Digging into the Digital Divide: Workers Exposure to Digitalization and its Consequences for Individual Employment

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Abstract

While numerous studies have analyzed the aggregate employment effects of digital technologies, this paper focuses on the employment development of individual workers exposed to digitalization. We use a unique linked employer-employee data set for Germany and a direct measure of the first-time introduction of cutting-edge digitalization technologies in establishments between 2011 and 2016. Applying a matching approach, we compare workers in establishments investing in digital technologies with similar employees in establishments that do not make such an investment. We find that the employment stability of incumbent workers is lower in investing than non-investing establishments, but most displaced workers easily find jobs in other firms, and differences in days in unemployment are small. We also document substantial heterogeneities in the employment effects across skill groups, occupational tasks performed, and gender. Employment reactions to digitalization are most pronounced for both low- and high-skilled workers, for workers with non-routine tasks, and for female workers. Our results underline the importance of tackling the impending digital divide among different groups of workers.

Zusammenfassung

Während viele Studien die aggregierten Beschäftigungseffekte digitaler Technologien analysiert haben, konzentriert sich die vorliegende Untersuchung auf die Beschäftigungsentwicklung von individuellen Beschäftigten, die der Digitalisierung ausgesetzt sind. Wir nutzen einzigartige verbundene Arbeitgeber-Arbeitnehmer-Daten für Deutschland und ein direktes Maß der erstmaligen Einführung von modernen digitalen (4.0-)Technologien in Betrieben zwischen 2011 und 2016. Unter Verwendung eines Matching-Ansatzes vergleichen wir Beschäftigte in Betrieben, die in digitale Technologien investieren, mit möglichst ähnlichen Beschäftigten in nicht-investierenden Betrieben. Es zeigt sich, dass die Beschäftigungsstabilität von Mitarbeiterinnen und Mitarbeitern in investierenden Betrieben geringer ausfällt als in nicht-investierenden Betrieben. Allerdings finden entlassene Beschäftigte meist leicht Jobs in anderen Firmen, und es gibt nur geringe Unterschiede bezüglich der Arbeitslosigkeitstage. Die Beschäftigungseffekte variieren stark nach Qualifikation, Tätigkeit und Geschlecht. Sie sind am stärksten ausgeprägt für Gering- und Hochqualifizierte, für Beschäftigte mit Nicht-Routinetätigkeiten und für Frauen. Unsere Ergebnisse unterstreichen, dass der digitale Graben zwischen Beschäftigtengruppen politisch angegangen werden sollte.

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1. INTRODUCTION

Modern forms of technological progress like digitalization, automation, and artificial intelligence (AI) are fundamentally changing working environments. These disruptive innovations have prompted fears of massive employment losses and technological unemployment. In recent years, a vastly growing literature in economics and the social sciences has empirically investigated these issues mainly based on aggregate data for the economy, specific sectors, and establishments, but analyses at the level of individual workers are rare (surveys are provided, inter alia, by Mokyr et al. 2015, Furman and Seamans 2019). This paper contributes to the empirical literature by focusing on how individual workers are affected by the first-time introduction of digitalization technologies in their establishments in terms of employment. We compare workers in establishments investing in cutting-edge digital equipment, such as smart factories, internet of things, or self-learning analytical tools, with similar employees in establishments that do not make such an investment. This allows us to trace workers' different labor market trajectories after being exposed to digitalization and to account of heterogeneities among the workforce in terms of skills, tasks, and gender.

The economic literature on the labor market effects of the adoption of new technologies comprises various strands and different levels of empirical analysis.[1] One primal strand has estimated to which extent occupations are at risk of being substituted by computers and algorithms (e.g., Frey and Osborne 2017), suggesting a substantial negative employment effect of new technologies. When acknowledging that job activities vary across individuals within the same occupation and that novel tasks allow a flexible adoption of human labor to technological progress, the negative estimates shrink significantly (Arntz et al. 2017) or even disappear entirely (Autor et al. 2015, Gregory et al. 2019). Furthermore, several related lines of research use specific technology measures to investigate the employment effects of the adoption of new technologies. The diffusion of information and communication technologies (ICT) across industries (Michaels et al. 2014) and establishments (Böckerman et al. 2019) seems to increase employment for high-skilled workers at the expense of routine and middle-skilled labor demand. In the face of advancing automation, especially in the manufacturing sector, researchers have used the prevalence of industrial robots as a measure for technological progress. The implementation of first generation 1990s manufacturing robots has restructured the workforce composition in U.S. establishments away from production workers towards more high-skilled workers. Numerous studies find a negative employment effect of robots for the American and Chinese labor market (Acemoglu and Restrepo 2020, Borjas and Freeman 2019, Cheng et al. 2019, Giuntella and Wang 2019). In Europe and several OECD countries, the estimated overall employment effect is neutral as negative

1 One strand not followed in this paper focuses on the innovation activity of establishments. Innovative establishments, measured as firms with high R&D expenditures (Aghion et al. 2017) or large numbers of granted patents (Autor and Salomons 2018, Mann and Püttmann 2018), do not shrink their workforce with increasing innovation activity but rather increase non-routine high-skilled and non-routine service employment.

employment effects for low-skilled or manufacturing workers are offset by an increase in high-skilled and service jobs (Dauth et al. 2021, EU Commission 2016, Graetz and Michaels 2018, Autor and Salomons 2018). Recent studies increasingly focus on firm-level outcomes and restructuring processes within firms (Acemoglu et al. 2020, Dixon et al. 2020, Bonfiglioli et al. 2020, Humlum 2019, Koch et al. 2021).

Surprisingly little is known about the employment effects of cutting-edge digitalization and automation technologies beyond industrial robots. Theoretical considerations predict that the latest wave of automation hits different tasks than previous technology, and the diffusion rates are much faster and penetrate all sectors of the economy (Brynjolfsson et al. 2018, Barbieri et al. 2020). Given its potential to affect all types of jobs, it is crucial to examine the labor market consequences of the latest technological progress empirically. The main reason for this gap in the literature is probably the scarcity of data sets that provide concrete measures of the degree of digitalization and include service technologies.[1]

A second gap in the literature is that in the context of technological change, little attention has been paid to the labor market experience of individual workers (as compared to shifts in the composition of aggregate employment). Using routine intensity of occupations as a proxy for technological change, some studies document a decreasing employment rate of routine, middle-skilled employees (Smith 2013, Groes et al. 2015, Cortes 2016, Bachmann et al. 2019). Individual-level effects of automation are analyzed by Dauth et al. (2021) and Bessen et al. (2019). The former look at the exposure of workers to industrial robots measured at the industry level. The latter use expenditures for third-party automation services as an establishment-level measure of new technologies. With Dutch matched employer-employee data, Bessen et al. (2019) find that individuals are more likely to separate from automated than non-automated establishments.[2] To our knowledge, we are the first to use a direct measure of the introduction of digital technologies in establishments and analyze how this technological shock affects the employment of individual workers in these plants. It is crucial to investigate the individual-level impact of digital technologies as various types of workers might be differently affected by new technologies. Looking at more aggregated levels might cover up opposing micro-level effects. Furthermore, following individual workers over time enables us to see how the digitalization shock affects their employment prospects not only inside the digitalizing establishment but also when separating from this establishment.

Considering the paucity of empirical evidence on direct individual-level impacts of establishment-level implementation of digitalization technologies, this study contributes to the existing literature mainly in three

1 Felten et al. (2018) provide a method to link AI advances to occupational tasks in the U.S., which seems to be complementary to human labor (Fossen and Sorgner 2019). Webb (2020) studies the occurrence of machine learning algorithms in U.S. patent data to measure AI exposure of occupations.

2 In contrast, Domini et al. (2020) show that imports of automation-intensive intermediate goods lead to lower separation rates in investing establishments and positively impact worker flows at the establishment level. However, this study is limited to establishment-level employment dynamics in the French manufacturing sector.

ways. First, we employ a novel direct measure of the first-time introduction of digital technologies in establishments. Using the "IAB-ZEW Labor Market 4.0 Establishment Survey", we analyze how the implementation of cutting-edge digital technology in establishments that did not make use of such technology in 2011 affected employment until 2016. Applying a matching approach, we compare incumbent workers in investing and non-investing plants, taking into account that the first-time introduction of digital technology may be an endogenous decision of the plant but can be regarded as an exogenous shock to the individual employees in these plants. Second, constructing a linked employer-employee data set from the German Social Security Administration, we study the resulting individual-level impacts of digitalization in the plants affected. Our high-frequency micro data allows tracking individual workers' experience on a daily basis, enabling us to shed light on what has happened to these workers after the introduction of digitalization. In addition to workers who stayed in their establishments over the entire observation period, we observe workers who leave their original employers across different labor market states. Consequently, we can investigate whether employment stability is higher in digital or other plants and whether employees end up unemployed. Third, we provide in-depth insights on heterogeneous subgroups of workers as our administrative micro data provides information on individual characteristics such as formal education and gender as well as on job characteristics such as occupational tasks. Thus, we can offer a differentiated answer to the frequently asked question which individuals gain and lose when exposed to recent technological progress.

