A How Technological Change Affects Regional Voting Patterns

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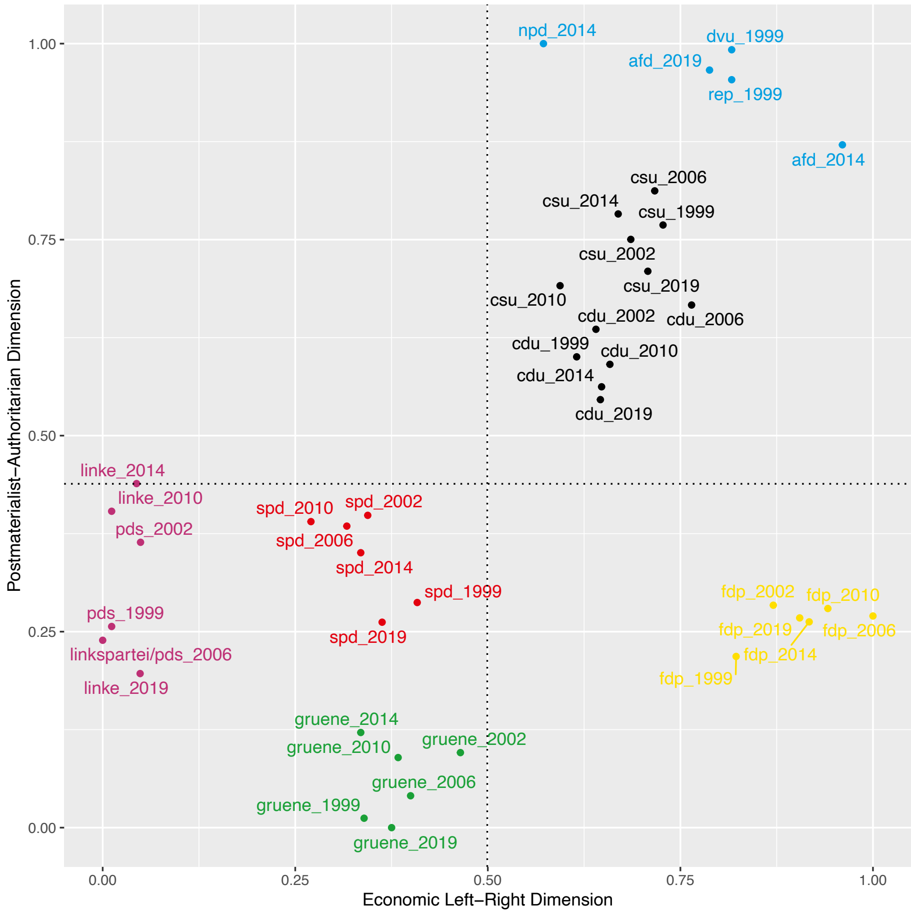
Online Appendix

Contents

A.1 The Political Space in Germany

Figure A.1 shows that party positions in Germany are broadly aligned along one dimension. They span from progressive-left (*Die Linke*) to authoritarian-right (*AFD* and other right-authoritarian parities). A notable exception is the pro-business party *FDP* which combines economic conservatism with social progressiveness. However, they do not play a central role in our analysis, as their electoral support does not seem to be affected by robot adoption.

Figure A.1: Political Parties in the Two-Dimensional Space



Note: Party positions based on Chapel Hill Expert Survey data between 1994 and 2019. Both lrecon and galtan dimensions are standardized between 0 and 1. The dotted lines show average values pooled over time, weighted by party-seat share.

A.2 Robustness Checks

In this section, we report in more detail on the robustness checks we briefly described in Section 5.1. We report one regression table for each economic and political outcome, once for robot adoption and once for ICT investment, in the section that follows. In the first column of each table, we present our baseline model, which relies on county and year fixed effects.[5] Note that the two-way fixed effect specification is already quite demanding, as it holds constant all factors that are either constant over time within a region (for example if a region historically was a manufacturing stronghold) or common shocks to all regions in a given year (for example changing party platforms or external events that affect the general success of parties).

