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Robots and Female Employment in German Manufacturing†

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With the advancement of automation technologies, robotics in particular, there is growing concern about how they affect employment and wages. Applications of automation to more routine tasks are thought to generally increase displacement risks (Acemoglu and Restrepo 2018). As robots are heavily used in the generally male-dominated manufacturing sector, the estimated effects are driven mainly by male employment. Less attention has been paid thus far to the potentially differential impact of robots on women and men. Whereas Black and Spitz-Oener (2010) find a lower routine task share for women than for men in Germany, Brussevich, Dabla-Norris, and Khalid (2019) report higher routine task intensity for women in a cross-country setting and for Germany in particular. Furthermore, male workers have a comparative advantage in performing physical manual jobs, which are more susceptible to robotization (Acemoglu and Restrepo 2022a). Much less is known about gender bias in the employment-increasing effects of robots—that is, the productivity and reinstatement channels (Acemoglu and Restrepo 2018).[1] Therefore, there is no clear-cut prediction a priori as to how robots affect female employment.

The existing empirical evidence, based predominantly on local labor market studies, is mixed. Robots are found to lower the employment and wages of men and women in the United States, with the effect being more negative for men (Acemoglu and Restrepo 2020; Ge and Zhou 2020; Anelli, Giuntella, and Stella 2021). Acemoglu and Restrepo (2022b) report that automation slightly reduces the US gender wage gap in general equilibrium. However, Aksoy, Ozcan, and Philipp (2021) and Blanas, Gancia, and Lee (2019) show no impact of robots on gender inequality in Germany and even a slight increase in Europe as a whole.

In the robot-intensive German economy, approximately 57 percent (64 percent) of women (men) aged between 15 and 65 were employed in 2019.[2] Women account for 46 percent of total employment in Germany but only 25 percent of total employment in manufacturing. Whereas 52 percent (88 percent) of female (male) workers work full time, these percentages are much higher in manufacturing (70 percent for female versus 97 percent for male workers).

We use German plant-level data to study the effect of robots on female employment in the manufacturing sector for the period from 2014 to 2018. We address a major data limitation in the literature: whereas most studies rely on industry-level robot data, this is the first paper to empirically examine the gendered labor market outcome of robots at the production-unit level. We further draw on worker-level social security data to also include the occupational dimension of female employment outcomes.

I. Data

We draw plant-level data on robots from the Institute for Employment Research (IAB) Establishment Panel, an annual high-quality survey of nearly 16,000 German plants. The survey data are nationally representative. In the 2019 wave, we included a dedicated section on robot use. In particular, we asked whether each plant had used robots in the past five years and, if

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[1] Aksoy, Ozcan, and Philipp (2021) report that the productivity effect benefits skilled men in a subset of European countries not including Germany.

[2] These and the following numbers are derived from the employment statistics of the German Federal Employment Agency and, as our micro data, pertain to employment subject to social security payments. The data thus exclude self-employed workers and civil servants.

so, how many robots were used in each year from 2014 to 2018. We adopted the International Organization for Standardization definition of robots and performed extensive pretesting and consistency checks to ensure data quality (Plümpe and Stegmaier 2022). The robot data were then linked with social security records of establishments (IAB Establishment History Panel (BHP)) and workers (IAB Employment History (BeH)), from which we constructed plant-level employment information by gender and occupation.[3]

Our analysis is based on plants in the manufacturing sector with at least ten employees. A plant is identified as a robot adopter if it had no robots in 2014 but a positive number of robots in subsequent years.[4] By construction, robot adoption could have taken place in one of the four years from 2015 to 2018, and correspondingly, there are four treatment groups. We organize the sample in relative time centered around the year of robot adoption. The control group consists of plants that neither already used robots in 2014 nor adopted them later. The control group is split randomly into four equally sized groups, each of which is assigned to one of the four treatment groups. The relative time for each control group follows the treatment group that it is assigned to.[5] We track each plant from three years before adoption to one year after adoption. The final sample is a five-year balanced panel that consists of 1,728 manufacturing plants, among which 114 plants are robot adopters: 24 plants adopted robots in 2015, 27 in 2016, 20 in 2017, and 43 in 2018.