Our results show that the first-time introduction of digital technology in an establishment leads to a higher probability of leaving the establishment for individual workers. Simultaneously, individuals separating from plants investing in digital technology seem to have better re-employment possibilities than individuals separating from non-digital plants, and there is no sizeable difference in days in unemployment. We document substantial heterogeneities in the employment effects across skill groups, occupational tasks, and gender. Both low-skilled and high-skilled workers work fewer days in investing establishments, whereas medium-skilled workers with vocational training experience high employment stability. Interestingly, the new digital technologies mainly affect workers with non-routine tasks irrespective of manual or cognitive work activities. Furthermore, it is primarily the female workforce that is fewer days employed in investing establishments compared to control group workers. These results imply that digitalization does not seem to be gender-neutral and that even high-skilled and non-routine employment is not safe anymore.

The remaining part of the paper is organized as follows. Section 2 provides some theoretical considerations. Section 3 introduces the matched employer-employee data and describes the sample. Section 4 explains our empirical strategy. Section 5 presents the empirical results, highlighting the impact of the first investment in digital technologies on individual workers as well as heterogeneities across different worker subgroups. Section 6 discusses some robustness checks on the main findings of the paper, and section 7 concludes.

2 THEORETICAL BACKGROUND

From a theoretical perspective, the net effect of the introduction of automation and digital technologies is ambiguous. The aggregate impact of the diffusion of robots (Benzell et al. 2015) or AI (Furman and Seamans 2019) is inconclusive since a labor enhancing effect driven by rises in product demand counteracts the more apparent direct labor displacement effect. Using a task-based approach (initially proposed by Autor et al. 2003, Acemoglu and Autor 2011), Acemoglu and Restrepo (2018b, c) develop a comprehensive framework that models new technologies not only as factor augmenting but also allows for the creation of new tasks. As in previous theoretical models, digitalization takes over tasks previously performed by labor. This displacement effect will decrease labor demand, employment, and wages. A countervailing mechanism is the productivity effect: digital technologies might lead to productivity gains, which reduce production costs and prices, resulting in increasing product demand, labor demand, employment, and wages. One novel aspect of the task-based framework recognizes the accompanying creation of new tasks in which labor has a comparative advantage. The creation of new tasks might increase labor demand (Acemoglu and Restrepo 2019). Acemoglu and Restrepo (2018c) understand "deepening automation" as another countervailing productivity effect that accounts for productivity gains in tasks that have already been digitalized. The framework has been further developed (see, for instance, Agrawal et al. 2019, Bessen 2018, Caselli and Manning 2019) and has been established as the main theoretical framework for recent empirical studies.

Since economic theory is not able to give a definite answer on digitalization's net effect on employment, several studies highlight the need for empirical evidence (Acemoglu and Restrepo 2018b, Agrawal et al. 2019, Bessen 2018, Barbieri et al. 2020). Especially heterogeneities within industries are still an open question, as the lack of establishment-level data leaves the adoption process within establishments unclarified. Therefore, there is a consensus in the literature that establishment-level evidence is needed (Raj and Seamans 2018, Furman and Seamans 2019). Furthermore, the task-based approach highlights the importance of individual-level outcomes as the exposure to automation might vary considerably across individuals even within the same occupation (Arntz et al. 2017), and this is the path we will take in our empirical investigation.

Previous literature has shown that technological change has diverse effects across the skill endowments of workers. The diffusion of information technologies like computers since the 1990s increased the demand for high-skilled workers disproportionally at the cost of less-educated low- and middle-skill workers (e.g., Goldin and Katz 2009). The continuing technological progress in ICT and automation technology leads to polarization in skill endowment of labor demand. Low-skilled workers and high-skill workers employment perspectives increased at the expense of middle-skilled employment (e.g., Autor and Dorn 2013, Michaels et al. 2014). From a theoretical perspective, Acemoglu and Restrepo (2018a) demonstrate that the latest technological advances such as AI may for the first time also have the potential to substitute more complex, high-skilled jobs. Webb (2020) strengthens this hypothesis by predicting (based on patent data) that high-skilled occupations, for example highly specialized medical occupations like radiologists, are most exposed to AI. To the best of our knowledge, there seem to be no empirical investigations available that study the subsequent labor market trajectories of workers after the adoption of the latest technologies such as AI and machine learning (ML) devices.

Looking beyond the formal education levels of workers, workers are to different extents affected by technological progress even within occupations. Very importantly, it is the tasks that workers conduct on their job which are at risk of automation rather than an occupation as a whole (Brynjolfsson et al. 2018). Computers and automation technology have both theoretically and empirically the potential to substitute routine tasks (Autor et al. 2003, Autor and Dorn 2013, Goos et al. 2014). Recent technical advances such as ML algorithms and AI, however, have differential effectiveness in different tasks, and consequently, the impact of cutting-edge technology diffusion will be uneven across occupations (Brynjolfsson et al. 2018, Levy 2018). Using patent data on automation and AI innovations, empirical evidence hints that especially cognitive tasks are replaceable by technology (Kogan et al. 2020, Webb 2020). Up to now, an empirical analysis of the labor market effects across task groups is lacking.

The importance of workers' activities on their job in discussing the technological impact on employment implies noticeable differences in the gender distribution across occupations. On the one hand, females disproportionally work in administrative support and service occupations and consequently in other professions than men (e.g., Blau and Kahn 2017). On the other hand, even within the same occupation, men conduct different tasks than women (Brussevich et al. 2019). This self-selection of women into different professions than men and the gender-specific task bundles even within the same occupations might yield heterogeneous automation risks by gender. This disparity, though, has not yet received much attention in the economic literature.

This paper fills these gaps in the literature by presenting empirical evidence on individual-level impacts of automation using a direct measure of the first-time implementation of cutting-edge digital technologies in establishments. Our empirical analysis will not investigate aggregate labor market effects but focus on digitalization effects at the workplace. If automation substitutes some tasks and creates new labor-intensive tasks (Acemoglu and Autor 2011, Acemoglu and Restrepo 2018c), the composition of employment in the establishment should change. At the individual level, capital-labor substitution implies the displacement or re-allocation of some workers within and across establishments. In contrast, other workers with skills that are complementary to digitalization face better employment prospects.

These considerations and the availability of our linked employer-employee data suggest addressing the following research questions in our empirical analysis, where we look at establishments that did not previously use digital technology. We analyze how the introduction of digital technology affects the jobs of individual workers (compared with similar workers in other establishments that did not introduce digital technology).

More specifically, we examine which workers leave the initial employer and document the labor market experience of separating individuals to analyze their re-employment chances and unemployment risks. Theory suggests that although the aggregate employment effects might be modest, opposing heterogeneous effects across different worker subgroups might be leading to rising inequality among workers. Against this background, we provide empirical evidence on individuals' labor market reaction across skill groups, occupational task groups, and gender.

3 DATA

To analyze the employment reactions of individuals exposed to digitalization, we use a novel linked employer-employee data set that combines establishment-level data on the introduction of digital technologies with extensive individual-level data from the German Social Security Administration.

The establishment-level data stem from the "IAB-ZEW Labor Market 4.0 Establishment Survey"[3], a representative establishment survey conducted in March 2016.[4] The sample was stratified by regional location, size, and sector of the establishment. It was drawn from the universe of all establishments with registered employment subject to social security contributions at the Federal Employment Agency of Germany.[5] Both manufacturing and service establishments participated in the CATI-based interviews, and, in total, 2,032 establishments responded. For a thorough assessment of the company's general situation, key characteristics such as revenues, utilization of third-party services, working hours and the size and composition of the workforce are inquired. Most important for our study, the questionnaire includes the establishments' degree of digitalization. First, the data contain managers' or technical experts' perception of the relevance of digital technologies for their business and the associated opportunities and risks. Second, the data include the automation level of all work equipment in the establishment. For both production technologies and office and communication technologies, we can distinguish between the share of cutting-edge digital technologies (also called 4.0 technologies with reference to the fourth industrial revolution) and the share of older technology classes. These modern 4.0 technologies conduct work processes self-contained and automatically. Examples of such production technologies include cyber-physical and embedded systems and smart factories, big data analytical tools, or cloud computing systems in office and communication technologies (see Appendix Table 1 for more examples of technologies belonging to each technology class).

