISIC Rev.4 industries in parentheses.

Sources: IFR, Comtrade, EU KLEMS, and IEB V12.00.00, own calculations.



(a) Occupation: Heterogenous Impacts

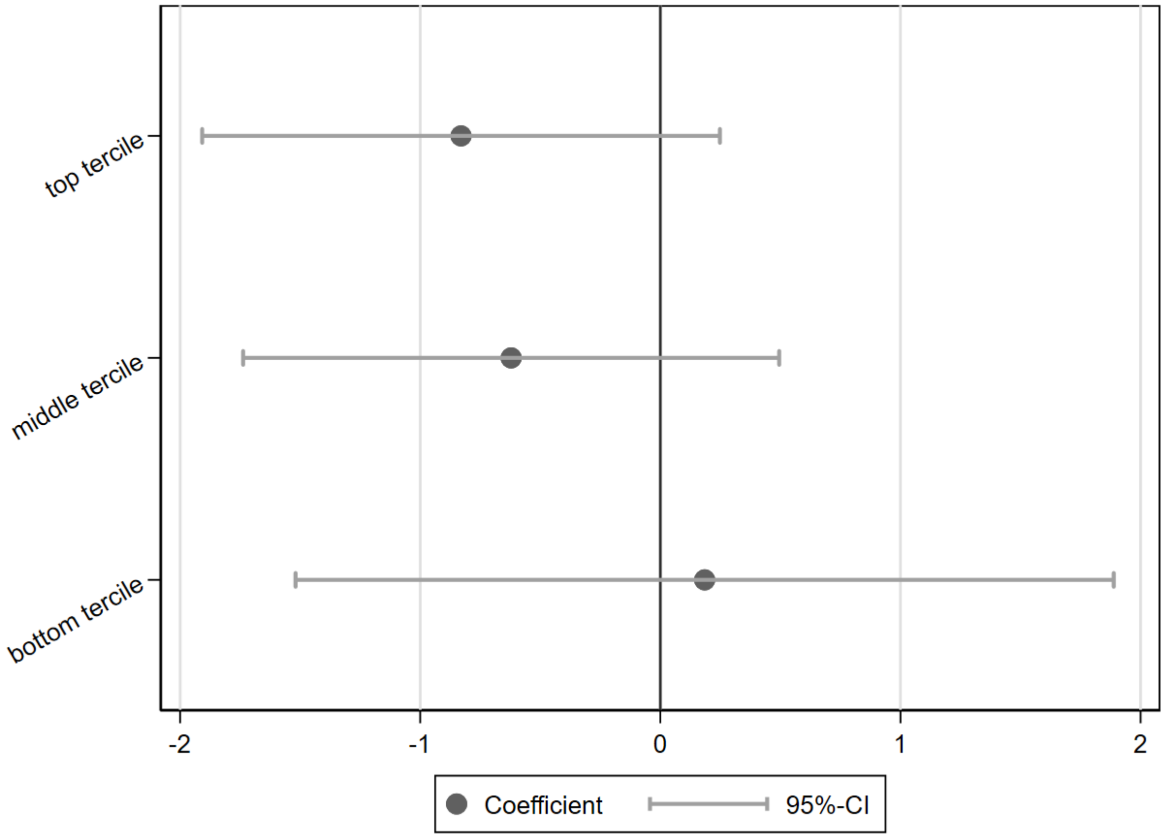


(b) Education: Heterogenous Impacts

Notes: The figures report the coefficients of interaction terms of Δ predicted robot exposure per 1000 workers and dummies indicating the respective worker group. The outcome variables are 100 x earnings (normalized by earnings in the base year) cumulated over the 20 years following the base year. In panel A, occupations base on the definition of aggregate occupational fields by the German Federal Institute for Vocational Education and Training (BIBB) with the following modifications: Sales and clerical occupations are combined and agriculture, mining, and construction (that would have a point estimate of zero with a huge standard error) are omitted. In panel B, high skilled is defined as having a degree from a university or university of applied sciences, and medium skilled is defined as having a vocational training degree. All other educational levels are subsumed as low skilled. All regressions include the same full set of control variables as in Table B.11. The confidence intervals are constructed from standard errors clustered by 20 ISIC Rev.4 industries.