Next, we add economic shocks as control variables to rule out that our results suffer from omitted variable bias. In column (2) of each table, we control for the net trade balance of each region vis-à-vis China and Eastern Europe. This is important as thriving manufacturing regions, which adopt robots at a fast pace, are likely to also be more involved in international trade and trade exposure may also affect political preferences. We find that this is not a major confounder as the unconditional correlation of net exports and robot intensity (0.04) or ICT (0.12) is low and also the estimated effect of regional robot intensity and regional ICT investment on regional election results and regional economic outcomes remain stable. Column (3) includes the other source of technological change as an additional control. Again, the concern is that it is an alternative economic shock is correlated with our technology shock.As noted before, the correlation between per worker ICT capital stocks and robot intensity is rather low (0.12). The effect of robotization on voting patterns virtually disappears after controlling for ICT. The effect of ICT on regional-level election outcomes on the other hand is not affected. As a third control, we include GDP per capita (column 4). This is important as robot adoption could be just one symptom of generally thriving regions (on the other hand, it could also be argued that GDP is a bad control as it is part of the mechanism of how technological change affects economic and political outcomes). Similar to controlling for the influence of the other technology, the point estimates of ICT on voting shares is not affected, whereas there is no effect of robotization on party support after controlling for GDP growth. Regarding the labor market consequences of technological change, it turns out that point estimates become more negative after controlling for GDP growth. This is intuitive as newly created job usually go hand in hand with economic growth.

Next, we use an instrumental variable approach where we instrument industry-level technology adoption in Germany with values from other European countries.[6] As argued before, the pace of robot adoption or ICT investment might be influenced by surrounding labor market institutions. In Germany,

[5]To be precise, we use election fixed effects for political outcomes. These differ from year fixed effects in the case of state elections, as each state has its own fixed effect.

[6]For robotization, we use data on all European countries included in the IFR database: Sweden, Denmark, Italy, Belgium, Netherlands, Austria, Slovenia, Spain, Slovakia, France Finland, Czech Republic. For ICT, we use data from all other EU member state countries (EU28 including the UK).

workers councils and trade unions are known to affect the process how companies digitalize. Simultaneously, labor unions have strong linkages to leftist and social democratic parties, which could create an omitted variable bias in our OLS estimates. Using the speed of adoption in other European countries as a valid instrument implies the exclusion restriction that specific labor market and political institution in Germany do not affect industry level decision to adopt new technologies abroad. Instead, it is assumed to be driven by a technological frontier. In a second panel of each table, we replicate all specifications using a 2SLS estimator. We find that labor market outcomes are comparable to the OLS estimates when considering ICT. Again, for robotization, the result are less stable. Concerning the case of robots, it has been noted that despite the strong first stage, using other Western countries as an instrument might be problematic in the case of Germany as it precedes other Western countries when it comes to adopting robots. Nevertheless, we included the instrumental variable analysis to facilitate the comparison to previous research.

Finally, we use the number of robots per thousand workers in levels (not in logs) as main explanatory variable (third panel). This gives more weight to outlier regions (recall that a few manufacturing hotspots attracted the bulk of new robots). The voting pattern results completely change, and this analysis suggests that automation is associated with less support for progressive-left parties and more support for conservative and authoritarian-right parties. However, as is shown in the last panel of each table, this pattern reverts if we exclude the top ten regions in terms of robot intensity. The estimated labor market consequences of both specifications are similar and in line with the results described previously. This suggests that the general distributive effects are captured with either approach. However, voting results depend on the specification. We interpret this as further evidence that here, the compositional and the treatment are of similar strength.

Summing up, we find stable results for ICT with respect to voting and labor market outcomes. Regarding robotization, the labor market effects are relatively robust, the political consequences are robotization are not robust.

A.3 Regression Tables

A.3.1 Robots & Election Outcomes

Table A.1: Fixed-effects estimation of robot exposure on support for *Die Grünen*

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.544**	0.577**	0.272	0.372	0.279
	(0.228)	(0.231)	(0.239)	(0.238)	(0.248)
Net Exports		−0.034			−0.042
		(0.034)			(0.032)
ICT			0.352***		0.238**
			(0.096)		(0.106)
GDP per capita				0.038***	0.033***
				(0.012)	(0.011)
2SLS					
Robots	−0.176	−0.157	−0.229	−0.206	−0.180
	(0.326)	(0.329)	(0.318)	(0.354)	(0.351)
First-stage F-stat	262.1	129.18	160.9	152.28	82.58
Non-logged robots					
Robots	0.0004	0.001	−0.014*	−0.020***	−0.027***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Non-logged robots exclude outliers					
Robots	0.027	0.029	0.011	−0.0005	−0.003
	(0.027)	(0.027)	(0.025)	(0.026)	(0.025)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.937	0.937	0.937	0.937	0.938