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3 Due to data protection requirements, these new data are not yet available to the scientific community. However, the Research Data Center (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) will provide a scientific use file in the future (see http://fdz.iab.de).

4 For a more detailed description, see Arntz et al. (2019), Genz et al. (2020), and Genz et al. (2019b).

5 The employment notifications collected by the Federal Agency are registered at the establishment-level and not at the firm-level. Therefore, we refer in the remaining of the paper to establishments or plants as the location of work.

Since the technology-specific distribution of the work equipment is reported for the years 2011 and 2016, we can identify investments into new digital technologies that took place between 2011 and 2016.

Note that three related papers use the same survey data but pursue different approaches and identification strategies. Merging yearly social security data to the surveyed establishments, Genz et al. (2019b) show that investments in new digital technologies at the establishment level positively affect the wages of incumbent workers staying in these establishments, especially of low- and medium-skilled workers. Arntz et al. (2019) explore job creation and job destruction channels at the establishment level, whereas Genz et al. (2020) examine employment and wage dynamics at the individual level. However, these two studies use a different establishment selection, apply distinct identification strategies, and focus on other outcome variables.

We restrict our attention to establishments that did not use cutting-edge digital devices in 2011 to identify the employment effect of the first introduction of modern 4.0 technologies on incumbent workers.[6] Consequently, we exclude establishments founded after 2011 and establishments that do not employ any worker subject to social security contributions. We complement the survey data with administrative data from the Establishment History Panel (BHP), which provides a wide range of longitudinal, administrative establishment characteristics.[7] As Table 1 shows, these restrictions leave us with 1,024 establishments. More than one-quarter of these establishments invest in modern digital technologies until 2016 (hereafter referred to as *investors*) whereas the majority of establishments refrain from such investments until 2016 (hereafter referred to as *non-investors*). One limitation of this data is that we do not know precisely in which year (between 2011 and 2016) the investment took place. A closer look at the establishment data (not reported in Table 1) shows that although investors also invest in modern production technologies, they mainly introduce cutting-edge digital technologies to their office and communication equipment from 2011 to 2016. Within the group of investing establishments, the digital share among the office and communication equipment rises from 0% to 13.3%.

6 Note that in terms of establishment and workforce characteristics, this restricted sample of establishments not yet using digital technologies does not differ substantially from those survey establishments that already use digital technologies in 2011.

7 This study uses the weakly anonymous Establishment History Panel 1975-2017 (Version: BHP_7517_v1). Data access was provided by the Institute for Employment Research (IAB) of the German Federal Employment Agency. DOI: 10.5164/IAB.BHP7517.de.en.v1. For further information, see Schmucker et al. (2018).

Table 1: Sample composition

	(1) All	(2) Investors	(3) Non-Investors
Selection process			
Establishments	1,024	271	753
Workers employed at non-digital establishments on June 30, 2011	98,157	39,100	59,057
Surviving until June 30, 2016	97,627	38,894	58,733
Aged 15-60 on June 30, 2011	92,890	37,230	55,660
Complete employment notification on June 30, 2011	91,013	36,444	54,569

Notes: Establishments that do not use digital technologies in 2011 and that employ at least one worker subject to social security contributions on June 30, 2011. Establishments in the temporary agency sector are excluded from the analysis. The sample excludes individuals with missing information in important variables (nationality, education, part-time employment notification, requirement level of the job, main task type of the occupation) on June 30, 2011.
Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.

We create a matched employer-employee data by linking detailed German individual-level employment records through a unique establishment identifier available in both data sets. The individual-level data comprise the Integrated Employment Biographies (IEB) provided by the IAB.[8] They contain data on employment, benefit receipt, participation in measures of active labor market policy, and job-search status. Employees not subject to social security contributions, such as civil servants, self-employed and students, are not documented. We link the employment records of all the 98,157 individuals employed on June 30, 2011, in one of the surveyed establishments to the establishment-level data. We observe workers' full employment biographies from 1999 to 2016. They contain detailed individual-level information, including date of birth, gender, nationality, education, and job-specific information such as occupation, part-time employment, and marginal employment. A major advantage of the data is that we can track workers across different labor market states on a daily basis, allowing us to observe all days worked, and we can distinguish between days in unemployment and days out of the labor force.[9]

Despite its high accuracy and reliability, the IEB has a few moderate limitations. First, information on workers' formal education suffers from missing values and inconsistencies with the reporting rule. We apply a standard version of the approach proposed by Fitzenberger et al. (2006) and impute the information concerning education according to the information available in individuals' employment history. Second, due to the reclassification of the German Occupation Codes (KldB1988 to KldB2010), the occupational variable contains a significant amount of missing values in 2011 and 2012. Therefore, we apply a harmonization to reduce

8 For our analyses we use administrative data of the Institute for Employment Research (Version: IEB V13.01.01 – 190111). The data are social data with administrative origin which are processed and kept by IAB according to Social Code III. There are certain legal restrictions due to the protection of data privacy. The data contain sensitive information and therefore are subject to the confidentiality regulations of the German Social Code (Book I, Section 35, Paragraph 1).

9 The status "out of labor force" includes also employment states that do not fall under the reporting obligation of the German Social Security Administration as for instance civil service and self-employment.

missing occupational information, as explained in appendix section A.2.1. Third, we harmonize the information on individuals' nationality registered in the employment notifications at the Federal Agency, which is explained in appendix section A.2.2. Finally, the spell structure of the IEB allows multiple employment and contemporaneous unemployment or job search periods at a time. As explained in appendix section A.2.3, we restrict the attention to one main (un)employment event per day, leaving side-jobs outside the scope of the analysis.

The employment records of the IEB data contain very detailed, disaggregated occupational information, the German classification of occupations KldB2010, which describes the occupation workers perform in the employment relationship with the employer. This occupation variable allows us to assign a core task to each observed occupation by linking task information from the German occupational database BERUFENET to the employment records.[10] The core task requirements for each occupation are constructed following Dengler et al. (2014) and differentiate occupations across the two dimensions routineness and activity load following Autor et al. (2003).[11] Workers repeatedly conducting tasks that follow well-described rules are labeled as routine occupations, while non-routine activities require a high degree of flexibility from the worker. The second dimension differs between manual and cognitive work requirements. Occupations that predominantly involve physical activities are classified as manual jobs, whereas mental workload is referred to as cognitive work requirements. This operationalization yields four core task types: non-routine manual, routine manual, routine cognitive, and non-routine cognitive.[12]

We exclude persons who die within the observation period from June 30, 2011 to June 30, 2016. We focus on individuals aged 15-60 employed on June 30, 2011 in one of the sample establishments (see Table 1). Our sample shrinks by about 1,800 individuals who record missings in crucial variables like skills, tasks, and part-time work. Consequently, on June 30, 2011 we observe 91,013 individuals with complete employment

[10] The BERUFENET is an online database that describes all occupations of the German classification of occupations KldB2010. The list contains recognized formal occupations as it lists vocational training occupations, further training occupations, university occupations, and study subjects. Experts of the German Federal Employment Agency update the content on a daily basis and provide very detailed information about every single occupation, e.g., entrance requirements, typical activities performed in the occupation, work tools used on the job, and employment perspectives. The database is freely accessible under https://berufenet.arbeitsagentur.de/.

[11] The task operationalization of Dengler et al. (2014) follows the approach in the U.S. and uses expert knowledge about competencies and skills that are usually required for performing an occupation. For Germany, also occupational task measures exist which use survey data, for example the approach proposed by Spitz-Oener (2006). The survey task operationalization faces, however, several limitations, as for example survey items to measure tasks are not consistent over time. A critical discussion of the survey data that is the basis for such operationalization is provided by Rohrbach-Schmidt and Tiemann (2013) and Autor (2013).

[12] German task operationalizations often use five task categories by additionally separating non-routine cognitive task into non-routine analytical and non-routine interactive tasks. We refrain from making this additional differentiation for two reasons. On the one hand, we want to connect to previous studies and facilitate the comparison to existing theoretical and empirical studies in the U.S. On the other hand, non-routine interactive tasks are commonly used across multiple occupations, but few occupations have non-routine interactive tasks as core activities and would therefore be referred to as non-routine interactive occupations.

notifications. In total, 36,444 of these workers are employed in establishments investing in digital technologies until 2016, whereas 54,569 employees work in establishments that are not investing until 2016.

