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Digitalization is not gender-neutral

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ABSTRACT

Using unique linked employer-employee data for Germany and a matching approach, we provide novel insights on the individual-level employment effects of digitalization. We show that the first-time introduction of digital technology in an establishment affects women more strongly than men. This holds both in terms of lower days employed and higher days unemployed. We find that employment losses are largest for individuals conducting non-routine tasks, and again it is women who suffer the most. Our insights imply that digitalization is not gender-neutral, suggesting that it is important to avoid a gender bias in technological progress.

1. Introduction

Although numerous studies have investigated the aggregate employment effects of automation and digitalization (e.g., Acemoglu and Restrepo, 2019), relatively little is known about the effects at the level of individual workers and along the gender dimension. Moreover, existing studies (in particular those on robots) often focus on the male-dominated manufacturing sector (e.g., Dauth et al., 2021) and thus provide few insights on gender heterogeneity.[1] In contrast, this paper looks at individual workers and analyzes whether digitalization affects males and females differently, thus contributing to labor market inequality.

There are various reasons why exposure to new technology and its employment effects may vary by gender. Females disproportionately work in administrative support and service occupations while men are more likely to work in blue-collar jobs (Blau and Kahn, 2017). Even within the same occupation, men often conduct different tasks than women (Brussevich et al., 2019). Gender segregation in the labor market and self-selection into different professions and task bundles within the same occupation both contribute to heterogeneous automation and digitalization risks for men and women (Black and Spitz-Oener, 2010; Cortes et al., 2020). Despite early considerations of technology and gender (Wajcman, 1991), the topic remains under-researched, especially concerning digitalization.

To investigate whether digitalization is gender-neutral, we analyze employment developments of male and female workers in Germany, a country in which gender equality with respect to digital transformation has gained considerable political attention (e.g., Bonin et al., 2021; Sachverständigenkommission, 2021. Using novel linked employer-employee data from 2011 to 2016 and applying a matching approach, we examine establishments and their workers after the first-time introduction of digital technologies. We compare workers in investing establishments with similar workers in establishments that do not make such an investment. We find that the employment stability of incumbent workers is lower in investing than in non-investing establishments and that this difference is more pronounced for women than for men. We further document substantial heterogeneity in the employment effects across occupational tasks, which again differs by gender.

2. Data and methods

To examine individuals' employment reactions to digitalization, we use a novel linked employer-employee dataset (also used

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[1] A recent exception is Bessen et al. (2023) which covers all non-financial industries in the Netherlands and shows that individuals are more likely to separate from automating than non-automating establishments.

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in ongoing research by Genz et al., 2021). The establishment-level data stem from the representative "IAB-ZEW Labor Market 4.0 Establishment Survey", which contains information on the usage of different technologies for production and office and communication equipment in 2016 and 2011 (Hanebrink et al., 2021). We link employment records from the German Social Security Administration of 91,013 individuals employed on June 30, 2011, in one of the surveyed establishments (see Appendix A.2).

We focus on 1,024 establishments that did not use self-contained and autonomous devices in 2011 to identify the employment effect of the *first* introduction of advanced technologies on incumbent workers until 2016. Our treatment measures whether establishments report introducing frontier technology to conduct work processes in a self-contained and automatic manner without human interaction. Examples include cyber–physical, embedded systems, smart factories, big data analytical tools, and cloud computing (Appendix Table A.1). One-quarter of our establishments invest in frontier digitalization technology until 2016 (*investors*) whereas the majority of establishments still report not using self-contained and autonomous work equipment in 2016 (*non-investors*). One limitation of this data is that we do not know precisely in which year the investment took place, which impedes exploiting differences in the event timing.

We analyze the (non-)employment of comparable workers in investing and non-investing establishments to test whether digitalization affects males and females differently. Although the first-time introduction of advanced technologies is an endogenous decision of the plant, it can be regarded as exogenous for those workers employed in the establishment before the investment took place. Our identification strategy requires selecting the subset of untreated workers in non-investing establishments who have observable characteristics in 2011 similar to the treated workers in investing establishments.