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.2: Fixed-effects estimation of robot exposure on support for *Die Linke*

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.368	0.344	−0.064	0.214	−0.137
	(0.248)	(0.246)	(0.277)	(0.253)	(0.274)
Net Exports		0.024			0.021
		(0.022)			(0.022)
ICT			0.562***		0.584***
			(0.128)		(0.128)
GDP per capita				0.011	−0.003
				(0.008)	(0.008)
2SLS					
Robots	0.300	0.276	0.243	0.170	0.143
	(0.351)	(0.351)	(0.370)	(0.352)	(0.371)
First-stage F-stat	245.37	120.8	147.9	147.95	77.79
Non-logged robots					
Robots	0.009	0.009	−0.010	−0.001	−0.015
	(0.010)	(0.010)	(0.011)	(0.012)	(0.013)
Non-logged robots exclude outliers					
Robots	0.050	0.049	0.029	0.034	0.021
	(0.031)	(0.031)	(0.032)	(0.029)	(0.029)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,792	3,792	3,792	3,651	3,651
Adjusted R^2	0.888	0.888	0.890	0.892	0.894

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Fixed-effects estimation of robot exposure on support for SPD

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.088	0.115	−0.181	−0.230	−0.415
	(0.398)	(0.403)	(0.444)	(0.419)	(0.448)
Net Exports		−0.027			−0.026
		(0.046)			(0.045)
ICT			0.349*		0.364*
			(0.194)		(0.207)
GDP per capita				0.015	0.007
				(0.019)	(0.019)
2SLS					
Robots	−0.127	−0.106	−0.171	−0.691	−0.686
	(0.685)	(0.695)	(0.694)	(0.593)	(0.599)
First-stage F-stat	262.1	129.18	160.9	152.28	82.58
Non-logged robots					
Robots	−0.009	−0.009	−0.022	−0.031	−0.039*
	(0.013)	(0.013)	(0.016)	(0.020)	(0.021)
Non-logged robots exclude outliers					
Robots	−0.017	−0.016	−0.032	−0.056	−0.061
	(0.042)	(0.042)	(0.043)	(0.041)	(0.042)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.962	0.962	0.963	0.962	0.963

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and year fixed effects. Standard errors reported in parentheses are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.4: Fixed-effects estimation of robot exposure on support for FDP

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	0.001	0.041	0.134	−0.062	0.105
	(0.162)	(0.163)	(0.166)	(0.170)	(0.169)
Net Exports		−0.041**			−0.044**
		(0.020)			(0.020)
ICT			−0.172**		−0.204***
			(0.077)		(0.078)
GDP per capita				0.010	0.016**
				(0.007)	(0.006)
2SLS					
Robots	−0.055	−0.019	−0.037	−0.077	−0.021
	(0.254)	(0.257)	(0.259)	(0.252)	(0.254)
First-stage F-stat	262.1	129.18	160.9	152.28	82.58
Non-logged robots					
Robots	0.004	0.005	0.010	0.004	0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Non-logged robots exclude outliers					
Robots	0.006	0.008	0.012	−0.003	0.003
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.917	0.917	0.917	0.917	0.918

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.5: Fixed-effects estimation of robot exposure on support for CDU / CSU

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	−0.836	−0.937*	−0.358	−0.052	0.008
	(0.546)	(0.546)	(0.609)	(0.590)	(0.613)
Net Exports		0.106			0.123
		(0.082)			(0.081)
ICT			−0.619***		−0.331
			(0.223)		(0.239)
GDP per capita				−0.096***	−0.090**
				(0.036)	(0.037)
2SLS					
Robots	0.035	−0.047	0.121	0.697	0.588
	(0.952)	(0.959)	(0.962)	(0.861)	(0.867)
First-stage F-stat	262.1	129.18	160.9	152.28	82.58
Non-logged robots					
Robots	−0.021	−0.023	0.001	0.032	0.038
	(0.021)	(0.021)	(0.023)	(0.028)	(0.029)
Non-logged robots exclude outliers					
Robots	−0.058	−0.065	−0.034	0.034	0.032
	(0.063)	(0.063)	(0.063)	(0.064)	(0.065)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.924	0.924	0.924	0.926	0.926

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county. *p<0.1; **p<0.05; ***p<0.01

Table A.6: Fixed-effects estimation of robot exposure on support for right-authoritarian Parties