4 EMPIRICAL STRATEGY

We analyze the (non-)employment of comparable workers of investing and non-investing establishments to test whether and how the introduction of digital technologies affects incumbent workers' employment. We define the first-time introduction of digital technologies in establishments as our treatment, thus considering plants not using any digital devices in 2011 but having in place digital technologies in 2016 as investors, and the workers employed in these establishments in 2011 as treated individuals. Comparable workers in establishments not using any digital technology in 2011 and 2016 form our control group of untreated individuals. The "treatment effect" is the difference in the development of employment until 2016 between the workers in investing establishments and comparable workers in non-investing establishments. Although the first-time introduction of digital technology may be an endogenous decision of the plant, it can be regarded as exogenous for the incumbent workers who were employed in the establishments at the beginning of the observation period 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 as comparable as possible to the treated workers in investing establishments. Generally, the application of matching approaches needs to satisfy the conditional independence assumption. In our context of digital investments, the identifying assumption is that workers in establishments investing in digital technologies (our treatment group) would have experienced the same employment development as the workers in non-investing establishments (control group) if they had not experienced their establishments' investment in digital technologies. The credibility of this assumption depends on the included observable characteristics entering the matching approach. To ensure that workers are similar between the two groups, we restrict our sample to the existing workforce before the investment takes place and we control in our matching approach for a large number of individual, job, and establishment characteristics.[13]

We apply a nearest neighbor matching approach that combines exact matching and propensity matching (as robustness tests, we also make use of other matching approaches and report their results in section 6). In our baseline specification, we match treated and untreated employees on pre-treatment characteristics as follows: We require an *exact matching* of individuals on gender and age group (above or below 40 years of age in 2011) so that we avoid mixing up potentially different results for men and women or younger and older

[13] Rosenbaum and Rubin (1983) address potential sample selection problems and propose the estimation of propensity score models to remove bias due to observable covariates in order to estimate causal effects. Caliendo and Kopeinig (2008) describe the application of propensity score matching and guide through the implementation in empirical designs.

workers. We also exactly match individuals on their formal level of skills (low-skilled: no vocational training, medium-skilled: vocational training; high-skilled: university degree) and on the tasks they perform (non-routine manual, routine manual, routine cognitive, non-routine cognitive). Finally, we require an exact matching on two important characteristics of the establishments where workers are employed, namely their sector affiliation (production or service sector) and their size in terms of employment categories (1-29 employees, 30-149 employees, 150 and more employees). This requirement ensures that we do not confuse potentially different results for workers in small or large establishments and different sectors.

In addition, we apply *propensity score matching* for additional worker and establishment characteristics. The additional worker characteristics for the estimation of the propensity score from a probit regression include age, part-time work, occupation (and an interaction term between the latter two variables), a routine-work dummy based on occupation, daily wage, nationality (German or non-German), and an interaction term between nationality and the urban area of the residence of living. Moreover, our rich data set also allows us to include information on workers' employment biography such as tenure (up to ten years or more), the number of previous employers, the number of years since the first appearance in the data, and the share of days in employment in total days observed. Additional establishment characteristics include finer grids on sector aggregates, establishment age (three categories), number of employees subject to social security contributions, employment turnover rate (measured as the personnel fluctuation rate between 2010 and 2011), urban area location (four categories), and regional location (North, West, South, East Germany). We restrict our sample to the region of optimal common support following Crump et al. (2009) to estimate our average treatment effect on the treated most precisely. The matching process applies one-to-five nearest neighbor matching with replacement. Consequently, each worker in an investing establishment is matched to five similar colleagues in non-investing establishments, resulting in statistical twin groups. This procedure ensures that the workers in the two groups of investing and non-investing establishments are comparable at the starting point of our analysis.

Table 2 indicates that our matching was successful. Our matched sample contains 62,420 workers, of which 30,068 are employed in investing establishments, and 32,352 are employed in non-investing establishments. A comparison of the mean values of variables before matching reveals some statistically significant differences between workers in investor and non-investor establishments (columns 1-3). For instance, workers in establishments investing in digital technologies tend to be less often female, high-skilled, and part-time workers, and they have slightly different occupational tasks and labor market experience than workers in non-investing establishments. Reducing the sample to the subset of comparable individuals in investing establishments (column 4) and in non-investing establishments (column 5) by applying our described matching approach successfully dissolves statistically significant differences.[14]

The main question to answer in this paper is: (how) does the first-time introduction of cutting-edge digital technologies within establishments affect the employment of incumbent workers? The first adjustment channel prominently discussed in the media is whether workers separate from their establishments due to automation. Figure 1 displays the yearly share of workers employed without any interruption at investing and non-investing establishments. Continuous employment is defined as remaining employed at the original employer without unemployment interruptions, switches to other employers, and less than 31 days of non-participation. This figure is constructed using the sample of matched workers. The share of workers is measured on June 30 each year between 2011 and 2016 and is weighted with the matching weights.

Table 2: Mean values of individual characteristics of investor and non-investor individuals

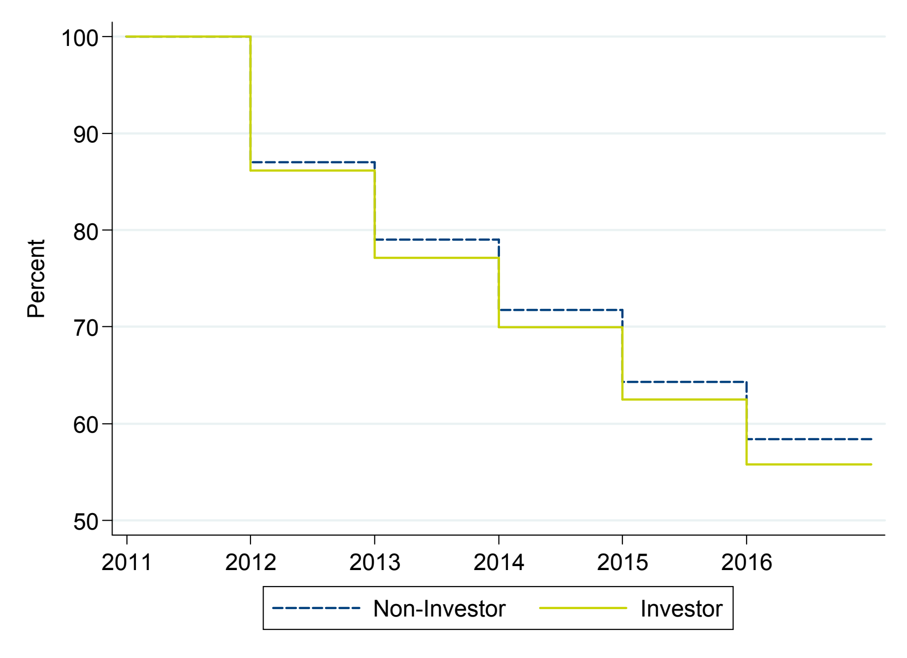
	(1) Investor individuals (before matching)	(2) Non-investor individuals (before matching)	(3) t-test (1)-(2)	(4) Investor individuals (after matching)	(5) Non-investor individuals (after matching)	(6) t-test (4)-(5)
Individual characteristics						
Share of females	.39916	.46143	-18.60**	.32656	.32656	-0.00
Share of foreign nationality	.05803	.0401	12.50**	.04812	.04923	-0.63
Mean age in 2011 (in years)	40.545	40.667	-1.57	40.719	40.828	-1.18
Qualification level						
low-skilled	.11173	.10165	4.85**	.10829	.10829	0.00
medium-skilled	.69183	.68576	1.94	.70058	.70058	0.00
high-skilled	.19644	.21259	-5.90**	.19113	.19113	0.00
Job characteristics						
Main task						
non-routine manual	.18121	.20563	-9.10**	.10526	.10526	0.00
routine manual	.18889	.1558	13.06**	.22439	.22439	-0.00
routine cognitive	.31794	.31505	0.92	.35549	.35549	0.00
non-routine cognitive	.31196	.32352	-3.67**	.31485	.31485	-0.00
Share of part-time workers	.17709	.25908	-29.10**	.14594	.14337	0.89
Previous labor market experience (since 1999)						
Years since first appearance	10.554	10.416	6.79**	10.641	10.626	0.61
Share employed	.89483	.85792	27.62**	.8979	.89949	-1.12
No. of previous employers	2.7753	2.8945	-8.31**	2.7442	2.7409	0.20
No. of individuals	36,444	54,569		30,068	32,352	
∑	91,013			62,420		

Notes: Shares are displayed as fraction [0,1].The information refers to the base year of 2011.
*** and * denote statistical significance at the 1 and 5 percent level. Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.*

14 Furthermore, Rubin's B falls from 30.4 before matching to 2.2 after matching, and Rubin's R increases from 0.89 to 1.00, which again underscores the high quality of matching (for further details on the thresholds for sufficient balance, see Rubin (2001)).