Figure B.1: Heterogeneous earnings effects by occupation and education

Appendix



Notes: The figures report the coefficients of interaction terms of Δ predicted robot exposure per 1000 workers and dummies indicating the respective worker group. The outcome variables are 100 x earnings (normalized by earnings in the base year) cumulated over the 20 years following the base year. All regressions include the same full set of control variables as in Table B.11. The confidence intervals are constructed from standard errors clustered by 20 ISIC Rev.4 industries.

Figure B.2: Heterogeneous earnings effects by earnings tercile

Table B.12: Balancing tests for regional characteristics in 1978 and 1894.

	Dependent variable:				
	ln(residualized wage)	% Unemp. rate	% high skilled	% un-skilled	% manuf. employment
	(1)	(2)	(3)	(4)	(5)
[A1] Unconditional, 1978					
△ predicted robot exposure	0.2155	-0.0812	0.3215	-0.0004	0.5936
	(0.035)	(0.072)	(0.052)	(0.012)	(0.072)
	[0.225]	[0.104]	[0.284]	[0.015]	[0.419]
R^2	0.081	0.014	0.080	0.000	0.157
[A2] Conditional on full controls, 1978					
△ predicted robot exposure	0.0139	0.0016			
	(0.031)	(0.011)			
	[0.036]	[0.008]			
R^2	0.857	0.984			
[B1] Unconditional, 1984					
△ predicted robot exposure	0.2431	0.3414	0.0025	-0.0221	0.6350
	(0.034)	(0.064)	(0.014)	(0.045)	(0.065)
	[0.237]	[0.275]	[0.019]	[0.050]	[0.437]
R^2	0.103	0.000	0.002	0.085	0.193
[B2] Conditional on full controls, 1984					
△ predicted robot exposure	0.0629	0.0648			
	(0.035)	(0.087)			
	[0.045]	[0.052]			
R^2	0.856	0.708			

Notes: $N = 325$ West German local labor market regions (*Landkreise und kreisfreie Staedte*, data for East Germany not available before 1990). Each entry represents the coefficient of a regression of the respective variable on the predicted change in robot exposure per 1000 workers between 1994 and 2014. All specifications include a constant. In panel B, we control for broad region dummies (west (reference); north; south; or east), employment shares of female, foreign, age ≥ 50, medium skilled (with completed apprenticeship), and high skilled (with a university-degree) workers relative to total employment (reference category: unskilled workers and with unknown education), broad industry shares (agriculture (reference); food products; consumer goods; industrial goods; capital goods; construction; consumer related services; business related services; public sector), and the change in German net exports vis-Ãă-vis China and 21 Eastern European countries (in 1000 € per worker), and the change in ICT equipment (in € per worker), both between 1994 and 2014. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, Comtrade, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.13: Robustness checks.