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	−0.172	−0.185	0.053	−0.249	−0.049
	(0.170)	(0.175)	(0.181)	(0.193)	(0.207)
Net Exports		0.014			0.016
		(0.033)			(0.033)
ICT			−0.280***		−0.371***
			(0.104)		(0.114)
GDP per capita				0.005	0.014*
				(0.007)	(0.007)
2SLS					
Robots	−0.370*	−0.385*	−0.345	−0.457*	−0.479*
	(0.217)	(0.222)	(0.221)	(0.253)	(0.257)
First-stage F-stat	244.88	120.88	146.66	149.01	77.08
Non-logged robots					
Robots	0.010*	0.010*	0.023***	0.010	0.020**
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Non-logged robots exclude outliers					
Robots	−0.022	−0.022	−0.007	−0.017	−0.009
	(0.017)	(0.017)	(0.016)	(0.019)	(0.017)
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,280	3,280	3,280	3,139	3,139
Adjusted R^2	0.932	0.932	0.932	0.931	0.931

Note: Fixed-effects regressions of party vote share (in %) on log number of robots per 1000 workers for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*) and once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county. *p<0.1; **p<0.05; ***p<0.01

A.3.2 ICT & Election Outcomes

Table A.7: Fixed-effects estimation of ICT on support for *Die Grünen*

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.391***	0.395***	0.352***	0.263**	0.238**
	(0.092)	(0.092)	(0.096)	(0.104)	(0.106)
Net Exports		−0.030			−0.042
		(0.032)			(0.032)
Robots			0.272		0.279
			(0.239)		(0.248)
GDP per capita				0.033***	0.033***
				(0.011)	(0.011)
2SLS					
ICT	0.854***	0.856***	0.866***	0.777***	0.780***
	(0.167)	(0.167)	(0.179)	(0.183)	(0.193)
First-stage F-stat	306.23	152.04	124.81	144	70.74
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.937	0.937	0.937	0.937	0.938

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in €1000) for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Fixed-effects estimation of ICT on support for *Die Linke*

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.553***	0.549***	0.562***	0.573***	0.584***
	(0.118)	(0.118)	(0.128)	(0.123)	(0.128)
Net Exports		0.021			0.021
		(0.022)			(0.022)
Robots			−0.064		−0.137
			(0.277)		(0.274)
GDP per capita				−0.003	−0.003
				(0.008)	(0.008)
2SLS					
ICT	0.619***	0.617***	0.630***	0.635***	0.648***
	(0.179)	(0.179)	(0.193)	(0.184)	(0.193)
First-stage F-stat	254.2	126.31	102.84	118.01	58.46
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,792	3,792	3,792	3,651	3,651
Adjusted R^2	0.890	0.890	0.890	0.894	0.894

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in €1000) for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Fixed-effects estimation of ICT on support for SPD

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.323*	0.328*	0.349*	0.316	0.364*
	(0.177)	(0.177)	(0.194)	(0.201)	(0.207)
Net Exports		−0.030			−0.026
		(0.045)			(0.045)
Robots			−0.181		−0.415
			(0.444)		(0.448)
GDP per capita				0.004	0.007
				(0.019)	(0.019)
2SLS					
ICT	0.241	0.242	0.250	0.237	0.266
	(0.270)	(0.270)	(0.291)	(0.295)	(0.304)
First-stage F-stat	306.23	152.04	124.81	144	70.74
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.963	0.963	0.963	0.962	0.963

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in €1000) for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.10: Fixed-effects estimation of ICT on support for FDP

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.153**	−0.147**	−0.172**	−0.198**	−0.204***
	(0.073)	(0.074)	(0.077)	(0.077)	(0.078)
Net Exports		−0.038**			−0.044**
		(0.019)			(0.020)
Robots			0.134		0.105
			(0.166)		(0.169)
GDP per capita				0.016**	0.016**
				(0.007)	(0.006)
2SLS					
ICT	−0.048	−0.046	−0.052	−0.070	−0.073
	(0.124)	(0.124)	(0.132)	(0.132)	(0.137)
First-stage F-stat	306.23	152.04	124.81	144	70.74
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.917	0.917	0.917	0.918	0.918

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in €1000) for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.11: Fixed-effects estimation of ICT on support for CDU / CSU