As is evident in Figure 1, the percentage of workers still employed at the original employer is lower and decreases more strongly across time in investing establishments. In 2012, 86.2% of the pre-existing workforce from 2011 is still employed at investing establishments, and this fraction shrinks strongly until 2016 to only 55.8%. In 2016, the share of workers continuously employed at their original employer is 2.61 percentage points lower in investing than in non-investing establishments, and this difference is highly statistically significant. This result suggests that pre-existing workers are less likely to remain employed at their employers due to technology adoption. Figure 1 also highlights that workers' probability of separating from their employer following the first-time introduction of the latest technologies is rising over time compared to workers who are not exposed to digital technologies.

Figure 1: Continuous employment at investing and non-investing establishments



Notes: The figure displays the share of 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. Unobserved periods of up to 30 days count as continuous employment.
Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.

Separation from the original employer is only one dimension to measure displacement effects after technology adoption. The following section goes beyond the yearly observation of the employment status by using daily employment biographies. To obtain a complete picture of the resulting adjustment channels, we also shed light on the unemployment and non-employment periods of workers after technology adoption.

5 Results

Our data set enables us to look at four possible outcomes in terms of (non-)employment that individuals may experience after being subjected to the introduction of the latest digital technologies. First, we can measure the direct impact of introducing digitalization technologies by calculating the number of days that affected and non-affected individuals are employed at their original establishments in our observation period from June 30, 2011 to June 30, 2016.[15] Of course, a higher separation rate from the original employer would not necessarily mean that individuals struggle in the labor market. If fired, they may find subsequent employment in other establishments or employees may voluntarily switch employers for the sake of career progress. Therefore, we use the number of days individuals are employed in other establishments as a second measure. Third, we have information on the number of days individuals spend in unemployment. Finally, we also know the number of days employees are out of the labor force.

Starting with the first and arguably most important outcome variable, Table 3 shows that over the observation period 2011 to 2016, individuals at investing establishments record, on average, 25 days less in employment with their original employer than comparable workers in non-investing establishments. At the same time, they are, on average, 22 more days employed at other establishments. Both differences, which reflect the average treatment effects on the treated (ATT), are statistically significant at the 1% level, and they are also economically relevant. In contrast, differences in workers' days of unemployment or out of the labor force are marginal and not statistically significant. These results thus suggest that digitalization does cause (moderate) employment effects. However, although affected workers separate from their original employer more often than comparable non-affected workers, they seem to find jobs elsewhere easily and do not experience prolonged unemployment.[16] Put differently, individuals initially employed at establishments investing in digital technologies are indeed hit by digitalization, but their overall employment prospects are not worse than those of individuals in comparable non-investing establishments.

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[15] We are aware that adjustments may also occur via the number of working hours. Although we do not have information about the exact number of working hours in our sample, we know whether individuals are working full- or part-time. We can see that switches from full- to part-time work (or the reverse) are rare and do not differ substantially between workers in investing and non-investing establishments.

[16] Moreover, individuals who separate from their investing employer do not switch sectors or broad occupational groups more often than matched individuals leaving non-investing establishments to find re-employment.

Table 3: Labor market experiences of all comparable individuals employed at investors and non-investors

Average…	(1) Investor individuals (treatment group)	(2) Non-investor individuals (control group)	(3) ATT	(4) *t*-stat
Days employed at original employer	1457.51	1482.66	-25.14	-3.77**
Days employed at other employers	228.11	206.15	21.96	4.14**
Days unemployed	35.94	33.88	2.06	1.27
Days out of labor force	106.43	105.31	1.12	0.34
No. of individuals	30,068	32,352		
∑	62,420			

Notes: The sample includes matched individuals who were employed on June 30, 2011 in one of the sample establishments. The information summarizes the averages over the observation period June 30, 2011 to June 30, 2016.
*** and * denote statistical significance at the 1 and 5 percent level.*
Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.

The results across all workers may mask differences between workers of different skill levels. Previous technological advances such as computers disproportionally displace low-skilled and medium-skilled workers who conduct very repetitive jobs (e.g., Goldin and Katz 2009, Autor and Dorn 2013, Webb 2020). Theory suggests that the latest technological advances like AI and ML may, for the first time, also affect high-skilled workers who perform complex and less repetitive activities on their jobs (Acemoglu and Restrepo 2018a). Empirical evidence on the exposure of occupations to AI supports this hypothesis, as high-skilled occupations are strongest exposed to AI applications (Webb 2020). Observing the first-time introduction of the latest digitalization technologies within establishments, we now test the hypothesis that workers adjust differently depending on their skill levels. In our analysis with individual-level data, we can distinguish between three levels of formal skills workers possess. Low-skilled workers do not have completed vocational training, medium-skilled workers have completed vocational training, and high-skilled workers hold university degrees or equivalent qualifications. Table 4 reports our four outcome variables for these three skill groups.

Table 4: Labor market experiences of matched individuals across different qualification levels

Average…	(1) Investor individuals (treatment group)	(2) Non-investor individuals (control group)	(3) ATT	(4) *t*-stat
Days employed at original employer				
low-skilled	1200.32	1253.31	-52.99	-2.15*
medium-skilled	1509.08	1513.81	-4.73	-0.63
high-skilled	1414.21	1498.42	-84.20	-5.36**
Days employed at other employers				
low-skilled	370.37	324.59	45.78	2.48*
medium-skilled	190.16	186.59	3.57	0.58
high-skilled	286.60	210.76	75.84	6.10**
Days unemployed				
low-skilled	59.04	52.74	6.31	1.14
medium-skilled	34.92	33.32	1.60	0.85
high-skilled	26.59	25.24	1.35	0.36
Days out of labor force				
low-skilled	198.26	197.36	0.90	0.06
medium-skilled	93.83	94.28	-0.45	-0.13
high-skilled	100.60	93.59	7.02	0.90
No. of individuals	30,068	32,352		
∑	62,420			

Notes: The sample includes matched individuals who were employed on June 30, 2011 in one of the sample establishments. The information summarizes the averages over the observation period June 30, 2011 to June 30, 2016.

*** and * denote statistical significance at the 1 and 5 percent level.*

Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.

Looking at the number of days workers stay employed at their original employer, Table 4 indicates that it is mainly the low-skilled and the high-skilled workers in establishments undertaking digital investments who record significantly fewer workdays at their original employer. In contrast, medium-skilled workers experience the same risk of separating from their initial employment in investing and non-investing plants. Interestingly, they also record the highest absolute number of days employed at the original employer in both groups of establishments (which may reflect the importance of vocational training in Germany). The same pattern can be observed for the days employed at other employers, which are significantly higher for the groups of low-skilled and high-skilled workers that experienced the introduction of digital technologies. Again, there is no difference between workers affected and not affected by digitalization in the group of medium-skilled workers. As in Table 3, there are no statistically significant differences in workers' days of unemployment or out of the labor force when distinguishing between workers' skill levels.

To summarize, while low-skilled and especially high-skilled workers are affected by the introduction of cutting-edge digital technologies, their separation from investing employers does not seem to translate into struggles in the labor market. The fewer days employed at the original employer transfer almost to the same extent to more days employed at other employers compared to control group workers.

To further understand why employers demand particular skills, it is crucial to consider the activities workers perform on the job. The occupational information allows us to classify jobs according to their core task requirement, which refers to the workers' main activities while conducting a particular profession (e.g., Autor et al. 2003). It is particularly interesting to study the labor market effect of recent technologies as theoretical considerations have suspected that cutting-edge digital technologies for the first time offer the potential to substitute all types of workers (Brynjolfsson et al. 2018, Levy 2018), including those in very complex and decision-making tasks (Acemoglu and Restrepo 2018a). Up to now, empirical evidence on this issue is sparse. Measuring exposure to automation and AI using patent data, first evidence suggests that recent technologies expose cognitive tasks to a high displacement risk (Kogan et al. 2020, Webb 2020).[17] In our analysis, we distinguish between four main task types based on the activities workers predominantly perform in their job. Occupations in which physical work requirements dominate fall into the manual core task categories. Workers who mainly conduct non-routine manual activities within their occupation are, for example, janitors, while the job title machine operator is an example of routine manual occupations as the job activities are repetitive and follow well-described rules. In the remaining two categories, cognitive job requirements dominate, as workers' daily tasks require a high degree of thinking, interactions with other human beings and problem-solving. The job title secretary is a typical example for a routine cognitive occupation, while engineer jobs are non-routine cognitive occupations.