We apply a nearest neighbor matching approach that combines exact matching and propensity score matching. We require *exact matches* on gender, age groups, education groups, task groups, establishment size groups and whether the establishment is a manufacturer to assure that individuals employed at investors and non-investors share identical features in these crucial dimensions (Appendix A.5). Simultaneously, we apply *propensity score matching* for additional control variables. The additional worker characteristics for estimating the propensity score from a probit regression include age, part-time work, occupation, routine-work content, daily wage, nationality, tenure, number of previous employers, years since first appearing in the data, and the share of days in employment in total days observed. We also account for the age and task structure of the workforce, for establishments' age and size, sector affiliation, employment turnover rate, previous employment growth, urbanization, and region. We restrict our sample to the region of optimal common support and apply one-to-five nearest neighbor matching with replacement. Our matched sample contains 60,160 workers, of which 29,112 are employed in investing and 31,048 in non-investing establishments. This procedure ensures that changes in the workforce composition do not drive our results. Results are robust to alternative matching techniques such as varying the number of neighbors and applying non-parametric or ridge kernel matching procedures.

3. Results

We first examine the share of male and female workers who stay employed at their initial employer after 2011. Fig. 1 shows that separation rates are higher for women than for men. More important, over the entire observation period the share of males remaining employed at investing employers (blue solid line) is very similar to the share remaining employed at non-investing employers (blue dashed line). For women, a higher share of workers separates from investing employers (green solid line) compared to non-investing employers (green dashed line).

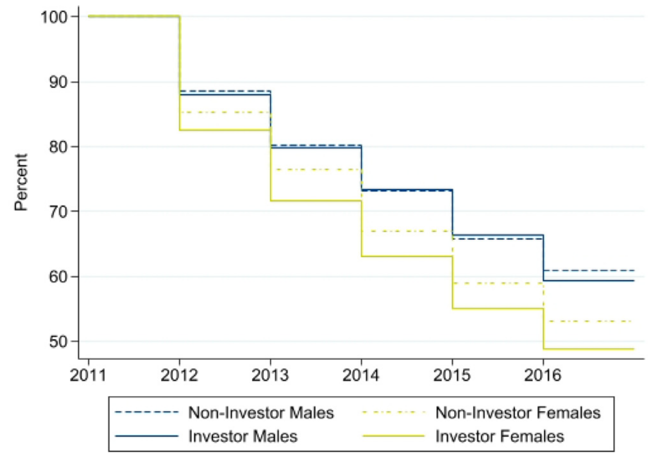

Fig. 1. Continuous employment at investing and non-investing establishments. Notes: The figure displays the share of matched female (green) and male (blue) workers in investing and non-investing establishments who are still employed at their original employer on June 30 of each year, without any employment interruption such as unemployment periods or switching to another employer. Figures are weighted with matching weights.

In 2016, the share of females continuously employed at their original employer is 4.57 percentage points lower in investing than non-investing establishments, and this difference is highly statistically significant. Fig. 1 suggests that incumbent female workers are less likely to remain employed at their employers after technology adoption, whereas for males it seems irrelevant if they are exposed to digital technologies. To obtain a more granular picture of employment adjustments after technology adoption, including employer switching and non-employment, we next exploit workers' daily employment biographies.

Table 1 displays average labor market outcomes of males and females in investing and non-investing establishments. Overall, men experience similar employment days across treatment and control groups (columns 1–3). In contrast, females in investing establishments are employed one month less than their peers in non-investing establishments (column 6). Thus, on average, females do worse than males.

These differences are even more pronounced when focusing on days at original employers. On average, female workers are two months less employed in their original investing establishments compared to similar females employed at non-investors, whereas no statistically significant difference arises between males in investing and non-investing establishments. At the same time, women are 39 more days employed at other establishments than their control group peers. Consequently, female workers experience more days unemployed and out of the labor force after separating from digitalizing establishments.