Robot adopters have a lower share of female employees. The average female employment share across robot-adopting plants is 24 percent, compared with 29 percent for nonadopters.[6] When we restrict our attention to full-time female employees, plant-level female shares are comparable between robot adopters (17 percent) and nonadopters (18 percent). As is now well known in the literature, robot adopters are significantly larger than nonadopters. Despite having a relatively low female employment share, robot adopters on average employ 55 female workers, whereas the mean female employment of nonadopters is 25.

Female employees in robot adopters have, on average, lower qualifications than those in nonadopters. We group occupations into three categories by their level of job qualification: (i) low-qualified occupations are unskilled manual, service, commercial, and administrative occupations; (ii) medium-qualified occupations are skilled manual, service, commercial, and administrative occupations; and (iii) high-qualified occupations are managers, engineers, technicians, and other professionals.[7] The plant-level share of the low qualified out of all female workers is 45 percent and the medium-qualified (high-qualified) share is 45 percent (11 percent). At plants that did not adopt robots, the corresponding figures are 38 percent, 49 percent, and 13 percent, respectively.

II. Empirical Framework

The estimation equation for our event study approach is

$$Y_{it} = \alpha_i + \sum_{k=-2}^{1} \beta_k T_t^k + \sum_{k=-2}^{1} \gamma_k Robot_i T_t^k + \epsilon_{it},$$

which relates plant i's outcome variable of interest Y_{it} in relative time t to the event of robot adoption. We control for a plant fixed effect α_i. T_t^k is a relative time dummy that equals one if $t = k$. $Robot_i$ is the time-invariant treatment group indicator for robot adopters, and the main coefficient of interest is γ_k. It measures the development of Y_{it} in the treatment group relative to the outcome in the control group. The

[3] The BeH data we used is customized data extract from BeH version 10_05_01. The DOI to the BHP data is 10.5164/IAB.BHP7519.de.en.v2, and the DOI to the IAB Establishment Panel is 10.5164/IAB.IABBP9319.de.en.v1.

[4] To focus on the effect of first-time adoption, we exclude plants with reported robot use in 2014, the first year for which we have plant-level robot information.

[5] The relative time approach sidesteps the problems with multiple-period difference-in-difference settings thematized—for example, in Goodman-Bacon (2021).

[6] All descriptive statistics are measured as of three years prior to robot adoption. We do not apply survey weights. Tables in the online Appendix include sample means of all dependent variables separately for adopters and nonadopters.

[7] The three main categories are based on the occupation categories created by Blossfeld (1987) and available in the IAB BHP data. The original Blossfeld (1987) categories provide precise definitions for which skilled and unskilled occupations are explicitly distinguished. For instance, medium-qualified workers usually have formal vocational training.

Table 1—Robot Adoption and Female Employment, Hires, and Separations

	All female			Full-time female		
	Employment (1)	Hire (2)	Separation (3)	Employment (4)	Hire (5)	Separation (6)
γ_{-2}	0.2157	−0.3427	−0.3368	0.2593	0.8278	−0.6389
	(0.9426)	(1.0887)	(0.8218)	(0.8588)	(0.8132)	(0.7436)
γ_{-1}	−0.1403	−0.4191	0.1586	0.3633	1.2435	−0.0973
	(1.2578)	(1.3246)	(0.7825)	(1.0871)	(0.6525)	(0.7258)
γ_0	2.8846	2.8465	0.0433	3.5126	3.4904	0.0964
	(2.4821)	(2.0501)	(0.8954)	(2.4866)	(1.8016)	(0.8857)
γ_1	2.5832	0.0152	0.5381	3.5056	1.2453	0.3589
	(2.5112)	(0.7165)	(1.0122)	(2.7992)	(0.5917)	(0.9590)
R^2	0.0059	0.0091	0.0033	0.0072	0.0124	0.0035

Notes: This table reports event study results based on the model described in the text (number of observations = 8,640). The dependent variables are obtained directly from the plant-level BHP data. They are female employment in columns 1 and 4, female hires in columns 2 and 5, and female separations in columns 3 and 6. Columns 1–3 refer to all female employees, whereas columns 4–6 refer to full-time female employees only. Plant and (relative) time fixed effects are included. Standard errors in parentheses are clustered at the plant level. Within R^2 is reported in the last row.