Table 5 displays the outcomes for workers falling into these four categories of tasks. Starting with the number of days employed at the original employer, we see that the shock of digitalization affects all groups of workers negatively, with the notable exception of workers in routine manual jobs.

Table 5: Labor market experiences of matched individuals across different main task types

Average…	(1)	(2)	(3) ATT	(4) *t*-stat

[17] In the literature strand on the adoption of industrial robots, usually the task dimension of workers cannot be measured. One exception is the study by Cheng et al. (2019), which assesses tasks using information collected at the worker level. The authors find that in Chinese plants robots are more prevalent where employees are commonly doing manual tasks. However, this study does not examine the direct displacement effects of industrial robots on workers across different task groups.

	Investor individuals (treatment group)	Non-investor individuals (control group)		
Days employed at original employer				
non-routine manual	1362.17	1430.95	-68.77	-3.55**
routine manual	1505.56	1482.77	22.79	1.32
routine cognitive	1454.49	1472.39	-17.90	-1.72
non-routine cognitive	1458.57	1511.46	-52.90	-4.94**
Days employed at other employers				
non-routine manual	274.46	224.10	50.36	3.23**
routine manual	186.79	190.60	-3.81	-0.28
routine cognitive	226.07	211.24	14.82	1.87
non-routine cognitive	244.36	205.49	38.87	4.23**
Days unemployed				
non-routine manual	61.87	52.41	9.46	1.38
routine manual	38.37	41.69	-3.33	-0.81
routine cognitive	32.50	31.06	1.43	0.56
non-routine cognitive	29.44	25.29	4.15	1.98*
Days out of labor force				
non-routine manual	129.50	120.55	8.96	1.01
routine manual	97.28	112.94	-15.66	-1.72
routine cognitive	114.95	113.31	1.64	0.29
non-routine cognitive	95.63	85.75	9.88	2.25*
No. of individuals	30,068	32,352		
	∑ 62,420			

Notes: The sample includes matched individuals who were employed on June 30, 2011 in one of the sample establishments. The information summarizes the averages over the observation period June 30, 2011 to June 30, 2016.
*** and * denote statistical significance at the 1 and 5 percent level.*
Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.

Probably the latter group was already affected in previous years by purely mechanical automation technologies and previous ICT (Autor et al. 2003, Autor and Dorn 2013, Goos et al. 2014). The latest digital technologies mainly seem to affect non-routine workers. Whether they are doing manual or cognitive work, workers with non-routine tasks spend significantly fewer days at their original employer in investing than non-investing establishments. In parallel, workers with these two main tasks types record more days employed at other employers when initially employed in an establishment that invests in digital technology. These results suggest that the new digital technologies penetrate into domains that in the past were regarded as safe havens of employment (Barbieri et al. 2020). Concerning non-employment, it is mainly the rather specialized group of workers with non-routine cognitive tasks that seems to be more strongly affected by digitalization. Non-routine cognitive workers, on average, spend four days more in unemployment and almost ten days more out of the labor force when initially employed in an establishment that decided to invest in digital technology compared to the control group workers. However, considering that these differences accumulate across the five-year observation horizon, the economic relevance of these differences is negligible.

To summarize, consistent with theory, almost all types of workers across different occupational tasks are affected by adopting the latest technologies. Unlike previous technology shocks, also non-routine cognitive workers separate from investing employers. These complex cognitive workers cannot translate the fewer days employed at the original employer fully into re-employment at other establishments. However, the magnitude of the experienced periods in non-employment is not economically relevant.

The observed heterogeneous employment adjustment across workers with different core tasks directly raises the question of whether men and women are differently affected by the adoption of digital technologies. Previous studies have shown that females disproportionally work in administrative support and service occupations while men typically work in blue-collar jobs (e.g., Blau and Kahn 2017). This gender segregation is also evident in our sample, as almost one-third of all male workers conduct routine manual occupations while only 8% of females work in blue-collar occupations. Additional to these heterogeneities in the self-selection into occupations, even within given occupations women and men specialize in a different set of task bundles (Brussevich et al. 2019). To test empirically whether males and females react differently to the first-time introduction of the latest technologies, columns 1 and 2 of Table 6 display the resulting (non-) employment adjustment process across genders. Overall, female workers are, on average, two months less employed in adopting establishments compared to control group workers, whereas no statistically significant difference arises between males in adopting and non-adopting establishments. At the same time, women are, on average, 38 more days employed at other establishments compared to their control group peers. Consequently, female workers experience more days unemployed and out of the labor force after separating from adopting establishments. This pattern holds for female workers across all skill groups and is most pronounced for women in non-routine manual occupations (that include, for instance, nurses).[18] Concerning male workers, the overall pattern emerges that especially high-skilled workers in establishments undertaking digital investments record significantly fewer workdays at their original employer. However, the fewer days employed at the initial employer for high-skilled workers transfer again to more days employed at other employers than control group workers, without notable differences in unemployment and non-employment experiences. Taken together, our analysis suggests that employment adjustment processes following the first-time introduction of digital technologies are most pronounced among female workers. In other words, digitalization seems to be an example of gender-biased technological change.

Table 6: Heterogeneity across gender and sector

∆Investor – Non-investor on average…	Gender		Sector	
	(1) Male	(2) Female	(3) Production	(4) Service
Days employed at original employer				

[18] Looking more closely at non-routine occupations, we find that there is a clear gender segregation within this task type: Females' largest occupational categories are medical-related occupations such as nurses and emergency medical services, where automated health monitoring devices have already been brought into use. In contrast, males with non-routine tasks predominantly work in building construction and as vehicle drivers, where self-driving vehicles do not have legal permission in Germany yet.

All individuals	-7.27	-62.00**	-9.89	-46.20**
Qualification level				
low-skilled	-41.61	-69.85*	-49.81	-57.66
medium-skilled	18.77	-52.83**	-0.60	-11.07
high-skilled	-79.96**	-95.24**	-24.94	-138.25**
Main task				
non-routine manual	3.60	-137.01**	33.25	-107.20**
routine manual	38.92*	-86.72*	33.80	-24.73
routine cognitive	-9.59	-31.45	-18.20	-17.45
non-routine cognitive	-51.27**	-56.00**	-57.62**	-48.28**
Days employed at other employers				
All individuals	14.19*	37.98**	13.48	33.66**
Qualification level				
low-skilled	46.87	44.16	48.99*	41.06
medium-skilled	-9.71	30.77**	1.38	6.94
high-skilled	80.34**	64.14**	44.68**	104.25**
Main task				
non-routine manual	-1.18	98.96**	-27.46	79.68**
routine manual	-12.25	53.53*	-15.99	48.80
routine cognitive	15.72	13.36	15.07	14.45
non-routine cognitive	41.40**	34.06*	53.35**	24.71
Days unemployed				
All individuals	-2.62	11.73**	-0.06	5.00*
Qualification level				
low-skilled	3.27	10.81	5.82	7.02
medium-skilled	-3.37	11.79**	-0.12	4.25
high-skilled	-2.83	12.23**	-3.98	6.20
Main task				
non-routine manual	-11.05	28.80**	-9.93	16.76**
routine manual	-6.68	19.43*	-2.66	-6.22
routine cognitive	-2.13	7.25*	2.67	-0.42
non-routine cognitive	2.78	6.76	1.06	7.17*
Days out of labor force				
All individuals	-4.29	12.28*	-3.52	7.54
Qualification level				
low-skilled	-8.53	14.88	-5.00	9.58
medium-skilled	-5.69	10.27	-0.67	-0.12
high-skilled	2.46	18.87	-15.77	27.79*
Main task				
non-routine manual	8.63	9.26	4.14	10.77
routine manual	-19.99*	13.76	-15.15	-17.85
routine cognitive	-4.00	10.85	0.46	3.42
non-routine cognitive	7.09	15.19	3.21	16.40*
No. of Investor individuals	20,249	9,819	17,438	12,630
No. of Non-Investor individuals	19,129	13,223	14,185	18,167
∑	39,378	23,042	31,623	30,797

Notes: The sample includes matched individuals who were employed on June 30, 2011 in one of the sample establishments. The information summarizes the averages over the observation period June 30, 2011 to June 30, 2016.
*** and * denote statistical significance at the 1 and 5 percent level.*

Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.