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.669***	−0.685***	−0.619***	−0.316	−0.331
	(0.202)	(0.205)	(0.223)	(0.231)	(0.239)
Net Exports		0.101			0.123
		(0.080)			(0.081)
Robots			−0.358		0.008
			(0.609)		(0.613)
GDP per capita				−0.087**	−0.090**
				(0.037)	(0.037)
2SLS					
ICT	−1.034***	−1.041***	−1.030***	−0.771*	−0.794*
	(0.344)	(0.347)	(0.362)	(0.393)	(0.404)
First-stage F-stat	306.23	152.04	124.81	144	70.74
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	4,276	4,276	4,276	4,135	4,135
Adjusted R^2	0.924	0.925	0.924	0.926	0.926

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in €1000) for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.12: Fixed-effects estimation of ICT on support for right-authoritarian parties

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.272***	−0.275***	−0.280***	−0.374***	−0.371***
	(0.100)	(0.100)	(0.104)	(0.112)	(0.114)
Net Exports		0.016			0.016
		(0.033)			(0.033)
Robots			0.053		−0.049
			(0.181)		(0.207)
GDP per capita				0.014*	0.014*
				(0.008)	(0.007)
2SLS					
ICT	−0.467***	−0.470***	−0.488***	−0.546***	−0.552***
	(0.144)	(0.144)	(0.154)	(0.161)	(0.166)
First-stage F-stat	234.32	116.37	93.92	107.17	53.25
Region FE	X	X	X	X	X
Election FE	X	X	X	X	X
Observations	3,280	3,280	3,280	3,139	3,139
Adjusted R^2	0.932	0.932	0.932	0.931	0.931

Note: Fixed-effects regressions of county-level party vote share (in %) on ICT capital stocks per worker (in €1000) for federal, state and European Elections. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per 1000 workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and election fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

A.3.3 Robots & Labor Market Composition

Table A.13: Fixed-effects estimation of robot exposure on total employment

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	1.875**	1.853**	1.328*	−0.228	−0.158
	(0.854)	(0.855)	(0.741)	(0.473)	(0.458)
Net Exports		0.023			0.012
		(0.064)			(0.054)
ICT			0.772**		−0.172
			(0.304)		(0.206)
GDP per capita				0.238***	0.242***
				(0.022)	(0.025)
2SLS					
Robots	1.042	1.004	1.030	0.374	0.349
	(0.832)	(0.835)	(0.807)	(0.580)	(0.588)
First-stage F-stat	210.06	102.49	127.29	147.67	81.01
Non-logged robots					
Robots	0.150***	0.150***	0.138**	0.004	0.007
	(0.055)	(0.055)	(0.055)	(0.019)	(0.019)
Non-logged robots exclude outliers					
Robots	0.159**	0.156**	0.147**	0.032	0.036
	(0.066)	(0.065)	(0.066)	(0.046)	(0.045)
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.978	0.978	0.978	0.985	0.985

Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and year fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.14: Fixed-effects estimation of robot exposure on manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	−0.267	−0.278	−0.049	−1.154**	−0.805
	(0.621)	(0.627)	(0.605)	(0.562)	(0.629)
Net Exports		0.011			0.010
		(0.062)			(0.065)
ICT			−0.308		−0.733***
			(0.193)		(0.179)
GDP per capita				0.080***	0.098***
				(0.020)	(0.021)
2SLS					
Robots	0.154	0.149	0.158	−0.145	−0.215
	(0.597)	(0.606)	(0.600)	(0.660)	(0.683)
First-stage F-stat	210.06	102.49	127.29	147.67	81.01
Non-logged robots					
Robots	0.049	0.049	0.065**	−0.010	0.005
	(0.033)	(0.033)	(0.032)	(0.022)	(0.020)
Non-logged robots exclude outliers					
Robots	0.009	0.009	0.026	−0.019	−0.010
	(0.055)	(0.056)	(0.054)	(0.052)	(0.049)
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.958	0.958	0.959	0.965	0.966

Note: Fixed-effects regressions of manufacturing employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and year fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.15: Fixed-effects estimation of robot exposure on non-manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
Robots	2.142***	2.130***	1.377*	0.925*	0.647
	(0.669)	(0.676)	(0.717)	(0.513)	(0.582)
Net Exports		0.012			0.002
		(0.043)			(0.040)
ICT			1.080***		0.562***
			(0.197)		(0.170)
GDP per capita				0.158***	0.143***
				(0.027)	(0.027)
2SLS					
Robots	0.888	0.855	0.872	0.518	0.565
	(0.740)	(0.751)	(0.714)	(0.594)	(0.616)
First-stage F-stat	210.06	102.49	127.29	147.67	81.01
Non-logged robots					
Robots	0.101***	0.101***	0.073***	0.013	0.002
	(0.026)	(0.026)	(0.027)	(0.015)	(0.015)
Non-logged robots exclude outliers					
Robots	0.150***	0.147***	0.120**	0.051	0.046
	(0.049)	(0.049)	(0.047)	(0.038)	(0.038)
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.979	0.979	0.980	0.984	0.984