$t = -3$ period serves as the reference period, so point estimates are thus interpreted relative to three years prior to adoption. Outcome variables Y_{it} always pertain to *female* employment, hiring, and separations, respectively.

III. Results

Table 1 reports the event study results for female employment, hires, and separations. The first (last) three columns present the point estimates for all (full-time) female employees. As column 1 shows, robot adoption does not reduce female employment. In fact, the estimates for γ_0 and γ_1, albeit noisily estimated, suggest that following robot adoption, female employment at robot-adopting plants increases relative to that of nonadopters. In the year of adoption, there is a relative increase of 2.88 female workers. Compared with the reference-year adopters' sample mean of 55, the point estimate for γ_0 suggests that robot adoption raises female employment on average by approximately 5 percent. The increase in employment is not driven by a pretrend, and the estimated relative time fixed effects show a slight increase in female employment for the control group.[8] This finding contrasts with the negative association between robots and female manufacturing employment documented for US local labor markets (Acemoglu and Restrepo 2020).

The increase in female employment is accompanied by a substantial increase of 2.85 persons (40 percent increase against adopters' sample mean) in female hires in the year of robot adoption (column 2). Job separations increase with a smaller magnitude one year later (column 3). To see whether the increase in female employment is driven by additional part-time jobs, we report in the next three columns the regression results for female full-time workers. Results are more pronounced: an increase in full-time employment by 10 percent accompanied by a substantial increase in hiring by 107 percent.

Next, we turn to the effect of robots on female employment by occupation group. The results in Table 2 demonstrate that the positive association between robot adoption and female employment is driven largely by medium-qualified occupations. In particular, column 2 suggests that robot adoption raises female employment by 2.63 workers (15 percent increase against adopters' sample mean) for medium-qualified occupations, and this positive employment effect persists after robot adoption. In contrast, columns 1 and 3 show no strong association between robot adoption and female employment in either low- or high-qualified occupations. Interestingly, female

[8] Due to space limitations, we omit the estimates of β_k here and report them in the online Appendix tables.

Table 2—Robot Adoption and Female Employment by Occupation Group

	Low-qualified (1)	Medium-qualified (2)	High-qualified (3)
γ_{-2}	−0.3711	0.8289	−0.2002
	(0.4563)	(0.7038)	(0.1407)
γ_{-1}	−0.6300	0.8736	−0.2195
	(0.7622)	(0.7661)	(0.2003)
γ_0	0.1995	2.6282	−0.0198
	(1.1635)	(1.8695)	(0.2855)
γ_1	0.1430	2.4217	−0.0896
	(1.3139)	(1.7995)	(0.3421)
R^2	0.0006	0.0079	0.0064

Notes: This table reports event study results based on the model described in the text (number of observations = 8,640). The dependent variables, plant-level female employment by occupation group, are computed from the worker-level BeH data. Low-qualified occupations are unskilled manual, service, commercial, and administrative occupations. Medium-qualified occupations are skilled manual, service, commercial, and administrative occupations. High-qualified occupations are managers, engineers, technicians, and other professionals. Plant and (relative) time fixed effects are included. Standard errors in parentheses are clustered at the plant level. Within R^2 is reported in the last row.

employment in high-qualified occupations experiences a steady increase for the control group over the sample period. Hence, robot adopters keep up with this trend and additionally upgrade their female workforce with medium-qualified workers.

IV. Conclusion

Robots are heavily used in male-dominated manufacturing, and any overall employment effects are thus driven mainly by male workers. Little is known about the effects of robots on female employment, and no studies have used data on robot use at the production-unit level. Using German plant-level data, we document that robot adoption yields a modest gain in female employment driven by increased hiring. The positive effect on female employment is concentrated on medium-qualified occupations and full-time workers. Therefore, female workers seem to participate in the positive firm-level employment effect of robots in Europe documented in Koch, Manuylov, and Smolka (2021) for Spain; in Acemoglu, Lelarge, and Restrepo (2020) for France; and in studies presented at the 2023 Allied Social Sciences Associations meetings (Aghion et al. 2023; Deng et al. 2023) using data for France and Germany, respectively.

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