Finally, exploiting our data set's advantage that information on the adoption of latest technologies is both collected among manufacturers and service providers, we provide separate results for these two sectors. Table 6 displays the employment reactions of workers employed on June 30, 2011 in the production sector (column 3) and the service sector (column 4). Consistent with the fact that in our sample investing establishments primarily adopt autonomous and self-learning office and communication technologies, workers in the service sector are most strongly affected. Workers initially employed in service establishments record, on average, 46 days less in employment with their adopting employer and about 34 more days employed at other establishments compared to their peers in non-investing establishments. This pronounced employment reallocation in the service sector could not be investigated in extant studies on the displacement effects of industrial robots that are restricted to the manufacturing industry. Our empirical evidence confirms that cutting-edge autonomous technologies affect all types of occupations and our results highlight the importance of studying the latest technologies' diffusion across all sectors. Additional results, which are available on request, show that workers' employment adjustments are more pronounced in large adopting establishments.

6 Discussion

Our results point towards modest but statistically significant effects of the first-time introduction of digital technologies in establishments on the subsequent employment trajectories of individuals exposed to the adoption compared to similar workers in non-investing establishments. This section evaluates the robustness and validity of our results.

Appendix Table 2 shows that our main results do not depend on the applied matching technique. For ease of comparison, column 1 summarizes the results of our main specification using nearest neighbor matching with five neighbors and with replacement. Increasing the number of neighbors to 15 nearest neighbors virtually leaves our results unchanged, as reported in column 2. Columns 3 and 4 present the results of non-parametric matching estimators. The kernel matching procedure with a bandwidth of 0.03 and an Epanechnikov kernel function increases the number of control group workers but yields very similar results. Finally, applying ridge kernel matching with cross-validation for the bandwidth selection with respect to our main outcome variable days employed at the original employer, as suggested by Frölich (2004), again confirms the main results. Thus, the major conclusions of this paper are robust to the choice of the matching technique.

Our empirical strategy faces three limitations. First, our matching procedures cannot entirely rule out concerns on unobserved heterogeneity between individuals in investing and non-investing establishments. We include a battery of observable variables related to individual, job, and establishment characteristics in our propensity score estimation. The inclusion of several variables on the employment biography of individuals (such as the number of previous employers or the share of days worked in total days in the labor market) may indirectly reflect some non-observable worker characteristics like motivation or diligence at work.

Second, the German Social Security data does not record the reason why employment relationships end. Therefore, our analysis cannot distinguish whether workers separate from their employer voluntarily or are laid off against their will. On the one hand, to study the displacement effects of the latest technology adoption in the most literal sense, it would be ideal to directly measure the share of laid-off workers in investing compared to non-investing establishments. On the other hand, workers might voluntarily leave the adopting establishment for personal reasons such as skepticism towards new technologies or fear of future dismissal. Such voluntary separations are one substantial employment adjustment channel and should be taken into account even if it was possible to distinguish between voluntary and involuntary separations. Our approach does capture both involuntary and voluntary employment adjustments, but it might be fruitful to distinguish the two channels.

Third, unfortunately, our technology measure does not contain information on the exact date of digital technologies' adoption in an establishment – we only know that it took place between 2011 and 2016. We, therefore, cannot exploit differences in the adoption event timing, as for example an event study difference-in-difference approach would do. Given that we do not observe the investment date, the main employment impacts on some incumbent workers might occur after the end of our observation horizon. This suggests that our results might be a lower bound of the actual employment adjustments. It remains to future research to analyze the long-term effects of digitalization on individual workers' employment trajectories.

Concerning the external validity of our results, we would argue that Germany is a highly relevant country for studying the adoption of cutting-edge autonomous technologies given its' long-term pioneering role in developing and applying innovative technologies (in particular in manufacturing). Previous research has demonstrated that Germany holds the highest number of automation patents in machinery worldwide (Dechezleprêtre et al. 2019) and the highest robot density in Europe, which is even three times higher than in the United States (Dauth et al. 2021, Graetz and Michaels 2018). Our technology measure covers both manufacturing and service establishments and therefore broadens the scope of empirical analyses to the important dimension of cutting-edge service innovations. We believe that our results yield informative insights into workers' employment adjustment process outside Germany when keeping the following two institutional settings in mind.

First, our finding that workers in adopting establishments record on average 25 days less in employment at their original employer than comparable workers in non-investing establishments can be seen as a modest employment reaction given the observation horizon of five years. One possible explanation of this modest separation rate from adopting establishments might be employment protection legislation. German employers are restricted in their decision to lay off workers by several hurdles, such as the Employment Protection Act, collective agreements, and institutionalized forms of employee representation as works councils. In Germany, works councils voluntarily elected by an establishment's workforce are an important mediator helping to exploit the benefits of digitization for specific subgroups and mediate between management and workforce in digital technologies' implementation process (Genz et al. 2019a). Collective bargaining can play a similar role, but both bargaining coverage and works council coverage have fallen over time in Germany (Oberfichtner and Schnabel 2019). As our data set does not contain information on the existence of works councils and collective agreements in the establishments analyzed, we cannot investigate to which extent observed separations are affected by these institutions. All in all, the employment adjustments we identify for Germany may be regarded as a lower bound as compared to other institutional settings with less stringent employment dismissal protection, such as the United States.

Second, Germany is known for its' strong tradition of vocational training, which yields a relatively high share of medium-skilled employees (e.g., Zwick 2005). Formal vocational training equips workers with skills needed to conduct a specific occupation and the ability to work in complex, diversified work environments and to adapt to the changing demands of their fields. Our insight that the employment of medium-skilled workers is not much affected by the introduction of new technologies may thus be a consequence of the strong vocational training background and may not hold in other countries where formal vocational training does not play such a prominent role as in Germany.

Against this background, it is interesting that in a related empirical study for the Netherlands which also focuses on individual workers and looks at firms' expenditures for third-party automation services, Bessen et al. (2019) obtain similar insights. The automation at the firm increases the probability of incumbent workers to separate from their employer. Similar to our results, the study shows that high-skilled workers experience the highest firm separation rate, and at the same time, they can easily find re-employment at other employers. One advantage of our study is that we have reliable educational and occupational information for all individuals observed. Therefore, our approach is able to detect that it is mainly non-routine workers who separate from their original employer. Another study that at first sight seems to be related to our investigation and also covers Germany is by Dauth et al. (2021). The authors do not find evidence for increasing job displacement of manufacturing workers in Germany between 1994 and 2014, as industrial robots' adoption leads to higher occupational mobility within the original employer, and they suggest that is mainly middle-skilled workers who are strongly affected by automation in manufacturing. However, in contrast to Dauth et al. (2021), who exploit the adoption of manufacturing industrial robots across industries, our study builds on an establishment-level measure of the introduction of cutting-edge digital technologies, and we look at both service providers and production establishments. The different research designs, data sets, and observation periods of the Dauth et al. (2021) and our study make comparisons difficult, but it becomes apparent that it is fruitful to move beyond the manufacturing sector and industrial robots when investigating the labor market effects of the latest technologies.

7 Conclusion

Based on a unique linked employer-employee data set for Germany and applying a direct measure of the first-time introduction of cutting-edge digitalization technologies within establishments between 2011 and 2016, this paper has analyzed the employment development of individual workers exposed to digitalization. Using a matching approach, we focus on workers who were employed in 2011 in establishments that did not use any digital technologies and compare the labor market histories of similar employees in establishments that introduced digital technology and in establishments that did not make such an investment. Although the first-time introduction of digital technology may be an endogenous decision of the plant, it can be regarded as an exogenous shock to these plants' employees.

We first show that the employment stability of incumbent workers is lower in establishments investing in digital technologies than in non-investing establishments. Our results indicate that over the observation period 2011 to 2016, individuals at investing establishments record, on average, 25 days less in employment with their original employer than comparable workers in non-investing establishments. However, these workers are on average 22 more days employed at other establishments and there is no sizeable difference in days in unemployment or out of the labor force. Thus, the digitalization shock does not seem to hit workers severely – at least in our observation period characterized by an economic upswing and rising employment in Germany.

Our second key contribution is to document substantial heterogeneities in the employment effects across skill groups, occupational tasks performed, and gender. The reduction in the number of days spent at the original employer following the introduction of digital technologies is particularly pronounced for low-skilled and high-skilled workers, whereas medium-skilled workers with vocational training experience high employment stability. Interestingly, the new digital technologies mainly seem to affect workers with non-routine tasks. They spend significantly fewer days at their original employer in investing than non-investing establishments, no matter whether they are doing manual or cognitive non-routine work. These results suggest that modern digital technologies penetrate into areas that used to be regarded as safe havens of employment, such as high-skilled work and non-routine tasks.

Since women predominantly work in non-routine service occupations whereas men disproportionally conduct routine manual occupations, we also investigate heterogeneous employment adjustments across gender. Female workers are, on average, two months less employed in adopting establishments compared to control group workers, whereas no statistically significant difference between males in adopting and non-adopting establishments arises. At the same time, women experience more days unemployed and out of the labor force after separating from adopting establishments compared to control group workers whereas men, on average, do not experience such problems. Digitalization thus does not seem to be gender-neutral.