	Employment			Average Wages		
	(1) Total	(2) Manuf.	(3) Non-Manuf.	(4) Total	(5) Manuf.	(6) Non-Manuf.
	Baseline Results 1994-2014					
△ predicted robot exposure	0.0866	-0.4380	0.6990	-0.0345	-0.0972	0.0804
	(0.122)	(0.158)	(0.275)	(0.049)	(0.058)	(0.039)
	[0.163]	[0.278]	[0.435]	[0.029]	[0.070]	[0.061]
N	402	402	402	7235	6896	7231
	[A1] Pre-Trends 1984-1994					
△ predicted robot exposure	0.1075	0.4022	-0.0077	0.0172	-0.0044	0.0309
	(0.159)	(0.206)	(0.121)	(0.021)	(0.027)	(0.026)
	[0.115]	[0.202]	[0.097]	[0.023]	[0.019]	[0.040]
N	325	325	325	5828	5224	5810
	[A2] Include lagged dependent outcome (to check for mean reversion) 1984-1994					
△ predicted robot exposure	-0.0132	-0.4338	0.5721	-0.0351	-0.1540	0.1086
	(0.168)	(0.177)	(0.293)	(0.050)	(0.063)	(0.036)
	[0.121]	[0.236]	[0.380]	[0.026]	[0.064]	[0.072]
Outcome in 1984-1994	0.3770	0.2946	0.3617	-0.2133	-0.1732	-0.2341
	(0.114)	(0.094)	(0.122)	(0.032)	(0.040)	(0.025)
N	325	325	325	5828	5224	5810
	[B] 1994-2007					
△ predicted robot exposure	0.1904	-0.1230	0.3673	0.0296	0.0035	0.0544
	(0.113)	(0.200)	(0.234)	(0.036)	(0.082)	(0.050)
	[0.128]	[0.236]	[0.184]	[0.036]	[0.107]	[0.054]
N	402	402	402	7235	6897	7231
	[C] Include "marginal" workers					
△ predicted robot exposure	0.0486	-0.4461	0.6623	-0.0345	-0.0972	0.0804
	(0.130)	(0.161)	(0.285)	(0.049)	(0.058)	(0.039)
	[0.162]	[0.282]	[0.427]	[0.029]	[0.070]	[0.061]
N	402	402	402	7235	6896	7231
	[D] West Germany					
△ predicted robot exposure	0.0089	-0.4406	0.6430	-0.0403	-0.1446	0.0962
	(0.139)	(0.174)	(0.276)	(0.049)	(0.060)	(0.037)
	[0.124]	[0.245]	[0.394]	[0.028]	[0.066]	[0.065]
N	325	325	325	5849	5545	5845
	[E] Federal state dummies					
△ predicted robot exposure	0.0629	-0.4233	0.6722	-0.0418	-0.1315	0.0869
	(0.126)	(0.166)	(0.274)	(0.051)	(0.059)	(0.039)
	[0.163]	[0.259]	[0.407]	[0.029]	[0.075]	[0.059]
N	402	402	402	7235	6896	7231
	[F1] 258 Local labor markets					
△ predicted robot exposure	-0.1074	-0.6404	0.5218	-0.0431	-0.0940	0.1026
	(0.153)	(0.293)	(0.214)	(0.064)	(0.071)	(0.054)
	[0.168]	[0.441]	[0.291]	[0.036]	[0.093]	[0.070]
N	258	258	258	4643	4489	4643
	[F2] 141 Local labor markets					
△ predicted robot exposure	0.0668	-0.4073	0.4271	-0.0259	0.0164	0.1210
	(0.301)	(0.409)	(0.340)	(0.064)	(0.108)	(0.066)
	[0.308]	[0.439]	[0.408]	[0.054]	[0.130]	[0.083]
N	141	141	141	2538	2489	2538
	[G] Split automotive and other manufacturing in treatment variables					
△ predicted robot exposure *automobile industry*	0.0891	-0.4366	0.7062	-0.0338	-0.0974	0.0887
	(0.113)	(0.155)	(0.245)	(0.048)	(0.058)	(0.036)
	[0.155]	[0.286]	[0.386]	[0.029]	[0.069]	[0.046]
△ predicted robot exposure *other industries*	-0.1287	-0.5614	0.0586	-0.0951	-0.1137	-0.0875
	(0.202)	(0.413)	(0.254)	(0.075)	(0.111)	(0.046)
	[0.200]	[0.520]	[0.272]	[0.068]	[0.110]	[0.067]
N	402	402	402	7235	6896	7231
	[H] Split automotive and other manufacturing in outcome variables					
	total manuf.	car manuf.	other manuf.	total manuf.	car manuf.	other manuf.
△ predicted robot exposure	-0.4380	-5.1868	-0.5258	-0.0975	-0.1145	-0.1743
	(0.158)	(21.902)	(0.240)	(0.058)	(0.127)	(0.104)
	[0.278]	[18.688]	[0.319]	[0.068]	[0.131]	[0.079]
N	402	382	402	6896	2830	6866

Notes: This table presents modifications the baseline specifications for employment and average wages as of columns 1, 4 and 7 of Table B.2. The dependent variables are employment growth rates (column 1-3) and log-differences in average wages (column(4-6). Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.
Sources: IFR, COMTRADE, EU KLEMS, and BHP 7514 v1, own calculations.

Table B.14: Robots and skill share of people younger than 40

	Dependent variable: 100 x △ Share of workers with		Task intensity	
	university degree	apprenticeship degree	abstract	routine
	(1)	(2)	(3)	(4)
△ predicted robot exposure	0.0916	-0.0917	0.0666	-0.0571
	(0.046)	(0.036)	(0.030)	(0.018)
	[0.053]	[0.060]	[0.041]	[0.038]

Notes: In this table, we analyze the effect of robots on occupational quality of younger workers. The estimates are based on $N = 402$ local labor market regions (*Landkreise und kreisfreie Staedte*). The dependent variables is the change in various measures for occupation quality of workers 40 years old or less between 1994 and 2014: Share of workers with university degree (column 1), share of workers with apprenticeship degree (2), average abstract task intensity (3), and average routine task intensity (4). In all regressions, the variable of interest is the predicted change in robot exposure per 1000 workers between 1994 and 2014. The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.15: Disaggregating the Service Sector