Note: Fixed-effects regressions of non-manufacturing employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in €1000), column (3) adds ICT capital stocks per worker (in €1000), column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specifications as above. Once instrumenting robot adoption in Germany with values from other EU countries (*2SLS*), once using the number of robots per 1000 workers in levels instead of logs (*Non-logged robots*) and once using robots in levels but excluding 10 outlier counties (*Non-logged robots exclude outliers*). All models include region and year fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

A.3.4 ICT & Labor Market Composition

Table A.16: Fixed-effects estimation of ICT on total employment

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	0.943***	0.936***	0.772**	−0.184	−0.172
	(0.356)	(0.356)	(0.304)	(0.212)	(0.206)
Net Exports		0.038			0.012
		(0.062)			(0.054)
Robots			1.328*		−0.158
			(0.741)		(0.458)
GDP per capita				0.241***	0.242***
				(0.024)	(0.025)
2SLS					
ICT	0.044	0.041	−0.143	−0.651**	−0.657**
	(0.365)	(0.364)	(0.406)	(0.304)	(0.307)
First-stage F-stat	223.93	111.56	93.48	103.23	52.76
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.978	0.978	0.978	0.985	0.985

Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per thousand workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specification as above while instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and year fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.17: Fixed-effects estimation of ICT on manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	−0.314	−0.316	−0.308	−0.805***	−0.733***
	(0.215)	(0.217)	(0.193)	(0.168)	(0.179)
Net Exports		0.011			0.010
		(0.063)			(0.065)
Robots			−0.049		−0.805
			(0.605)		(0.629)
GDP per capita				0.094***	0.098***
				(0.023)	(0.021)
2SLS					
ICT	−1.068***	−1.069***	−1.118***	−1.393***	−1.353***
	(0.288)	(0.289)	(0.305)	(0.336)	(0.304)
First-stage F-stat	223.93	111.56	93.48	103.23	52.76
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.959	0.959	0.959	0.966	0.966

Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per thousand workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specification as above while instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and year fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

Table A.18: Fixed-effects estimation of ICT on non-manufacturing employment

	(1)	(2)	(3)	(4)	(5)
OLS					
ICT	1.256***	1.252***	1.080***	0.621***	0.562***
	(0.198)	(0.198)	(0.197)	(0.156)	(0.170)
Net Exports		0.027			0.002
		(0.042)			(0.040)
Robots			1.377*		0.647
			(0.717)		(0.582)
GDP per capita				0.147***	0.143***
				(0.028)	(0.027)
2SLS					
ICT	1.112***	1.110***	0.975***	0.743**	0.697**
	(0.397)	(0.397)	(0.354)	(0.323)	(0.300)
First-stage F-stat	223.93	111.56	93.48	103.23	52.76
Region FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	7,774	7,774	7,774	7,492	7,492
Adjusted R^2	0.980	0.980	0.980	0.984	0.984