Next, we differentiate workers across the two dimensions routineness and manual versus cognitive occupations (see Appendix A.4). Table 2 reveals that females in non-routine occupations drive the difference in the employment response between investing and non-investing establishments. Females in non-routine manual jobs are on average four months less employed with their investing employer than their peers at non-investing employers. Since these females are only 76 days more employed at other employers, they spend on average 24 days more in unemployment than females in non-investing establishments. A similar pattern arises for females in non-routine

Table 1
Labor market experiences of comparable individuals employed at investors and non-investors.

Average days...	Males			Females		
	(1) Investor individuals	(2) Non-investor individuals	(3) ATT =(1)–(2)	(4) Investor individuals	(5) Non-investor individuals	(6) ATT =(4)–(5)
employed	1712.72	1701.40	11.32*	1630.90	1660.15	−29.25**
at original employer	1499.81	1499.49	0.32	1373.69	1442.43	−68.75**
at other employers	212.91	201.91	11.00	257.21	217.71	39.50**
unemployed	30.47	34.92	−4.44*	45.64	34.45	11.19**
out of labor force	84.80	91.68	−6.88	151.46	133.40	18.06**
Observations	19,615	18,659		9,497	12,389	
$\sum$			60,160			

Notes: The sample includes matched individuals employed on June 30, 2011 in one of the sample establishments. The table presents average labor market outcomes from 2011 to 2016. ATT is the average treatment effect on the treated.
*Statistically significant at the .05 level.
**Statistically significant at the .01 level.

Table 2
Labor market experiences of comparable males and females across different main task types.

Average days...	Males (1)	Females (2)
employed		
non-routine manual	5.61	−41.83**
routine manual	32.35**	1.47
routine cognitive	3.39	−20.38*
non-routine cognitive	1.14	−42.43**
employed at original employer		
non-routine manual	−18.13	−118.32**
routine manual	49.20**	−24.18
routine cognitive	−4.41	−36.68*
non-routine cognitive	−36.70**	−97.32**
employed at other employers		
non-routine manual	23.74	76.49**
routine manual	−16.85	25.65
routine cognitive	7.80	16.30
non-routine cognitive	37.84**	54.89**
unemployed		
non-routine manual	−7.80	24.25**
routine manual	−14.72**	0.94
routine cognitive	2.11	5.12
non-routine cognitive	−0.86	15.37**
out of labor force		
non-routine manual	2.18	17.57
routine manual	−17.63*	−2.41
routine cognitive	−5.51	15.27
non-routine cognitive	−0.27	27.07**
No. of investor individuals	19,615	9,497
No. of non-investor individuals	18,659	12,389
No. of all individuals	38,274	21,886

Notes: The sample includes matched individuals employed on June 30, 2011 in one of the sample establishments. Column 1 (Column 2) presents the difference in average labor market outcomes between males (females) employed at investors and non-investors. Appendix A.3 contains details on the four task dimensions displayed.
*Statistically significant at the .05 level.
**Statistically significant at the .01 level.

cognitive jobs. These effects on (non-)employment are much smaller or even non-existent for male workers.

Zooming into non-routine manual jobs, we observe patterns of gender segregation within this task category: Females are predominantly concentrated in medical-related occupations, such as nurses and emergency medical services, where automated health monitoring devices have been implemented. Conversely, males with non-routine manual tasks are often employed as drivers of vehicles and equipment, which are not yet permitted to be self-driving in Germany.

Taken together, our analysis suggests that employment adjustment processes following the first-time introduction of autonomous and self-contained technologies are most pronounced among females. Our results are consistent with evidence from Portugal and the U.S. documenting that women move out of occupations exposed to automation more quickly than men (Cortes et al., 2020). In other words, digitalization seems to be an example of gender-biased technological change.

4. Conclusion

Using novel individual-level data for Germany, we provide evidence that digitalization is not gender-neutral. The first-time introduction of digital technology in an establishment affects women more strongly than men, both in terms of lower working days at their original employer and days unemployed. We find that employment losses are largest for workers conducting non-routine tasks, and again it is women who suffer most.

These insights on the recent wave of digitalization provide important lessons for assessing future waves of technological change, e.g. that non-routine jobs do not seem to be safe havens anymore and that it is important to avoid a gender bias in technological progress.

Data availability

The data that has been used is confidential

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2023.111256.

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