Concerning avenues of future research, the fact that our data enables us to include establishments both from the service and the production sector in the analysis and that we find workers to be affected by the adoption of new technology particularly in the service sector has an obvious implication. We suggest including service technologies and the service sector in the scope of further research when measuring the displacement effect of the latest technologies beyond industrial robots. While we have focused on the employment adjustment of the pre-existing workforce, future research could address the employment prospects of individuals joining the adopting establishments after the digital investment took place. In an aggregate perspective, it also might be interesting to see how employee turnover and total employment growth of adopting establishments differs from non-adopting establishments. Only if we know both the micro and macro effects of digitalization, economic and social policy will be able to pursue sustainable strategies for securing jobs and fostering employment growth.

All in all, our results underline the importance of tackling the impending digital divide among different groups of workers. To ensure that all employees keep pace with technological change, internal training and lifelong professional development should become of utmost importance, as stressed, e.g., by the Skills Strategy of the OECD (2019). The aim of labor market policy should be to provide incentives for educational upgrading that fits future technologies' needs. At the establishment level, prudent human resource management should offer occupational training opportunities that enable all employees to work in a digitalized work environment in the future. In addition, individual workers must be prepared to adapt to new work environments and to explore new activities in an increasingly digitalized world of work.

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APPENDIX

A.1 APPENDIX TABLES

Appendix Table 1: Technology class description

Technology Class	Degree of automation	Examples for work equipment: Production technologies	Examples for work equipment: Office and communication technologies
1.0/2.0	No automation: Humans operate equipment manually	• drilling machines • cars • X-ray machines	• telephones • fax machines • photocopiers
3.0	Semi-automation: Humans are indirectly involved in the work process	• CNC-machines • industrial robots • process plants	• computers • electronic cash registers • CAD-systems
4.0	Full-automation: Equipment conducts work process self-contained and automatically	• smart factories, • cyber-physical/ embedded systems • internet of things	• big data analytical tools • cloud computing systems • shop systems

Notes: This table describes the degree of automation across different technology classes, separately for production and office and communication technologies. The higher the technology class, the higher the degree of digitization/automation of the technology. The questionnaire contains this description, and each respondent receives these explanations and examples.
Source: IAB-ZEW Labor Market 4.0 Establishment Survey.

Appendix Table 2: Labor market experience of individuals - Results of different matching approaches

Average…	(1) NN5	(2) NN15	(3) Kernel	(4) Ridge CV
Days employed at original employer				
All individuals	-25.14**	-24.16**	-22.86**	-24.35**
Qualification level				
low-skilled	-52.99*	-51.59*	-40.83	-39.19
medium-skilled	-4.73	-10.33	-10.65	-11.19
high-skilled	-84.20**	-60.49**	-59.22**	-65.96**
Main task				
non-routine manual	-68.77**	-66.53**	-66.66**	-54.53**
routine manual	22.79	15.35	0.37	2.90
routine cognitive	-17.90	-14.06	-4.86	-11.82
non-routine cognitive	-52.90**	-49.91**	-46.48**	-48.92**
Days employed at other employer				
All individuals	21.96**	19.59**	18.90**	20.08**
Qualification level				
low-skilled	45.78*	40.71*	35.47*	33.71
medium-skilled	3.57	8.38	6.50	7.07
high-skilled	75.84**	49.64**	56.86**	61.84**
Main task				
non-routine manual	50.36**	51.57**	48.65**	38.23*
routine manual	-3.81	-1.92	6.90	7.46
routine cognitive	14.82	7.99	2.55	7.32
non-routine cognitive	38.87**	37.64**	36.94**	38.12**

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Days unemployed				
All individuals	2.06	2.19	3.21*	2.77*
Qualification level				
low-skilled	6.31	6.24	8.42	7.04
medium-skilled	1.60	1.85	2.68	2.40
high-skilled	1.35	1.20	2.23	1.70
Main task				
non-routine manual	9.46	7.99	9.83	8.22
routine manual	-3.33	-2.40	0.25	-1.38
routine cognitive	1.43	2.65	2.67	3.19
non-routine cognitive	4.15*	3.03	3.89*	3.56
Days out of labor force				
All individuals	1.12	2.39	0.74	1.50
Qualification level				
low-skilled	0.90	4.63	-3.06	-1.56
medium-skilled	-0.45	0.11	1.48	1.73
high-skilled	7.02	9.65	0.13	2.42
Main task				
non-routine manual	8.96	6.97	8.18	8.09
routine manual	-15.66	-11.03	-7.51	-8.98
routine cognitive	1.64	3.42	-0.35	1.32
non-routine cognitive	9.88*	9.25*	5.65	7.24
No. of Investor individuals	30,068	29,794	29,475	29,568
No. of Non-Investor individuals	32,352	42,310	48,899	49,109
∑	62,420	72,104	78,374	78,677

Notes: The sample includes matched individuals who were employed on June 30, 2011 in one of the sample establishments. The information summarizes the averages over the observation period June 30, 2011 to June 30, 2016. All matching procedures are restricted to the optimal interval of common support following the approach of Crump et al. (2009), which yields in our case α=0.107 as optimal bound. Column 1 presents our main results of nearest-neighbor matching using 5 neighbors. In column 2, nearest-neighbor matching using 15 neighbors is deployed. Column 3 shows the results of kernel matching with an Epanechnikov kernel function and imposing a bandwidth of 0.03. Results of a ridge kernel matching with cross-validation for the bandwidth selection with respect to the main outcome variable days employed at the original employer as suggested by Frölich (2004) is used. The ridge kernel matching further applies an Epanechnikov kernel function and uses the proposed ridge parameter of 5/16 as proposed by Frölich (2005).*

*** and * denote statistical significance at the 1 and 5 percent level.*

Source: IAB-ZEW Labor Market 4.0 Establishment Survey, IEB; own calculations.

A.2 Data procession

A.2.1 Harmonizing missing information in occupation notifications

Due to the change in the occupational code of the employment notifications from KldB1988 to KldB2010 in 2011, the fraction of employment spells with missing occupational information is significantly higher in notifications between January 2011 and June 2012. We reduce the missings in the occupational variable in a two-step procedure. First, if the employment relationship between individuals and establishments continues between 2011 and 2012, the first occupational information in the new classification code KldB2010 is transferred back to the missing values in employment spells between 2011 and 2012. For remaining missing information in occupational notifications, the last notified occupational code of the year 2011 is transferred forward to spells between 2011 and 2012. Second, if the individual changes employers between 2011 and 2012, the first occupational information in the new classification code KldB2010 is transferred back to the missing values in employment spells of former work relations between 2011 and 2012. For remaining missing information in occupational notifications, the last notified occupational code of the year 2011 is transferred forward to any employment spell between 2011 and 2012.

A.2.2 Harmonizing missing information in nationality notifications

Within the obligatory employment notification process, it may occur that the employer does not report the nationality of the worker to the Federal Agency. For individuals with gaps in the nationality notifications but otherwise consistent reports of one single nationality, the notified nationality is transferred to periods with missing information, if the predecessor and successor nationalities are the same. In very rare cases, no employer notifies a nationality in the employment notifications. We assume that those individuals are not from German origin and assign them the code "unknown foreign country".

A.2.3 Selection of main spell

The Integrated Employment Biographies (IEB) comprise the universe of individual labor market data of the Institute for Employment Research. The data set contains information on employment, benefit receipt, participation in measures of active labor market policy and job search. As a result, one person may have multiple notifications at the same time, for example, an employment spell and a parallel job-search spell. Given the aim to identify the employment effects of individuals exposed to digitalization, we simplify this complex data structure by selecting only one primary spell at each point in time. First, in case of parallel non-employment notifications, we choose Benefit Recipient Histories (LeH) over Unemployment Benefit II Recipient Histories (LHG), Participants-in-Measures History Files (MTH and XMTH) and Jobseeker Histories (ASU and XASU). Second, if employment and non-employment spells occur to the same point in time, we keep the employment notification. Third, for parallel employment notifications within the same establishment, we prioritize the notification with a higher wage, prioritize regular employment over other types of employment, prioritize longer durations of the original notification and sort according to the reasons of notification. Fourth, for parallel employment notifications across different establishments, we prioritize the notification with higher wage, prioritize regular employment over other types of employment, prioritize longer durations of the original notification, prioritize the longer employment duration in the establishment, prioritize employment notifications in sample establishments over other establishment notifications, and prioritize those notifications with fewer missing information in important control variables (education, full-time employment and occupational tasks).