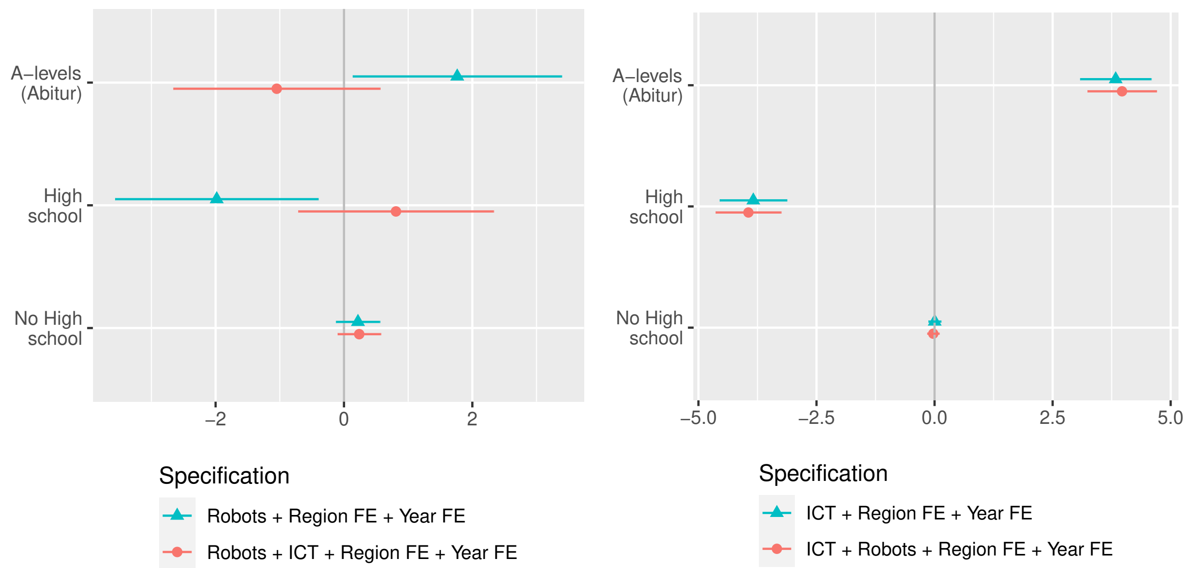
Note: Fixed-effects regressions of total employment to population ratio (in %) on log number of robots per 1000 workers. Column (2) adds net exports per worker (in €1000), column (3) adds log number of robots per thousand workers, column (4) adds GDP per capita (in €1000). Column (5) adds all three controls jointly. Below are reported the estimates for our variable of interest, using the same specification as above while instrumenting ICT capital stocks in Germany with values from other EU countries (*2SLS*). All models include region and year fixed effects. Standard errors reported in parentheses are clustered by county: *p<0.1; **p<0.05; ***p<0.01.

A.4 Additional Evidence on Mechanisms

A.4.1 Skill Requirements instead of Education

Similar to our findings presented in the main body of the text, we also find that education requirements are changing in technology-exposed regions, with a more pronounced polarization of within the workforce (see Figure A.2). Investment in robots or ICT increases the share of workers with at least a university entrance degree (Abitur) but decreases the share of workers with only High school degrees. Interestingly, with respect to education requirements, we find some evidence of polarizing labor markets in the sense that technology adoption does not reduce the share of workers who did not finish secondary school. These workers presumably find jobs in low-skilled services, which are created due to positive spillover effects of technology adoption (see Figure A.2). The described patterns are generally robust to controlling for the other type of technology adapted. Only the effect of robotization on the education composition of the labor force changes markedly. This again supports the conjecture that ICT has a stronger impact on the overall labor force than robotization, a reasonable finding in light of the strong concentration of robots in a few highly-exposed sectors.

Figure A.2: Technological change and Regional Education Levels



(a) Robot Intensity

(b) ICT

Note: All variables are expressed as changes in regional employment shares in percentage points, such that coefficients sum up to zero. Bars represent 95% confidence intervals, where standard errors are clustered at the commuting zone-year level.

A.4.2 Intragenerational Upskilling, Intergenerational Upskilling or Migration?

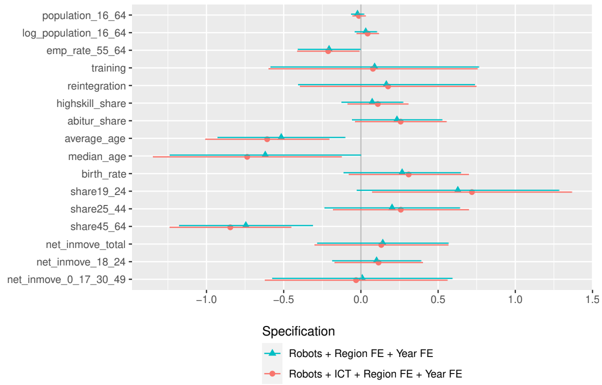
We use additional Kreis-level data from the Wegweiser Kommune (https://www.wegweiser-kommune.de/) to trace some observable implications of different channels contributing to a changing labor market composition. These indicators are available from 2006 onwards. The following evidence is thus restricted to a shorter time span than the results presented in the main body of the paper. We hope to provide some tentative insights on what happens in a region when its labor market composition changes but want to emphasize that other research with a more direct focus on allocation and reallocation of jobs in times of automation (especially Dauth et al. (2021)) are in a better position to tackle this specific question. We will hence treat the following results as suggestive and discuss them in tandem with existing research on related questions.