	Dependent variable: 100 x 2014 employment in industry / total non-manuf. employment in 1994					
	(1)	(2)	(3)	(4)	(5)	(6)
[A] Broad industry groups						
	Non-Manuf.	Agg/Mining	Constr.	Cons. serv.	Business serv.	Public sect.
△ predicted robot exposure	0.6990	0.0206	-0.0021	0.0404	0.5913	0.0334
	(0.275)	(0.020)	(0.027)	(0.063)	(0.212)	(0.035)
	[0.435]	[0.022]	[0.027]	[0.050]	[0.349]	[0.052]

Notes: $N = 402$. In this table, the employment growth rate in the non-manufacturing sector is the contributions of different industries. The dependent variables are constructed as 100x the number of employees in 2014 in each industry relative to total non-manufacturing employment in 1994. Consequently, the coefficients in each panel sum up to the coefficient in column 7 of panel A, Table B.2. In all regressions, the variable of interest is the predicted change in robot exposure per 1000 workers between 1994 and 2014. The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.16: Change in average age

	Dependent variable: change in average age between 1994 and 2014	
	Manufacturing	**Non-manufacturing**
	(1)	(2)
△ predicted robot exposure	0.6178	-2.5976
	(0.771)	(1.052)
	[0.939]	[1.644]

Notes: $N = 402$. The dependent variable is the change in the average age of workers in 1994 vs. 2014. In all regressions, the variable of interest is the predicted change in robot exposure per 1000 workers between 1994 and 2014. The regressions include the full set of control variables as in column 4 of Table 2. Standard errors clustered at the level of 50 aggregate labor market regions in parentheses. Shift-share standard errors in brackets.

Sources: IFR, COMTRADE, EU KLEMS, BEH V10.01.00, and BHP 7514 v1, own calculations.

Table B.17: Pre-trends for Individual Adjustment to Robot Exposure (Employment)

[A] Industry mobility	(1) all employers	(2) manufacturing	(3)	(4) service sector	
Same employer		yes	no	no	
[A1] Employment					
Δ robots per 1000 workers	1.6212***	1.3969	0.7060	-0.4816	
	(0.419)	(1.600)	(1.205)	(0.763)	
[A2] Earnings					
Δ robots per 1000 workers	0.4588	0.4147	0.1914	-0.1473	
	(0.296)	(0.619)	(0.406)	(0.249)	

[B] Occupational mobility	(1) all jobs	(2) same employer	(3)	(4) other employer	(5)
Same occupational field		yes	no	yes	no
[B1] Employment					
Δ robots per 1000 workers	1.6212	-0.1282	1.5250	-0.4726	0.6969
	(0.419)	(1.803)	(0.825)	(0.921)	(0.568)
[B2] Earnings					
Δ robots per 1000 workers	0.4588	-0.1824	0.5972	-0.1864	0.2304
	(0.296)	(0.635)	(0.312)	(0.291)	(0.201)

Notes: Based on 770,360 workers. OLS results for period 1978-1994. The outcome variables are days of employment (Panels A1, B1) and 100 x earnings (normalized by earnings in the base year, panels A2, B2), each cumulated over the 16 years following the base year and scaled to conform to a 20-year period. For column 1, employment days are cumulated over all employment spells in the 20 years following the base year. Panel A: For column 2 the outcomes are cumulated only when they occurred at the original workplace. For the other columns, employment days are cumulated only when they occurred at a different plant in the manufacturing sector (3) or outside the manufacturing sector (4), respectively. Panel B: Employment days are cumulated only when they occurred in the original occupation and workplace (column 2), in a different occupation but at the original workplace (3), in the original occupation but at a different workplace (4), and in a different occupation and workplace (5), respectively. Control variables are log base year earnings and indicator variables for gender, foreign nationality, birth year, educational degree (3 categories), tenure (3 categories), plant size (6 categories), manufacturing industry groups (8 categories), and 16 federal states. Standard errors are clustered by 20 ISIC Rev.4 industries in parentheses.

Sources: IFR, Comtrade, EU KLEMS, and IEB V12.00.00, own calculations.

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