A first relevant indicator is the size of the local population size, which provides hints about the relevance of occupational upskilling within the existing population as opposed to local upskilling based on moving patterns. Specifically, we look at the working age population (16-64 years old) in raw and logged form. A second set of indicators relates more directly to observable implications of intragenerational occupational change by looking at the prevalence of retraining (% of unemployed enter subsidized continuing education measures) and reintegration (% participants in measures of continuing vocational training are employed 3 months later) for unemployed citizens as well as at employment rates among citizens above 55 years. A next set of indicators studies the local skill mix (% with academic professional degree) and local educational attainment (% school leavers with advanced technical college/university entrance qualification). Then follows a set of indicators capturing the demographic profile of a Kreis (average/median age, birth rates, share of age groups). Finally, we also collected direct information on moving patterns (in-move minus out-moves overall and for specific age groups).

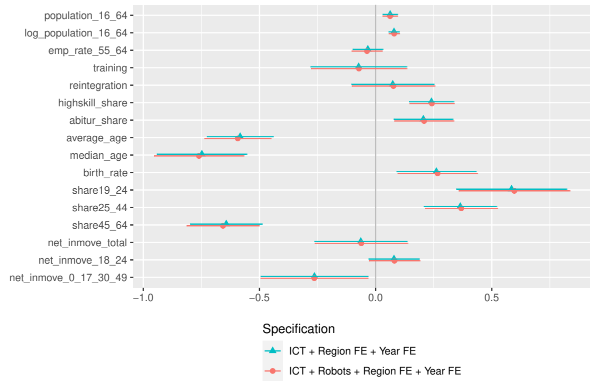
The results are based on the identical modelling strategy as described in the main body of the paper (equation 3) but with the just described regional-level indicators rather than election outcomes as dependent variable. Figure A.3 summarizes the results for robotization and ICT investment separately. The results provide both some commonalities and some interesting nuance with respect to the specific technology adopted. First and most importantly, the most consistent finding is that technology-adopting regions are characterized by a younger local population. Median and average age are lower in regions with above-average investment in robots or ICT and further differentiating by age groups shows that the population shares of those between 19 and 45 increase while the share of those between 45 and 64 decreases. In line with our expectations and the evidence presented above, technology-adopting regions tend to have more dynamic labor markets offering more job opportunities, especially in the growing service sector, that either attracts young workers from other regions or manages to keep local labor market entrants in the region.

To further differentiate between the intergenerational and the migration channel, we also look at population size and more direct indicators of net in-migration. Here, the results suggest slightly different patterns depending on the type of technology investment. In regions with above-average robotization, indication of in-migration is weak. Overall working-age population does not significantly increase and the evidence on net in-migration is not conclusive. A further indication of the muted influence of migration is the null finding with respect to the local share of high-skilled workers. In line with Dauth et al. (2021),

Figure A.3: Technological change and Labor Market Composition



(a) Robot Intensity



(b) ICT

Note: Bars represent 95% confidence intervals, where standard errors are clustered at the region-year level.

local robot adoption seems to primarily result in intergenerational adjustment where younger workers enter jobs in the growing service sector instead of manufacturing. In addition, incumbent workers in manufacturing may receive training at the workplace that enables them to upskill within the firm.

In contrast, our evidence suggests that the migration channel is more dominant when it comes to ICT investment. This type of technology seems to more strongly affect the composition of the local population by attracting young, skilled workers from other regions. Observable implications of this channel are increasing working age population and an increasing share of adults with academic professional degrees (without a similar increase in the share of local A-level degrees). Moreover, even though direct indicators capturing net in-migration do not indicate an overall increase, the results with respect to labor market entrants (aged 18-24) is weakly positive.

Taken together, these additional results suggest that both the intergenerational and the migration channel contribute to a changing labor market composition where the first dominates robot-adopting regions and the latter may have some traction – on top of intergenerational change – in regions that invest (more) in ICT. Both mechanisms contribute to a younger local population. The third possible mechanism, intragenerational occupational upgrading is harder to detect on the basis of regional-level data. We do not find much evidence with respect to government-led programs of retraining and reintegration, which may be due to the prevalence of firm-based retraining in the German labor market. We also do not find significant negative effect with respect to the employment rate among the population of 55 and above, a potential observable implication of intragenerational occupational adjustment if this comes at the cost of more widespread early retirement.